Evaluation of pre-processing techniques for the analysis and recognition of invoice documents

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Dissertation submitted in *partial* fulfilment of the requirements for the degree *Magister Scientiae* in Computer Science at the Potchefstroom Campus of the North-West University

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November 2015

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ACKNOWLEDGEMENTS

I would like to thank Prof Magda Huisman for her continuous guidance and inspiration throughout my years at the university. I would not have been able to make it this far without her. I would also like to thank Prof Gunther Drevin for his input, ideas, and wisdom that allowed me to successfully conduct experiments that yielded meaningful results. Lastly, I would like to thank all the Computer Science lecturers at the NWU for educating me and providing me with an environment in which I could learn and grow to prepare myself for the world.

The financial assistance of the National Research Foundation (NRF) towards the work done in this research is hereby acknowledged. Opinions expressed and conclusions arrived at are those of the author and are not necessarily to be attributed to the NRF.

ABSTRACT

The automatic extraction and handling of information contained on invoice documents holds major benefits for many businesses as this could save many resources, which would otherwise have been spent on manual extraction. Document Analysis and Recognition (DAR) is a process, which makes use of Optical Character Recognition (OCR) for the recognition and analysis of the contents of physical documents in order to digitally extract and process the information. It consists of four steps, namely pre-processing, layout analysis, text recognition, and post-processing.

Pre-processing is used to improve the overall quality of a document image in order to prepare it for the steps that follow. Techniques used for pre-processing have a direct influence on the resulting OCR accuracy as any small deficiencies that pass through this stage are dragged along the rest of the OCR process and ultimately recognized incorrectly. A significant contribution can be made to the relevant research areas and business communities by revealing which pre-processing techniques are the most effective for the analysis and recognition of invoice documents.

In order to approach this problem, an exploratory study was first conducted. Case studies were used during which owners and CEOs of five DAR-related companies were interviewed. Transcriptions and content analysis of these semi-structured interviews allowed prevalent themes to emerge from the data.

The second study was an experimental investigation. The experiments conducted involved taking a number of invoice document images, performing various pre-processing techniques on the images, and measuring the effect of the techniques on the recognition rates. By acquiring the recognition rates of the different techniques, it was possible to quantitatively compare the techniques with each other.

It was revealed that many businesses in the DAR industry make use of the same business process. Much was learnt about the DAR-related software used in the industry, how Intelligent Character Recognition (ICR) should be approached, and what the best scanning practices are. It was also discovered that the use of paper-based information and the need for the electronic processing thereof is increasing, thereby securing the future of the industry. Regarding the efficiency of pre-processing techniques, it was successfully revealed that some techniques do perform better than others. In addition, many findings were made regarding the functioning of some of the techniques used for the experiments.

SAMEVATTING

Die outomatiese onttrekking en hantering van inligting op faktuurdokumente hou groot voordele in vir baie besighede omdat dit hulpbronne kan spaar wat andersins vir data-onttrekking gebruik sou word. Dokumentanalise en Herkenning (DAR) is 'n proses wat gebruik maak van Optiese Karakterherkenning (OCR) vir die herkenning en ontleding van inhoud op dokumente sodat die inligting daarop digitaal onttrek en verwerk kan word. Die proses bestaan uit vier stappe, naamlik voorverwerking, uitleganalise, teksherkenning, en na-verwerking.

Voorverwerking word gebruik om die algehele gehalte van 'n dokumentbeeld te verbeter om dit voor te berei vir die stappe wat volg. Tegnieke wat gebruik word vir die voorverwerking het 'n direkte invloed op die OCR-akkuraatheid omdat enige klein tekortkominkie wat in hierdie stap ontstaan, saamgesleep word deur die res van die OCR-proses en uiteindelik verkeerd herken word. 'n Beduidende bydrae kan aan die relevante navorsings-gebiede en sakegemeenskappe gelewer word deur die voorverwerkingstegnieke wat die doeltreffendste is vir die analise en herkenning van faktuurdokumente te identifiseer.

Om hierdie probleem te benader is 'n verkennende studie uitgevoer. Daar is gebruik gemaak van gevallestudies waartydens 'n aantal onderhoude met mense in die DAR-bedryf gevoer is. Transkripsies en inhoudontleding van hierdie semi-gestruktureerde onderhoude het gelei tot die ontdekking van algemene temas in die data.

Vervolgens is 'n eksperimentele ondersoek uitgevoer. Gedurende die eksperimente wat uitgevoer is, is 'n aantal van die faktuurdokumentbeelde geneem en verskeie voorverwerkingstegnieke is op die beelde toegepas. Die invloed van die tegnieke is toe geneem deur na die herkenningresultate te kyk. Deur die verkryging van die herkenningresultate van die verskillende tegnieke, was dit moontlik om die tegnieke kwantitatief met mekaar te vergelyk.

Daar is ontdek dat baie besighede in die DAR-bedryf van dieselfde besigheidsprosesse gebruik maak. Daar is baie geleer oor die DAR-verwante sagteware wat in die bedryf gebruik word, hoe Intelligente Karakterherkenning (ICR) benader moet word, en wat die beste praktyke rakende skandering is. Daar is ook ontdek dat die gebruik van papiergebaseerde inligting en die behoefte aan die elektroniese verwerking daarvan aan die toeneem is. Ten opsigte van die doeltreffendheid van voor-verwerkingstegnieke, is daar suksesvol getoon dat sommige tegnieke beter presteer as ander. Daar is ook baie bevindinge gemaak ten opsigte van die funksionering van 'n paar van die tegnieke wat vir die eksperimente gebruik word.

KEY TERMS

OCR	**Optical Character Recognition**. The identification and digitization of printed characters on a document image. See Section 2.2, p. 7.
ICR	**Intelligent Character Recognition**. The identification and digitization of handwritten characters on a document image. See Section 2.2, p. 7.
DAR	**Document Analysis and Recognition**. The automatic extraction and processing of information presented on paper. See Section 2.3, p. 11.
Pre-processing	The first step in the DAR process; pre-processing aims to improve image quality for better recognition results. See Section 2.3.1, p. 11.
Noise reduction	A pre-processing step, which attempts to remove noisy pixels from an image. See Section 2.3.1.2, p. 13.
Binarization	A pre-processing step, which converts a greyscale image into a bi-level representation in order to separate the foreground from the background. See Section 2.3.1.3, p. 14.
Exploratory study	The first study of this research, which is used to gather more information before beginning with the experimental investigation. See Chapter 4, p. 40.
Experimental investigation	The second study of this research, which consists of experiments that compare the performance of pre-processing techniques. See Chapter 5, p. 47.
Ground truth text	The actual text that is contained in the original, unaltered document images. See Section 5.6, p. 60.

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CHAPTER 1 – INTRODUCTION

1.1 Introduction

The automatic extraction and handling of information contained on invoice documents holds major benefits for many businesses as this could save many resources, which would otherwise have been spent on manual extraction. The use of paper documents in the office is ineffective as documents are frequently copied, updated, written upon, and degraded. Electronic documents, on the other hand, always contain the updated information, are simultaneously available to all their users, and do not waste paper or space (Stoliński & Bieniecki, 2011:1). It is clear that digitization of information contained on paper documents is a good idea, but the implementation thereof is regrettably not as straight forward (Gatos *et al.*, 2014:131).

High quality documents that have been printed with a decent printer on good quality paper, have the potential to obtain higher than 99% recognition accuracy (Stoliński & Bieniecki, 2011:1). Documents used within businesses are unfortunately rarely of high quality, as they are often affected by degradation caused by age, photocopying, faxing, mark-up, etc. Techniques used during the pre-processing phase of the Document Analysis and Recognition (DAR) process attempt to remedy as many of these quality shortcomings as possible in order to improve the resulting recognition accuracy. These techniques are referred to as image enhancement techniques, and they have applications in many areas, such as medicine, space exploration, automated industry inspection, authentication, etc. (Vidyasaraswathi & Hanumantharaju, 2015:48).

Marinai (2008:1) points out that there are studies that reveal how paper is still being used as a medium for information, and its use is actually increasing. In addition, there are some application areas where paper is actually the favoured medium for knowledge work. This includes authoring work, reviewing documents, planning or organization, collaborative activities, and organizational communication (Sellen & Harper, 2003:3).

The rest of this chapter will be used to provide a problem statement in Section 1.2, and to state the research objectives, approach, and contributions in Section 1.3.

1.2 Problem statement

Document Analysis and Recognition is the complete process of analysing and recognizing the components of physical documents in order to digitally extract the information (Marinai, 2008:1). The DAR process starts off with a scanned document image, and consists of the following four phases (Marinai, 2008:4):

1. Pre-processing – The overall quality of the image is improved and the image is prepared for the processes to follow.

2. Layout analysis – The components of the document image are identified and classified.

3. Text recognition – This involves the conversion of the document image's text into a machine-understandable format. A process called Optical Character Recognition (OCR) is used for this.

4. Post-processing – The results of the recognition are verified based on the contextual information.

Techniques used for pre-processing have a direct influence on OCR accuracy (Khurshid *et al.*, 2009:72; Robertson *et al.*, 2014:167). It is also believed that these techniques could be the main source of various errors (Neves *et al.*, 2013:107; Patvardhan *et al.*, 2012:60). The reason for this is that any small deficiencies that pass through this stage, are dragged along the rest of the OCR process. For instance, noise speckles that are not removed during the pre-processing phase will move along to the text recognition phase and will mistakenly be identified as text. It is clear that pre-processing techniques are important, and the improvement thereof might lead to higher recognition rates on poor quality documents (Shivakumara *et al.*, 2005:140).

Organizations, such as DIBCO (Document Image Binarization COntest), DISEC (Document Image Skew Estimation Contest), and the ICDAR Table Detection and Structure Recognition Competition host contests in which participants compete to determine who is able to provide the most accurate pre-processing (binarization and skew estimation) and layout analysis (table detection and structure recognition) techniques.

There are many studies that attempt to compare pre-processing techniques with one another (Gupta et al., 2007:389; He et al., 2005:538; Shivakumara & Kumar, 2006:791), but according to the author none which do so specifically for invoice processing. This is surprising because of the large quantity of invoice processing software, which makes use of these techniques. This includes software, such as ABBYY FlexiCapture, EMC Captiva InputAccel, and PSI:Capture.

Vamyakas *et al.* (2008:525) point out the importance of having effective systems for processing documents because of the abundance of documents that exists in the world today, be it modern or historical. There is clearly a great need for the recognition and processing of scanned images. Using only manual data extractors for the processing of hundreds of thousands of documents seems nearly impossible when considering the logistics thereof.

In this study, the most effective pre-processing techniques to be used for the optimal recognition accuracy of invoice documents will be identified. This study will, however, be limited to noise reduction and binarization techniques, since these are two of the main pre-processing technique categories that directly affect the final recognition accuracy. The research will be done by comparing pre-existing techniques with one another and then measuring how the techniques affected the resulting recognition accuracy.

1.3 Research objectives

The main objective of this research is to compare various pre-processing techniques with one another in order to determine the most effective techniques to be used for invoice processing. In order to do this, the following objectives must be achieved:

1. Understand the functioning of the current DAR industry in South Africa.
2. Identify the different techniques used for pre-processing and establish how they work.
3. Determine what makes invoice documents unique from other documents.
4. Set up a platform in which different techniques can be compared to one another in respect of recognition accuracy, specifically for the recognition of invoices.
5. Compare different techniques with one another in order to determine the optimal results.
6. Analyse and review the results of the comparisons.
7. Suggest techniques that would provide optimal recognition accuracy.

In order to achieve the research objectives, two studies will be conducted, namely an exploratory study, and an experimental investigation. The exploratory study will consist of case studies during which companies that are involved in the DAR industry in South Africa will be interviewed in order to gather background information on the topic. This study is discussed in detail in Chapter 4. Once this is done, the experimental investigation will commence. Experiments will be conducted to determine which pre-processing techniques are the most effective. Chapters 5 and 6 will be used to discuss this process and the findings.

An academic and practical contribution will be made by achieving the desired objectives. On an academic level, the creation of an experiment method that could be used to compare the techniques could be used for future experiments. This method could be expanded upon in order to compare other techniques on different types of image. This study will also reveal the pre-processing techniques with the best performance on invoice documents. Explanations of the

results will reveal valuable insights into how these techniques work and why they work the way they do when applied to typical invoice documents.

For practical use, understanding the functioning of the DAR industry in South Africa could allow aspiring businesses to adjust their practices according to the knowledge gained. Furthermore, businesses could make use of the information regarding the most effective techniques in order to attempt to improve their recognition accuracy. Being able to find the optimal techniques for invoice processing will allow businesses to extract invoice data into their systems more accurately. This will save businesses time and money by allowing them to reallocate manual data capturers to other important tasks. Businesses could also learn more about the functioning of these pre-processing techniques, and apply the knowledge to their own DAR systems for better results.

1.4 Summary

In this chapter, it was revealed that automatic information extraction from invoice documents is something from which most businesses could benefit. The DAR process is used for this purpose, however there are many difficulties. One of the most prominent difficulties that makes DAR on invoice documents difficult is the poor quality of documents most businesses have to deal with. Fortunately, the pre-processing phase of the DAR process is capable of enhancing the quality of document images. Two main types of pre-processing techniques that have a direct influence on the recognition accuracy are noise reduction, and binarization. During this study, various techniques will be compared to each other in order to determine which noise reduction techniques and which binarization techniques are the most effective.

The rest of this dissertation is broken down into the following chapters:

- **Chapter 2 – Literature review**: The existing literature on the topic is revealed and discussed. This chapter will elaborate on OCR technologies, its history, recent trends and movements, and its applications. This chapter will also provide an in-depth explanation of DAR and all its phases; pre-processing, layout analysis, text recognition, and post-processing. Lastly, the functioning of the techniques to be used in this study will be discussed.

- **Chapter 3 – Research method**: This chapter will be used to explain the research approach taken for this study. This includes a look at the philosophical paradigms, research strategies, data-gathering techniques, and data-analysis techniques.

- **Chapter 4 – Current state of DAR in South Africa**: An exploratory study, which focuses on the DAR industry in South Africa, is revealed and discussed in this chapter.

- **Chapter 5 – Experimental investigation**: The technical details concerning the execution of the experiments for this research study are explained.

- **Chapter 6 – Results and discussion**: The results retrieved from the experiments are analysed and discussed.
- **Chapter 7 – Conclusion**: The final conclusions regarding the research studies are drawn and recommendations for future work are made.

CHAPTER 2 – LITERATURE REVIEW

2.1 Introduction

In the business world of today, information is one of the most important assets. Documents are used to store a collection of information. The two main mediums for preserving information in documents are physical paper-based documents and digital documents. Digital documents, which were brought on by the advent of personal computers, are still relatively new to the world. Physical documents, such as books, manuscripts, newspapers, etc. have, however, existed for a very long time.

Documents that are electronically created could easily be printed in order to convert them to physical documents, but the conversion of physical documents into machine-understandable digital documents is a whole different process (Shafait, 2009:1). There is a great need for the effective conversion of physical documents to electronic documents in the commercial world (Gupta *et al.*, 2006:58). Two main reasons for this are the preservation of historic documents, and the analysis and processing of physical documents into information systems (He *et al.*, 2005:538).

Figure 2-1 could be used to guide the reader through this chapter. The following section will be used to discuss OCR, as it is basically the driving force behind the DAR process. The history of OCR will be discussed in Section 2.2.1, followed by the development of new technologies in Section 2.2.2, applications of OCR in Section 2.2.3, and then recent trends and movements in Section 2.2.4. Once the basic concepts of OCR have been discussed and understood, the DAR process will be addressed. This is done in Section 2.3, where the pre-processing, layout analysis, text recognition, and post-processing phases are discussed in Sections 2.3.1 - 2.3.4, respectively. Lastly, the functioning of the techniques to be used for the experimental investigation are explained in Section 2.4, with all the noise reduction techniques in Section 2.4.1 and all the binarization techniques in Section 2.4.2.

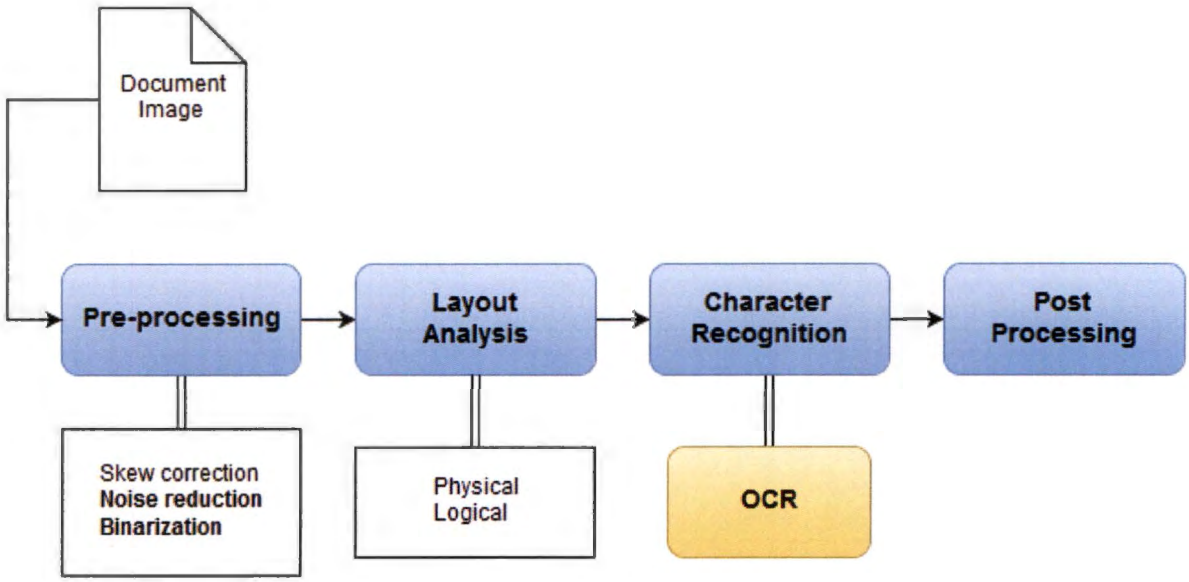


Figure 2-1 DAR process illustration

2.2 Optical Character Recognition

Optical Character Recognition could be defined simply as the identification of characters on a document image (Mori *et al.*, 1999:1). There are a handful of different approaches to the implementation of OCR.

According to Shivakumara *et al.* (2005:140; 2006:791), an OCR system makes use of four distinct phases. These are the pre-processing stage, a document layout understanding and segmentation stage, a feature extraction stage, and a classification stage. On the other hand, Shafait (2009:1) stated that a typical OCR system comprises three main components. The first is geometric layout analysis, which is used to locate the text lines in the scanned documents and to identify their order. The second component is text-line recognition, where the characters in the text lines are classified into recognized letters of a predefined alphabet. The last component is language modelling, which attempts to correct OCR errors from the text-line recognition output by using language specific information. Jung *et al.* (2004:980) make use of the term 'text information extraction', which is approached in five steps: text detection, text localization, tracking, extraction and enhancement, and recognition. Another version of this exists where text detection and text localization are merged into a single phase, and text tracking falls away completely (Zhang *et al.*, 2013:312). It is important to note, however, that text information extraction aims at the extraction of text from any type of image, including scene photos, videos, etc., which explains why there is a tracking step.

All these approaches have more or less the same steps in common. Most of these steps could fit somewhere into the DAR process (see Figure 2-1). This means that OCR should not be seen as a step in the DAR process, but rather as the underlying body of the process.

Another important topic that relates to OCR is Intelligent Character Recognition (ICR). ICR could be seen as handwriting recognition, and split up into two categories: off-line and on-line categories (Zagoris *et al.*, 2010:873).

On-line handwriting recognition makes use of techniques that automatically capture and process the characters as they are being written (Plamondon & Srihari, 2000:67). This is done by using a digitizer or an instrumented stylus, which records information about position, velocity, or acceleration over time.

Off-line handwriting recognition is the optical recognition of handwritten text. An off-line handwriting recognition system follows more or less the same process as a normal OCR system (Plamondon & Srihari, 2000:72). The document image is first handed into a pre-processing module for enhancement, after which it is imported into the segmentation model where each character is segmented. Segmented characters are then sent into the recognition module for identification, and the recognized characters are then sent to the post-processing module to be verified based on its context. The text is then ready to be displayed and used as computer-understandable text (Zagoris *et al.*, 2010:872).

On-line recognition usually makes use of tablet PCs as input with real-time acquisition and processing of the written text, whereas scanners are normally used for off-line systems (Marinai, 2008:8).

There are a couple of issues regarding the recognition of handwritten text, which include the following (Zagoris *et al.*, 2010:872):

- The quality of scanned images may not be optimal, which means that pre-processing steps need to be taken in order to enhance the quality.
- Recognition of handwritten text could be challenging because of characters that are intertwined.
- Each person has his/her own unique writing style.
- The absence of standard alphabets and the frequent use of unknown fonts make it difficult to develop a system that is able to recognize historical handwritten text (Vamvakas *et al.*, 2008:525).
- ICR is very challenging due to the cursive and unconstrained nature of handwritten text (Choudhary *et al.*, 2013:89).

The experiments of the study will focus solely on printed text, therefore ICR will not be implemented. The exploratory study, found in Chapter 4, does, however, investigate the use of ICR.

2.2.1 History of OCR

When pattern recognition was still in its infancy, most of the people involved were interested in OCR (Mori *et al.*, 1992:1029). It is stated that in 1929 G.Tauschek obtained a patent on OCR as the 'Reading Machine' in Germany, and in 1933 P.W. Handel obtained a patent in the USA as a 'Statistical Machine'. These were the first concepts of OCR (Mori *et al.*, 1992:1030). This concept would remain impossible at the time because of the lack of technology to support it, until the availability of transistor computers in the 1950s.

In 1956 Kelner and Glauberman made use of a magnetic shift register in order to project two-dimensional information into one-dimensional information (Mori *et al.*, 1992:1030). This means that only one line of characters could be scanned at a time by moving either the scanner or the paper (Cheriet *et al.*, 2007:2). This allowed them to apply template-matching methods by taking the total sum of the differences between sampled and corresponding values measured.

In 1962 W.J. Hannan created a very sophisticated technology which made use of both electronics and optical techniques. The machine was successful and Hannan reported that the program could use the mask-matching technique to accurately recognize the complete English and Russian fonts (Mori *et al.*, 1992:1031).

New fonts, named OCRA and OCRB, were designed in the 1970s specifically for the purpose of OCR. The fonts were designed by the American National Standards Institute (ANSI) and the European Computer Manufacturers Association (ECMA), respectively (Cheriet *et al.*, 2007:2). These fonts allowed for much higher OCR accuracy rates as opposed to OCR techniques applied to other fonts and entirely transformed the data-input industry (Schantz, 1982:4).

2.2.2 Development of new techniques

As the research on OCR evolved over the years, people started demanding advances on handwriting recognition in order to be able to process large quantities of data from various sources (Cheriet *et al.*, 2007:3). This included addresses written on envelopes, amounts written on checks, names, identity numbers, values written on invoices and forms, etc.

The advancement of handwriting recognition technology came a relatively long time after normal OCR on specified fonts (Cheriet *et al.*, 2007:3). This means that handwriting recognition solutions from the 1970s through to the 1980s made use of characters that had to be written in specific

shapes on allocated spaces in order for them to be understood by machines (Cheriet *et al.*, 2007:3).

2.2.3 Applications

Currently there is a considerable number of practical applications for OCR in the world. Some of these applications are document analysis, vehicle license plate extraction, technical paper analysis, object-oriented data compression, translators, video content analysers, industrial part identification, and so on (Jung *et al.*, 2004:977).

OCR applications can be divided into the following two categories (Marinai, 2008:2):

- **Business-oriented application** – As previously mentioned, the use of paper is prevalent for the purpose of storing information (Sellen & Harper, 2003:245), as many organizations today rely heavily on the flow of information. A typical business application is automatic check processing, which involves text and number recognition as well as signature verification. Other applications are information extraction from forms and invoices, and automatic document organization through use of page classification.

- **User-centred application** – User-centred applications put more focus on software tools and general purpose solutions for the individual. These applications include general purpose OCR software, recognition of printed music scores, analysis of drawings, such as maps, mobile device document processing systems, and improved access to digital libraries of historical documents and academic articles.

2.2.4 Recent trends and movements

With the recent surge in companies requiring better and more accurate OCR technologies there is a great need for research and progress in the field (Gatos *et al.*, 2014:131). The International Association for Pattern Recognition (IAPR) is a non-profit organization that aims to develop and promote pattern recognition and its related branches of engineering and science in order to stimulate research, development, and the application thereof. Some of the IAPR's international conferences and workshops are solely devoted to the rapid advancement of recognition techniques (Cheriet *et al.*, 2007:3). The most popular ones that relate to this study, are as follows:

- **ICPR - International Conference on Pattern Recognition**: A biennial conference during which the latest findings on various subjects of pattern recognition are presented. This includes various techniques, applications, comparisons, optimization methods, etc.

- **ICDAR – International Conference of Document Analysis and Recognition**: This conference presents the latest research on OCR technologies for the application on

Document Analysis and Recognition, with the most prominent subject areas as binarization, character segmentation, deskewing, noise reduction, ICR techniques, classification systems, and feature extraction improvement.

- **DAS - International Workshop on Document Analysis Systems**: A biennial conference that addresses trending research on document analysis systems. The most discussed topics at DAS include data extraction, document and text classification, document processing systems, AI applications for OCR, and real-time analysis.

- **ICFHR- International Conference on Frontiers in Handwriting Recognition**: A conference during which research on various subdisciplines of handwriting recognition and the implementation thereof is presented. This includes areas of research in on-line and off-line handwriting recognition, pen-based interface systems, form processing, handwritten-based digital libraries, and web document access and retrieval.

2.3 Document Analysis and Recognition

Shafait (2009:1) defines the term document image analysis as: "The field of converting paper documents into an editable electronic representation by performing OCR". Marinai (2008:1) provides a full definition as follows: "DAR aims at the automatic extraction of information presented on paper and initially addressed to human comprehension. The desired output of DAR systems is usually in a suitable symbolic representation that can subsequently be processed by computers".

For this study, these two definitions can be combined so that Document Analysis and Recognition could effectively be seen as the automatic extraction and processing of information presented on paper. The aim of a DAR system is to extract relevant data from the input that could then be processed and utilized by a computer program.

DAR involves the use of several classes of science, including image processing, pattern recognition, natural language processing, artificial intelligence, and database systems (Marinai, 2008:1).

The rest of this section will be used to discuss all the steps of the DAR process as illustrated in Figure 2-1, p. 7.

2.3.1 Pre-processing

The pre-processing step aims to improve image quality for better recognition results. This is also known as image enhancement. This step normally includes the following tasks:

- **Geometrical transformations** – Deskewing of the image. This will be discussed in subsection 2.3.1.1, p. 12.

- **Filtering** – There are three main filtering operations applied to the input image. These are

    - **Noise reduction** – Remove grainy, unwanted, salt-and-pepper-like textures from image. This will be discussed in subsection 2.3.1.2, p. 13.

    - **Signal enhancement** – Improve overall quality of image.

    - **Binarization** – Convert the image from RGB or greyscale to a binary image. This is usually accomplished by using a thresholding algorithm, which separates the background from the foreground. This will be discussed in subsection 2.3.1.3, p. 14.

- **Object boundary detection** – Detect object boundaries by making use of methods, such as the Hough transform.

- **Thinning** – Used to obtain skeletal remnants of objects, which preserves the connectivity while getting rid of unwanted foreground components.

In a 1974 study, which attempted to compare OCR algorithms by use of simulation, Himmel and Peasner (1974:239) stated that the purpose of the pre-processing step is to remove noise, fill in broken strokes, and to handle text-size variation. By comparing this to the purpose of relatively modern OCR pre-processing steps, it is clear that the pre-processing phase has evolved in order to attempt to optimize the efficiency of OCR.

The following techniques form part of the pre-processing phase:

2.3.1.1 Skew correction

Skew correction, also known as deskewing or skew detection, is the process that detects the deviation of the document image's orientation angle from the horizontal direction (Shafait, 2009:4). This is normally because the document to be scanned is placed on the scanner incorrectly (Ishitani, 1993:49). Liolios *et al.* (2002:253) add to this by saying that it could also be because the document could be stretched in a non-uniform manner due to the inconsistent motor speed of a scanning or copy machine.

A skew document image will have an adverse effect on document analysis, document understanding, and character segmentation (Ishitani, 1993:49). This is backed up by Shivakumara *et al.* (2006:791) who claim that most of the OCR stages will be ineffective when

applied to a skew document image. This led to the development of a couple of skew detection techniques.

Skew correction is important for several reasons (Bloomberg *et al.*, 1995:303). Firstly, it improves text recognition accuracy by making text easier to understand by character recognition systems. Secondly, it simplifies interpretation of page layout by making text lines and text columns easier to identify. It also improves baseline determination, and the overall visual appearance of the document.

For a skew correction system to be effective, it should be able to operate quickly regardless of the content of the image. It should consistently deskew images accurately with less than 0.1° error. In addition, segmentation of the image should not be necessary, skews should be able to be adjusted locally or globally, and a confidence measure or probable error estimate should be produced. Lastly, graphics within the image should not affect the results (Bloomberg *et al.*, 1995:302).

2.3.1.2 Noise reduction

Noise reduction is the process, which attempts to remove noisy pixels from a document image, which were caused by the scanning or binarization process (Shafait, 2009:4). Many types of noise could occur after the binarization of an image (Dassanayake *et al.*, 2013:2). Some of the noise types dealt with in this study are

- **Gaussian**: Gaussian noise is statistical noise which is additive in nature. This noise has a probability density function (PDF) which makes use of the Gaussian distribution. The PDF of a Gaussian random variable, z, is given by:

$$p(z) = \frac{1}{\sqrt{2\pi\sigma}} e^{-(z-\mu)^2/2\sigma^2} \quad (1)$$

  Where z is the intensity, μ is the average of z, and σ is the standard deviation (Gonzalez & Woods, 2006:314).

- **Poisson**: Poisson noise, or shot noise, is a type of digital noise that results when the amount of energy carrying particles in an optical device is so little that it noticeably fluctuates measurements (Patidar & Nagawat, 2010:47). Poisson noise is generated from the image data instead of being added artificially. The noise generated has a root mean square value proportional to the square root intensity of the image. Poisson noise corrupts the image by various proportions based on the input pixel values (Verma & Ali, 2013:618).

- **Salt-and-pepper**: This is also known as impulse noise. It consists of black and white dots that appear randomly throughout the image. This type of noise can be caused by dust particles in the scanner or by overheated components that are malfunctioning (Verma & Ali, 2013:617).

- **Speckle**: Speckle noise is caused by the coherent processing of backscattered signals from multiple distributed targets (Verma & Ali, 2013:618). Speckle noise is multiplicatively added to an image using the following equation:

$$J = I + n * I \quad (2)$$

  Where I is the original image, and n is uniformly distributed random noise with 0 mean and a specified variance v.

The descriptions of various noise reduction methods that are used during this study are further discussed in Section 2.4.1, p. 19.

2.3.1.3 Binarization

Binarization is the process of converting a greyscale document image into a bi-level representation, i.e. from where each pixel is represented by a greyscale value of 0 to 255, it is now represented by either a 0 or a 1 (Shafait, 2009:4). Binarization is one of the main processes in OCR and it should fundamentally provide the user with the foreground text in black, and the noisy background in white (Khurshid *et al.*, 2009:72). Like most image processing methods, some binarization methods might work better for some types of document while they provide inaccurate results for other types.

The descriptions of various binarization methods that are used during this study are further discussed in Section 2.4.2, p. 22.

2.3.2 Layout analysis

Also referred to as object segmentation, this component deals with the identification of objects within an input document. This is done by making use of word segmentation with methods, such as morphological processing and connected components clustering. Morphological processing deals with the extraction of useful components within an image. Connected components clustering is a morphological processing technique where all the pixels of the same type that are connected to each other are grouped together.

Layout analysis is performed to categorize objects within the document image into homogeneous content regions with their own meanings (Marinai, 2008:6). Gupta *et al.* (2006:58) state that document layout analysis is said to be the most crucial step in the DAR process, and define it as

"the function of separating text, graphics, and images, and then extracting isolated text blocks (layout objects) such as titles, paraphrase, headers, footers, and captions".

In order to build a comprehensive layout analysis system, the following should be taken into consideration (Ishitani, 1997:45):

- Pages could contain a combination of text, mathematical expressions, images, graphics, charts, and tables.
- Text within a page may be any language, font style, or character size. A combination of this can also occur.
- A document can contain both horizontal and vertical text areas.
- Documents have a complicated and irregular layout structure.

The extraction of information in text from documents with various formats is very challenging because the documents do not have precisely the same formats. Templates are generally format specific and systems are not really designed to allow the users to generate and input their own templates easily. In addition this normally requires a great deal of labour (Gupta *et al.*, 2006:58).

There are two steps to layout analysis, namely physical layout analysis and logical layout analysis. Physical layout analysis is concerned with the identification of the geometric page structure, and logical layout analysis is concerned with the assignment of labels and meaning to regions identified during the physical layout analysis (Marinai, 2008:6).

2.3.2.1 Physical layout analysis

Two main categories of image processing techniques are used for the physical layout analysis of a document. These are as follows (Marinai, 2008:6):

1. **Pixel classification** – For each pixel in the image, a label is given based on the pixel's colour and that of its neighbouring pixels. The regions are then extracted one by one by removing small elements which could be seen as noise, merging similar neighbouring regions, and then identifying connected components in the resulting image.
2. **Region-based segmentation** – There are two approaches to region-based segmentation; top-down and bottom-up. Top-down approaches work by segmenting the document from its largest components down to its smaller subcomponents. Bottom-up approaches work by merging small objects within the image based on the positioning of their connected components.

2.3.2.2 Logical layout analysis

As previously stated, logical layout analysis is concerned with assigning labels and meanings to regions identified during physical layout analysis. Features that have to be considered during this phase are the size of regions, mutual positions, and textual information, such as predominant font, character size, and spacing (Marinai, 2008:7).

According to Nagy *et al.* (1992:10), physical layout analysis and logical layout analysis can be performed at the same time. This works by assigning regions labels and meanings right after they are identified. In contrast, Marinai (2008:7) claims that this is not feasible because most of the time the classes can only be defined after analysing regions' positions in relation to the other objects in the page, or after analysing the content.

2.3.3 Text recognition

This step is essentially known as the OCR phase. It is concerned with the conversion of printed or handwritten text to a machine-understandable format, usually ASCII or Unicode (Marinai, 2008:8).

The text recognition process can be broken down into two main categories, namely segmentation, also known as text extraction, being the steps taken in order to accurately segment text characters, and classification, in which a feature extraction model and a supervised classifier is used for the classification of sets of characters.

2.3.3.1 Segmentation

Choudhary *et al.* (2013:88) claim that character segmentation is the most important step in the OCR process and that the algorithm selected for the segmentation of characters has a major influence on the accuracy of the system. This is the process that identifies text lines in a document image in relation to the columnar structure (Shafait *et al.*, 2006:368). Image enhancement pre-processing methods could also be included in this step (Marinai, 2008:8).

The properties of text in images are tabulated below in Table 2-1.

Table 2-1 Properties of text in images (Jung *et al.*, 2004:980)

	Property	Variants or sub-classes
Geometry	Size	Regularity in size of text Horizontal/vertical
	Alignment	Straight line with skew (implies vertical direction) Curves
	Inter-character distance	3D perspective distortion Aggregation of characters with uniform distance

Colour	Grey Colour (monochrome, polychrome) Static
Motion	Linear movement 2D rigid constrained movement 3D rigid constrained movement Free movement
Edge	Strong edges (contrast) at text boundaries
Compression	Un-compressed image JPEG, MPEG-compressed image

Zhang *et al.* (2013:310) back these properties up by stating that natural scene images can vary greatly in respect of font size, text alignment and geometric distortion, colours of characters, definition of edges, and perspective distortion as a result of the angle at which the image is captured.

Text could appear in a large variety of scenes, and a comprehensive text extraction system would be able to recognize text in all of them (Jung *et al.*, 2004:977). These would include single-column text documents, two-column text documents, electrical drawings with text, multi-colour document images, images with captioned text, and scene text images.

According to Zhang *et al.* (2013:312), there are four main method types used for detection and localization. These are

1. **Edge-based method** – Edges could be used for the detection of characters. This is normally done by using edge detection on an image, followed by morphological operations in order to extract the text from the image and to remove all the unwanted pixels. A common problem with edge-based methods, however, is that it is difficult to accurately detect edges that are under a shadow or highlighted. Ye *et al.* (2007:504) proposed an edge-based extraction technique that makes use of colour image filtering methods where the rims would initially be detected and then the contents would be analysed.

2. **Texture-based method** – This approach is based on the assumption that the text within the image comprises distinct textual properties that separate themselves from the rest of the image. Texture analysis methods such as Gaussian filtering, wavelet decomposition, Fourier transform, discrete cosine transform, and local binary pattern are used. The problem with this approach is that its speed is somewhat slow and its accuracy is dependent to the text alignment orientation.

3. **Connected component-based method** – This is a bottom-up approach where each pixel is connected to its neighbours of the same type in order to form components of the same type of pixel until all the regions in the image are identified. A geometrical analysis is sometimes

used later in order to identify the text components and to group them into localized text regions. Zagoris *et al.* (2010:873) explains how words are segmented by using the connected components of the pixels in the text image by getting rid of all the connected components that are smaller than a predetermined size. This also filters out accents, noise, and punctuation marks. Alternatively, after this is done, the connected components are expanded and merged in order to form words.

4. **Stroke-based method** – Strokes are a basic element of text strings that make available concrete features for text detection in natural scenes. Text can be shown as a mixture of stroke components with various orientations, and features of text can be extracted from combinations and distributions of the stroke components.

Many researchers have also developed new approaches that make use of a combination of methods.

2.3.3.2 Classification

The methods used for classification include template matching, structural analysis, and feature analysis. It is said that classification methods can be divided into the following two categories (Liu & Fujisawa, 2008:140):

- **Feature-vector-based methods** – These methods are prevalent for the off-line recognition of characters because of their ease of implementation and minimal computational difficulty.

- **Structural methods** – This method could easily extract a feature vector from a document image, but it struggles with the extraction of components or strokes.

2.3.4 Post-processing

Post-processing is used to check the results of the classification on the basis of contextual information. Contextual processing is used to evaluate the results of the recognized sets based on contextual information such as domain-specific dictionaries.

Liu and Fujisawa (2008:144) proposed some statistical techniques which, when applied to the patterns recognised, could be used to reject characters with low confidence. These techniques are elaborate density estimation, one-class classification, hybrid statistical/discriminative learning, and multiple classifier combination. Two other techniques frequently used for post-processing are:

1. **Dictionary support** – Words that contain characters that could be represented by more than one character code are run through the dictionary and the correct word is provided. The

following table, Table 2-2, shows how multiple characters are recognized, and by using dictionary support, the correct word can be identified.

Table 2-2 Dictionary support application

Character possibilities	I l 1 |	m rn	a	g 9	e
Actual text	**I**	**m**	**a**	**g**	**e**

The word could be run through the dictionary and the only matching word would be 'Image'.

2. **Manual-user input** – Many OCR systems provide the user with the opportunity to verify the data by reviewing that the correct character has been recognized for each character that is represented by more than one character code. Sometimes a spellchecker is also used and the user is required to verify that the detected misspelled words were recognized correctly.

It is important to evaluate the quality of all the processes involved in DAR in order to optimize each step (Rabeux *et al.*, 2014:125). The resulting accuracy of any processing technique, such as binarization, is directly affected by the overall quality of the document image to be processed.

2.4 Techniques

The purpose of this section is to provide more details on the functioning of the techniques used throughout this study. The rest of this section is divided into noise reduction and binarization techniques. The noise reduction techniques discussed are median filter, average filter, weighted smoothing linear filter, Gaussian filter, and Wiener filter. The binarization techniques discussed are global threshold, Otsu threshold, Niblack, and Sauvola.

2.4.1 Noise reduction

Noise reduction has two main goals; the first is to eliminate noise from image, and the second is to preserve the important features of the image (Tang *et al.*, 2007:1299).

2.4.1.1 Median filter

Gonzalez and Woods (2006:156) explain that a median, ξ, of a set of values is the value in the middle when the set is sorted from smallest to largest, such that half of the values are less than or equal to the median and the other half are greater than or equal to the median.

To apply a median filter to a neighbourhood, the following has to be done:

1. Sort the pixels in a 1-D array from smallest to largest based on their intensity.

2. Determine the median.
3. Assign the median to the corresponding pixel.

Figure 2-2 illustrates the results obtained (right) when applying a median filter of size 3×3 to an image that is corrupted by salt-and-pepper noise (left).

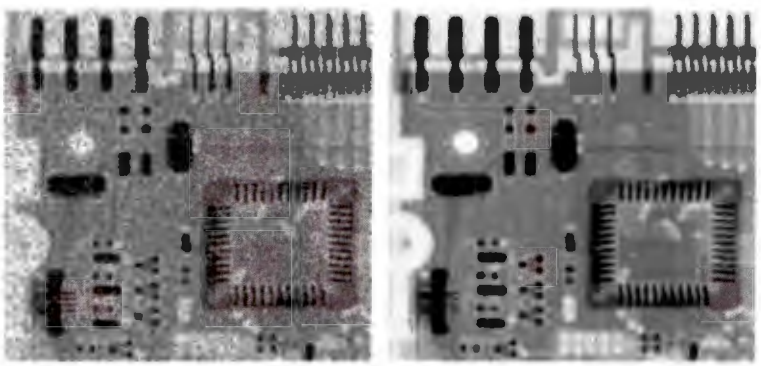


Figure 2-2 Median filter example (Gonzalez & Woods, 2006:157)

2.4.1.2 Average filter

An average filter is also known as a smoothing linear filter or mean filter. This filter works by setting the intensity value of a pixel to the average intensity of its neighbouring pixels. This is the most obvious technique used to handle noise reduction.

Figure 2-3 shows a standard average 3x3 filter mask.

$$\frac{1}{9} \times \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

Figure 2-3 Smoothing filter mask

Figure 2-4 shows the results of applying an averaging filter (right) of size 3×3 to an image that is corrupted by salt-and-pepper noise (left).

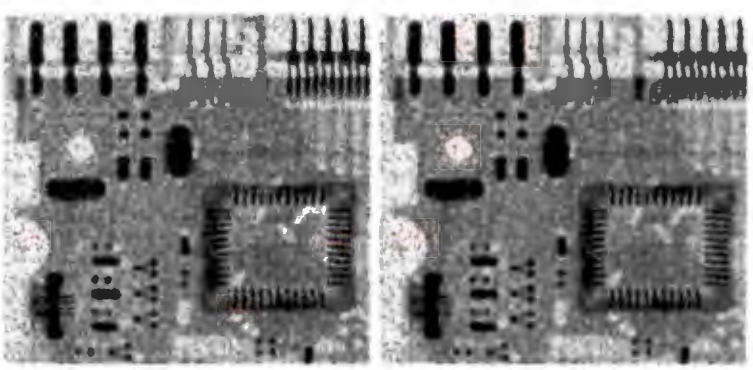


Figure 2-4 Averaging filter example (Gonzalez & Woods, 2006:157)

2.4.1.3 Weighted smoothing linear filter

The downside to a standard average filter is that it causes the resulting image to be blurred. This problem can be addressed by using a weighted average mask where certain pixels are seen as more important than others.

Figure 2-5 shows a weighted smoothing 3x3 filter mask where the pixel in the middle has the highest importance, thus preserving the edges of the original image.

$$\frac{1}{16} \times \begin{array}{|c|c|c|}\hline 1 & 2 & 1 \\ \hline 2 & 4 & 2 \\ \hline 1 & 2 & 1 \\ \hline \end{array}$$

Figure 2-5 Weighted smoothing filter mask

2.4.1.4 Gaussian filter

A Gaussian filter, also known as Gaussian blur or Gaussian smoothing is used to remove high frequency components within an image by blurring the image with a Gaussian function.

The Gaussian filter works in more or less the same way as the weighted smoothing filter, except that the weight of the pixels is based on their distance to the centre pixel of the selected neighbourhood. These weights are obtained using the following equation:

$$f(x,y) = \frac{1}{2_{\pi\sigma^2}} e^{\frac{x^2+y^2}{2_{\sigma^2}}} \quad (3)$$

The sigma parameter, σ, can be increased to lower the decay from the peak. The influence of different values of σ is illustrated in Figure 2-6.

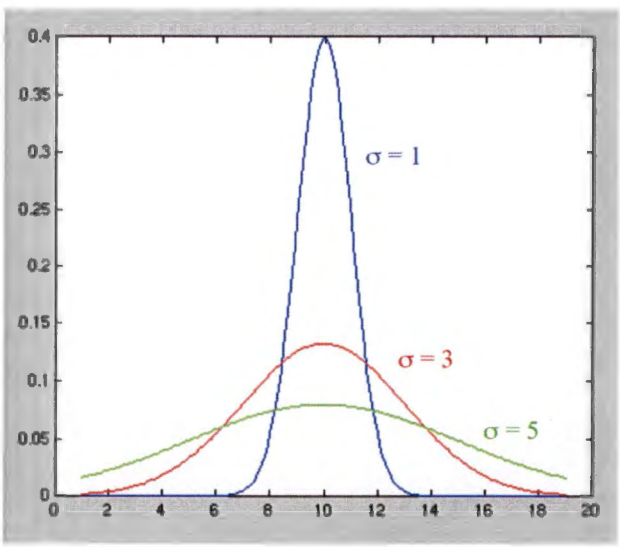


Figure 2-6 Sigma influence on peak

2.4.1.5 Wiener filter

The Wiener filter is applied by using the following equation (Patidar & Nagawat, 2010:46):

$$G(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + \frac{P_n(u.v)}{P_s(u,v)}} \quad (4)$$

Where

$H(u,v)$ = Degradation function

$H^*(u,v)$ = Complex conjugate of degradation function

$P_n(u,v)$ = Power spectral density of noise

$P_s(u,v)$ = Power spectral density of un-degraded noise

The term P_n/P_s can be interpreted as the reciprocal of the signal-to-noise ratio.

2.4.2 Binarization

Binarization techniques can largely be divided into the following two categories (Khurshid *et al.*, 2009:73):

- **Global thresholding** – This is used when there is a clear distinction between the text and the background throughout the entire image (Gonzalez & Woods, 2006:741). A single intensity threshold is applied to all the pixels in the image (Khurshid *et al.*, 2009:73). Some concerns with global thresholding techniques are that irregular illumination or noise may cause the binarization to be inaccurate, with reduced performance for poor quality images.

- **Local thresholding** – This is where a threshold is calculated for every pixel in the image based on various properties of the pixels in the surrounding neighbourhood. Local thresholding methods are typically more accurate on low quality images (Khurshid *et al.*, 2009:73).

2.4.2.1 Global threshold 128

A simple, but often ineffective global fixed threshold could be used where all the pixels with intensity values below 128 are converted to a 0, and all pixels with intensity values equal to or above 128 are converted to a 1 (Gupta *et al.*, 2007:389). A more effective, iterative approach is presented by (Gonzalez & Woods, 2006:741):

1. Select an initial estimate for the global threshold T.
2. Segment the image using T in the following equation.

$$g(x,y) = \begin{cases} 1 & if\ f(x,y) > T \\ 0 & if\ f(x,y) \leq T \end{cases} \quad (5)$$

This will produce two groups of pixels: G_1 consisting of all pixels with intensity values $> T$, and G_2 consisting of pixels with values $\leq T$.

3. Compute the average (mean) intensity values m_1 and m_2 for the pixels in G_1 and G_2, respectively.

4. Compute a new threshold value

$$T = \frac{1}{2}(m_1 + m_2) \quad (6)$$

5. Repeat Steps 2 through 4 until the difference between values of T in successive iteration is smaller than a predefined parameter ΔT.

A parameter ΔT is used to regulate the number of iterations needed when processing speed is important. Figure 2-7 illustrates an original input image of a finger print (left) and its corresponding intensity histogram (middle), and the results of this global threshold method applied to it (right).

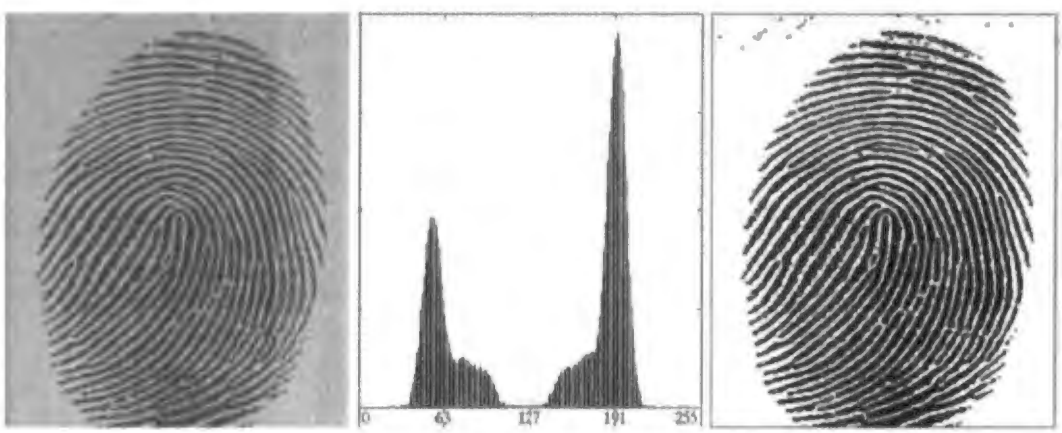


Figure 2-7 Application of global threshold (Gonzalez & Woods, 2006:743)

2.4.2.2 Otsu threshold

This method is also known as an optimum global thresholding method because it is concerned with finding the global threshold that minimizes the interclass variance of the resulting black and white pixels (Otsu, 1979:62; Zagoris *et al.*, 2010:873).

Gonzalez and Woods (2006:747) explains Otsu's algorithm as follows;

1. Compute the normalized histogram of the input image. Denote the components of the histogram by $p_i, i = 0,1,2,\ldots,L-1$

2. Compute the cumulative sums, $P_1(k)$, for $k = 0,1,2,\ldots,L-1$, using the following equation:

$$P_1(k) = \sum_{i=0}^{k} P_i \quad (7)$$

3. Compute the cumulative means, $m(k)$, for $k = 0,1,2,\ldots,L-1$, using the following equation:

$$m(k) = \sum_{i=0}^{k} iP_i \quad (8)$$

4. Compute the global intensity mean, m_G, using the following equation:

$$m_G = \sum_{i=1}^{L-1} iP_i \quad (9)$$

5. Compute the between-class variance, $\sigma_B^2(k)$, for $k - 0,1,2,\ldots,L-1$, using the following equation:

$$\sigma_B^2(k) = \frac{[m_G P_1(k) - m(k)]^2}{P_1(k)[1 - P_1(k)]} \quad (10)$$

6. Obtain the Otsu threshold, k^*, as the value of k for which $\sigma_B^2(k)$ is maximum. If the maximum is not unique, obtain k^* by averaging the values of k corresponding to the various maxima detected.

7. Obtain the separability measure, η^*, by evaluating the following equation at $k = k^*$

$$\eta(k) = \frac{\sigma_B^2(k)}{\sigma_G^2} \quad (11)$$

Figure 2-8 illustrates an original input image (top left) with its histogram (top right) as well as the application of a global threshold technique (bottom left) and the application of the Otsu threshold (bottom right).

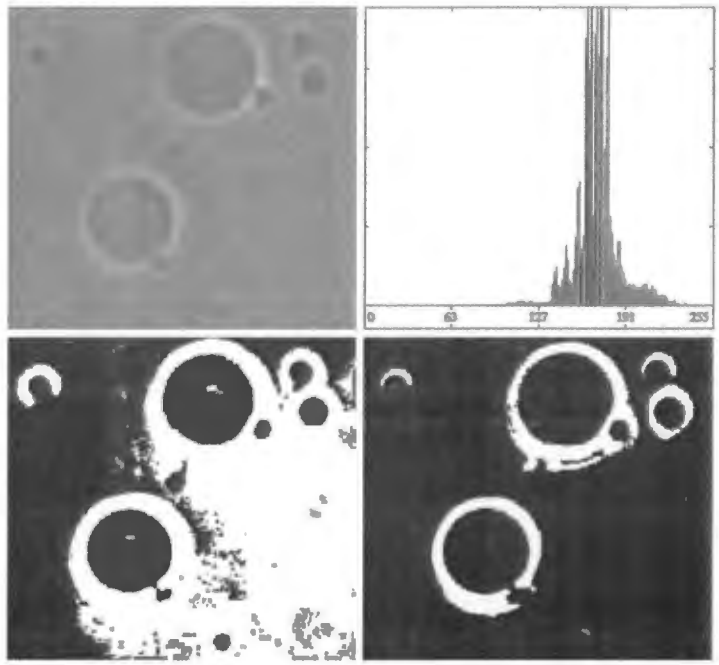


Figure 2-8 Application of Otsu's method (Gonzalez & Woods, 2006:748)

2.4.2.3 Niblack

The Niblack method makes use of a mask to calculate a pixel-wise threshold (Khurshid *et al.*, 2009:74). The computation of the threshold is based on the local mean m and standard deviation s of all the pixels contained in the mask and is given the following equation:

$$T_{Niblack} = m + k * s$$

$$= m + k\sqrt{\frac{1}{NP}\sum(p_i - m)^2}$$

$$= m + k\sqrt{\frac{\sum {p_i}^2}{NP} - m^2} \quad (12)$$

$$= m + k\sqrt{B}$$

Where NP is the number of pixels in the grey image, m is the average value of the pixels p_i, and k is fixed to -0.2 by the author.

The advantage of the Niblack method is that it always identifies the text accurately on the foreground but on the other hand it also recognizes a lot of noise as foreground text (Khurshid *et al.*, 2009:73).

2.4.2.4 Sauvola

Sauvola is also named the Sauvola-Niblack method. This makes use of Niblack's binarization in order to achieve the most accurate OCR on handwritten numbers. This is done by segmenting the image into adjacent non-overlapping blocks and then thresholding each pixel based on the local mean and local standard deviation. This method is seen as an evolved Niblack method (He *et al.*, 2005:541).

$$T_{Sauvola} = m * (1 - k * \left(1 - \frac{S}{R}\right)) \quad (13)$$

Where k is set to 0.5 and R to 128.

2.5 Summary

In this chapter, a number of technologies, techniques, and processes were discussed. The chapter started off by explaining the complexity of the task of converting a physical document to a machine-understandable document. It was then explained that OCR is the process in which characters in a document image are identified. The history of OCR, its development, applications, and recent trends and movement were then discussed.

It was then explained that DAR is the automatic extraction and processing of information presented on paper, and that OCR is the main driving force of this process. The four steps of the DAR process were explained. The first step, pre-processing, is used for improving the quality of the image for better recognition accuracy and involves skew correction, noise reduction, and binarization. The second step, layout analysis, is used to segment objects within the image. There are two types of layout analysis; physical layout analysis, which is concerned with the geometric page structure, and logical layout analysis, which is concerned with adding meaning to the identified regions. The third step is character recognition, which is where OCR takes place. It involves the segmentation of individual characters, and the classification of those characters. The last step, post-processing makes use of contextual information to evaluate and modify the recognized characters in order to improve recognition performance.

Lastly, the application of the techniques to be used in this study was explained. This included the explanation of the noise reduction techniques; median filter, average filter, weighted smoothing filter, Gaussian filter, and Wiener filter. This was followed by the explanation of binarization techniques; global threshold 128, Otsu threshold, Niblack, and Sauvola.

The following chapter will describe how the research study was approached with regard to philosophical paradigm, research strategy, data-generation techniques, and data-analysis techniques.

CHAPTER 3 – RESEARCH METHOD

3.1 Introduction

Oates (2006:5) explains that research is a manner of thinking that leads to the creation of new knowledge that satisfies the users of the research. This is done by identifying a problem, gathering data from multiple accurate sources, properly analysing that data, interpreting it, drawing conclusions based on the evidence, and professionally presenting the results. There are several categories of aspects which have to be taken into account for any research project. These are known as the six P's of research (Oates, 2006:11-12):

- **Purpose** - Research should have a good purpose, a valid reason for doing the research which explains why it is important or useful. The purpose is normally captured in the research question and the objectives of the research.

- **Paradigm** - A philosophical paradigm is a shared way of thinking on which the research has to be based. A research paradigm is concerned with the nature of the research question to be answered as well as the manner in which the answer is obtained.

- **Participants** - The participants are the people who are directly or indirectly involved in the execution of the research. This includes the researcher, the research supervisor, the people being studied, etc.

- **Process** - A research project should be executed according to a certain process, which normally involves the following:

    - Identification of research topic(s)
    - Establishment of a conceptual framework
    - Selection and use of a research strategy and data-generation methods
    - Analysis of data and the drawing of conclusions

- **Products** - Research should produce something which ultimately contributes to the applied knowledge area.

- **Presentation** - The research has to be disseminated and professionally explained to others. This could be done by writing it in a thesis, presenting a conference paper to an audience, or by demonstrating a computer-based product.

For this research project, two separate studies will be conducted. Firstly, an exploratory study will be used to gather background information on the DAR industry in order to be able to address the research question more effectively. This information will then guide the main study, which is an experimental investigation. This chapter will address the research methods used for these studies according to Oates' six P's of research. The purpose of these studies will be explained in Section 3.2. The research paradigms used will be discussed in Section 3.3. Following that, the participants will be discussed in Section 3.4 and the research process for each of the studies will be discussed in Section 3.5.1 for the exploratory study, and Section 3.5.2 for the experimental investigation. Lastly, the products and presentation of these studies will be addressed in Section 3.6.

3.2 Purpose

To understand the purpose of this research, the research objectives, as discussed in Chapter 1, will be revisited. The objectives can be divided into the following two categories:

- **Exploratory study** – The purpose of this part of the study is to understand the functioning of the current DAR industry in South Africa. This research will make use of case studies in order to study the DAR industry in South Africa to determine what the industry is like, how business is done in the industry, what software is used and how it is used in the industry, and any other relevant information regarding the industry. This study will also be used to determine what makes invoice documents unique from other document types.

- **Experimental investigation** – The purpose of this part of the study is to compare pre-processing techniques to each other in order to find the best techniques to be used for DAR on invoice documents. In order to accomplish this, the different techniques used for pre-processing first have to be identified. This will allow the researcher to implement the techniques on the test images in order to compare their recognition performance. The next step is to set up a platform in which different techniques can be compared to one another in terms of recognition accuracy, specifically for the recognition of invoices. Once this is done, the techniques can be compared to each other to measure their performance. The results can then be analysed and conclusions can be drawn. The techniques that would provide the optimal recognition accuracy for DAR can then be suggested.

3.3 Paradigm

Oates (2006:13) defines a paradigm as "a pattern or model or shared way of thinking". Patton (1990:37) elaborates upon this by saying that a paradigm is "a worldview, a general perspective, a way of breaking down the complexity of the real world". Another definition states that a paradigm is a revelatory framework guided by "a set of beliefs and feelings about the world and how it should be understood and studied" (Guba, 1990:17). Grbich (2013:5) defines it as "worldviews of beliefs, values, and methods for collecting and interpreting data".

The above-mentioned beliefs can be categorized into the following (Denzin & Lincoln, 2005:163):

- **Ontology**: An individual's views about the nature of our world (Oates, 2006:284).
- **Epistemology**: "A broad and high-level outline of the reasoning process by which a school of thought performs its logical and empirical work" (Lee, 2004:5). Oates (2006:282) states it simply as the "ways we can acquire knowledge about our world".
- **Methodology**: Process of how people know the world, or learn information about it.

When all this information is combined, it is possible to develop a definition for a philosophical research paradigm that will be applicable for this research.

For this study, a paradigm will be considered as a shared way of thinking based on a worldview, which provides us with methods that allow us to break down the complexity of the real world in order to study and understand it.

In this research study, two philosophical paradigms will be used independently of each other. This is because the exploratory study will be conducted first, using the interpretive paradigm. Following that, the experimental investigation will be executed using the positivistic paradigm. Hence, a mixed methods approach will be taken.

Mixed methods research was brought forward by a need for mixing methods in order to optimize their strengths and neutralize their weaknesses (Jick, 1979:604).

In order to understand the functioning of this approach, consider Figure 3-1. All the investigations make use of different research methods. The places where these areas overlap represent resulting information that concurs from more than one investigation. This area of knowledge is known as the apparent truth, as the results were proved accurate by all the investigations involved.

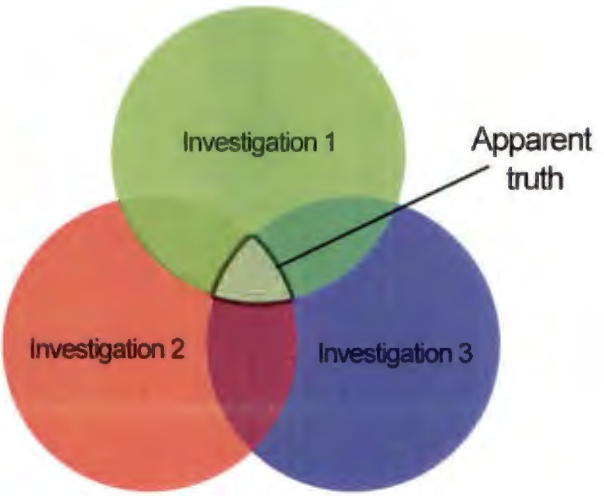


Figure 3-1 Mixed methods research

The main reason why the mixed methods approach was selected for this study is because it allows data to be gathered from multiple perspectives. In contrast to what is shown in Figure 3-1, the findings made during this research study will not overlap to solidify the same results, but will rather be complimentary so that the exploratory study's findings strengthens the experimental investigation, as illustrated in Figure 3-2.

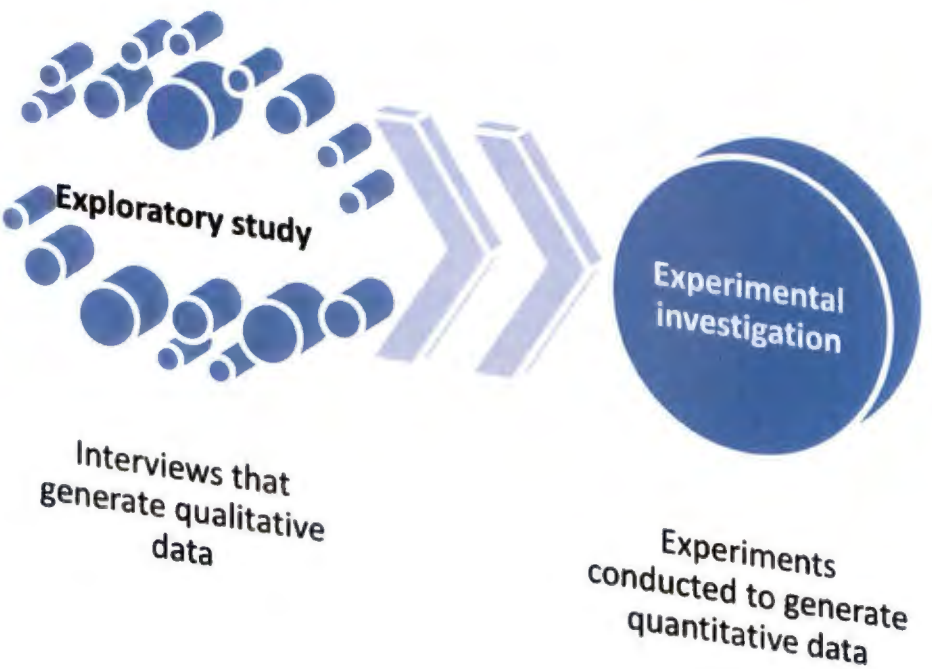


Figure 3-2 Research studies

Firstly, the interpretive research paradigm will be used for the exploratory study. The reason for choosing this approach is because it allows the researcher to qualitatively study the people

involved in the DAR industry. The research data is based on information provided by people, rather than by physical measurements. This will also allow the researcher to immerse himself in the subject in order to document the gathered data as effectively as possible. The aim is for the findings of this study to be transferable in the sense that some generalizations could be made so that the reader is able to judge for himself/herself whether the research applies to his/her situation or not.

One factor to be concerned about when using this paradigm is the trustworthiness of the interviewees since some of them may not know what they are talking about. This will be addressed by determining the position and relevant experience of the interviewee, and basing the reliability of the data on that.

A few matters that will be kept in mind while using the interpretive paradigm are (Oates, 2006:292)

- **Multiple subjective realities** – There is no single version of the truth. What people perceive to be real is only a construction of their minds, either individually or in a group. Therefore, none of the raw data will be considered as facts. Conclusions will only be drawn from the processed data.

- **Dynamic, socially constructed meaning** – An individual's or a group's reality can be retrieved and transited to others. People are able to explain the reality of something but it will still be based on their own social construction thereof. Thus, the researcher will bear in mind that the interviewees' opinions are based on socially constructed meanings from their previous experiences on the subject.

- **Researcher reflexivity** – Researchers are not neutral. Researchers' assumptions, beliefs, values, and actions will influence the research process and affect the situation. It is important for the researcher to be aware of the impact that the researcher has on the data gathered. Interviewees may not want to tell the whole truth because releasing vital information might possibly make them vulnerable.

- **Study of people in their natural social settings** – Interpretive research is aimed at studying people in their natural worlds, and not in an artificial setting. The researcher has to study the participant from the participant's perspective in his/her natural world without forcing his outsider perspective or expectation onto the situation.

- **Qualitative data analysis** – The data analysed is qualitative and is gathered from the words people use, metaphors they employ, and images they construct.

- **Multiple interpretations** – Researchers should not expect to arrive at one fixed explanation of what has occurred in the study. Instead, multiple possible explanations will be provided as discussions and explanations.

Once the functioning of the industry is understood, the experimental investigation can commence. This part of the research will focus on quantitative measurements of results from experiments, thus it will be grounded in the positivistic paradigm. This means that this study will make use of the three key techniques of positivism (Oates, 2006:285):

- **Reductionism** – This is the process of breaking complex things down into smaller, simpler units, which are easier to study. Through the experiments, the researcher will be able to study the techniques by looking at the effects they have on the image, resulting text, and their performance. This could provide clarity on how the techniques function and why they function the way they do.

- **Repeatability** – To be absolutely sure that the results are accurate and true, the experiment may be repeated several times in order to ensure that the results obtained have not been influenced by researchers, malfunctioning equipment, incorrect measurements or other circumstances. The experiments will be repeated at least twice in order to ensure their repeatability. In addition to this, the results will be thoroughly analysed to search for any sign of malfunction in the experiments.

- **Refutation** – A research experiment must be able to be duplicated by other researches and provide the same results. If not, the hypothesis may be refuted. This will be addressed by providing a detailed chapter on how the experiments will be conducted (see Chapter 5, p. 47). The original images on which the experiments will be conducted are also provided, allowing other researchers to duplicate the experiment.

3.4 Participants

The main participant involved in this study is the researcher, who is the author of this paper and is responsible for the execution of the study through the use of the six P's of research. During the exploratory study, the researcher will be seen as an external observer, learning and gathering information about the DAR industry without interfering. For the experimental investigation, the researcher will be an active participant by executing the experiments, manipulating the variables, and measuring the results. The researcher is therefore directly involved in the outcome of both these studies.

The next key participants are the research supervisors, who are responsible for keeping the researcher on track. The research supervisors play one of the most important roles as they practically guide the research by providing the researcher with opinions and suggestions on the

research. Other important participants in this researcher are the people to be interviewed during the exploratory study. The data generated from these people will be used to make findings and draw conclusions, therefore they will also directly influence the results, albeit only to the extent for which the researcher allows.

Other participants include the community of authors from which the literature used for this research is drawn. The information gained from these participants is crucial as it is used by the researcher to construct a reference framework on the subject.

The final participants for this study are the academic community, which may make use of the information learned through the research and possibly elaborate upon it for future studies, and the business community, which may make use of the information regarding the most effective pre-processing techniques in order to attempt to improve their own DAR systems. These participants are not involved in the process of discovering the findings, but they are responsible for the use of the findings after it has been made.

3.5 Process

The following two subsections will be used to describe the research process used for the exploratory study and the experimental investigation.

3.5.1 Process followed during the exploratory study

An exploratory study is used to define the questions or hypotheses to be used in a following study in order to aid the researcher in understanding the research problem. It is typically used when there is little literature on the topic (Yin, 2012:27).

This research will make use of case studies as research strategy in order to study the DAR industry in South Africa. Case studies will allow the industry to be studied in depth. Information about the case will be gathered from multiple relevant sources. These sources will include the existing literature on the topic and the people who work in the industry. This means that the interviewees will act as direct participants during this study as they will directly influence the results. The aim of this is to obtain a rich, detailed insight regarding the case and its complex relationships and processes.

For data-generation, interviews will be used. The reason why interviews were chosen is because it is an efficient way of obtaining detailed information. Interviews will allow the researcher to ask questions that are complex, open-ended, or which require different order and logic for different people. Furthermore, interviews allow the researcher to study the experiences and feelings of the interviewees, which cannot otherwise be easily obtained. Lastly, interviews can be used to

investigate sensitive issues or privileged information, which respondents might not share with someone they have not met.

According to Thomas (2010:314-315) and Oates (Oates, 2006:187-188), there are three different types of interview. These are

(1) **Structured interviews** – These interviews are used to gather specific pre-coded answers by making use of pre-determined, standardized, identical questions for all the interviewees.

(2) **Semi-structured interviews** – The interviewer is allowed to have a list of themes which should be covered or some questions that need to be answered, but the order of the questions and the flow of the conversation are flexible. This gives the interviewee an opportunity to elaborate in order to provide more relevant information on the topic.

(3) **Unstructured interviews** – The interviewer does not have much control as he/she only initiates the conversation with an introduction topic and the interviewee takes it from there.

For this study, semi-structured interviews will be used. Semi-structured interviews were chosen because it will allow the researcher to steer the interviews in order to touch on all the relevant topics, while allowing the interviewee to elaborate and provide more relevant information on the topics. This type of interview will be used to explore personal accounts, feelings, and opinions of the interviewees as it could reveal additional information, or be used to judge the reliability of their knowledge.

The following will be important for the interviews (Oates, 2006:188-189):

- **Role and identity**: The researcher will keep in mind that his age, sex, ethnic origin, accent, and status may have an influence on the interviewees' responses. The aim is to be professional, polite, punctual, receptive, and neutral.

- **Interview preparation**: Preparation for the interviews will include gathering background information on the interviewees. This will help highlight important issues that may be broached. It will also establish the researcher's credibility as a professional in the eyes of the interviewees, which might make them willing to reveal more. Lastly, it can help when assessing the accuracy of some of the information learned.

- **Scheduling**: The researcher will obtain an agreement for the interviews by telling the proposed interviewees the purpose of the interviews and the likely duration.

- **Recording**: The interviews will be recorded because relying on memory alone is not sufficient. Audio recordings will be made with the interviewees' consent. If audio recordings are not allowed, notes will be taken with pen and paper.

- **Transcribing**: After an interview, the researcher will transcribe the recordings. It is much easier to search through and analyse the data once it is in written form.

In order to execute this research study, the following must be done:

1. The businesses in the industry have to be identified. This will be done by simply searching for relevant businesses on the internet, and by using connections.

2. The identified businesses have to be contacted in order to arrange interviews if possible. A face-to-face interview would be preferred, but if that is not possible, a Skype or telephone interview would suffice.

3. An interview questionnaire has to be prepared. The interview questionnaire should contain relevant topics to be discussed, such as the following:

    - Background of the business, including its history, the services it provides and the size of the business
    - Explanation of the business process
    - Software used by the business (DAR-related software)
    - Scanner used by the business
    - The future of the OCR, data extraction, and data management industry

4. During the interview, the interviewer should record the conversation. The interviewer should also only steer the conversation towards the relevant topics so that the interviewee does most of the talking.

Once all the relevant data has been gathered, all the audio recordings will be transcribed and all the data will be placed in the same format. The data will then be coded and the relevant relationships within the data will be identified. This will be done by reviewing the gathered data, the summaries thereof, the analysis produced from it, the research notes taken, and any other evidence the researcher generated.

The analysis will make use of all the relevant evidence. All the main opposing interpretations will be considered, and each will be explored in turn. The researcher's existing expert knowledge in the field will also be drawn upon, but in an unbiased and objective manner.

3.5.2 Process followed during the experimental investigation

Oates (2006:127) defines an experiment as "a strategy that investigates cause and effect relationships, seeking to prove or disprove a causal link between a factor and an observed outcome".

For this study, experiments will be used as a research strategy. The reason experiments were chosen for this study is because they allow the researcher to manipulate variables in order to study a cause and effect relationship. The experiments will also allow the researcher to work with strictly quantitative data.

The research experiments will make use of the following (Oates, 2006:127):

- **Identification of relationships**: The techniques will be tested based on their recognition accuracy, therefore the various techniques will be viewed as the independent variables during experiments, and the resulting recognition accuracy will be regarded as the dependent variable. This means that the experiments will be based on the manipulation of the independent variables, the various techniques, and the effects on the dependent variable, the recognition accuracy.

- **Process**: An experiment process will be used to guide the experiments from start to finish. The complete experiment process is described in Chapter 5, p. 47.

- **Observation and measurements**: Precise observations and measurements will be made in order to capture the resulting outcomes of variables that are changed.

- **Manipulation of circumstances**: Different techniques will be applied to the same batch of documents.

- **Repetition**: The experiments will be repeated using various different input documents in order to ensure that the results are internally valid. This means that the same techniques be tested repeatedly.

For the data-generation, observations will be used. There are two main types of observation Oates (2006:204):

- **Systematic observation**: The researcher decides in advance what the specific types of event to be observed are and a pre-designed schedule is used to note the frequency or duration. This normally involves counting or timing and leads to the generation of quantitative data. Systematic observation is normally used for positivistic research.

- **Participant Observation**: The researcher partakes in the situation under study in order to experience it from the perspective of the people in the setting. This can be overt, meaning people are aware that the researcher is studying what they do, or it can be covert, meaning the people will be unaware that the researcher is studying them. Participant observation is frequently associated with the interpretive research paradigm, thus it will not be discussed further.

Systematic observations will be used in order to systematically measure and record the results of all the experiments. A schedule will be used, which will contain all the important information relevant to the experiments. This includes date, observation number, document batch processed, technique(s) used, resulting recognition accuracy, and notes.

Once the results have been observed, the data will be analysed. The resulting data will be ratio data as it will deal with percentages. This data will be quantitatively analysed by making use of statistical analysis and visual representations in order to identify valuable patterns in the data.

Tables and bar charts will be used to visually represent the data as they seem to be the most effective at representing the data dealt with in the study. The bar charts will effortlessly illustrate which techniques were the most effective.

3.6 Products and presentation

Once the research studies are complete, findings will be extracted, which will ultimately contribute to the applied knowledge area. The main products that will be delivered by these studies are

- Findings regarding practices in the DAR industry, such as business process used, software used, approach to scanning, and approach to ICR.
- A method that can be used to compare the effect of pre-processing techniques on invoice documents quantitatively.
- Data that shows which noise reduction and binarization techniques are the most and least effective for the processing of invoice documents.

The research will finally be written up in a dissertation, be presented to colleagues at a conference, and be reviewed by highly skilled examiners. The aim is then to divide the research findings into a conference article that addresses the exploratory study, which will be submitted to the the Multi Conference on Computer Science and Information Systems (MCCSIS 2015), and a journal article that will discuss the experimental investigation, which will be submitted to the International Journal on Document Analysis and Recognition (IJDAR).

3.7 Summary

In this chapter, the research methods to be used were discussed. The six P's of research were explained and the Purpose, Paradigm, Process, Participants, Products, and Presentation of both studies were revealed.

Figure 3-2, p. 30, illustrates how the exploratory study, which will gather qualitative data from multiple sources, will be used to provide background information on the experimental investigation, which will gather a large amount of quantitative data. Figure 3-3 summarizes the research method to be used during this study. It shows how the six P's are used as the backbone of the exploratory study and the experimental investigation. The figure also describes the most prominent features of both these studies.

Now that the research strategies behind the two studies have been outlined, the execution and findings thereof can be discussed. The next chapter will discuss the exploratory study and its findings.

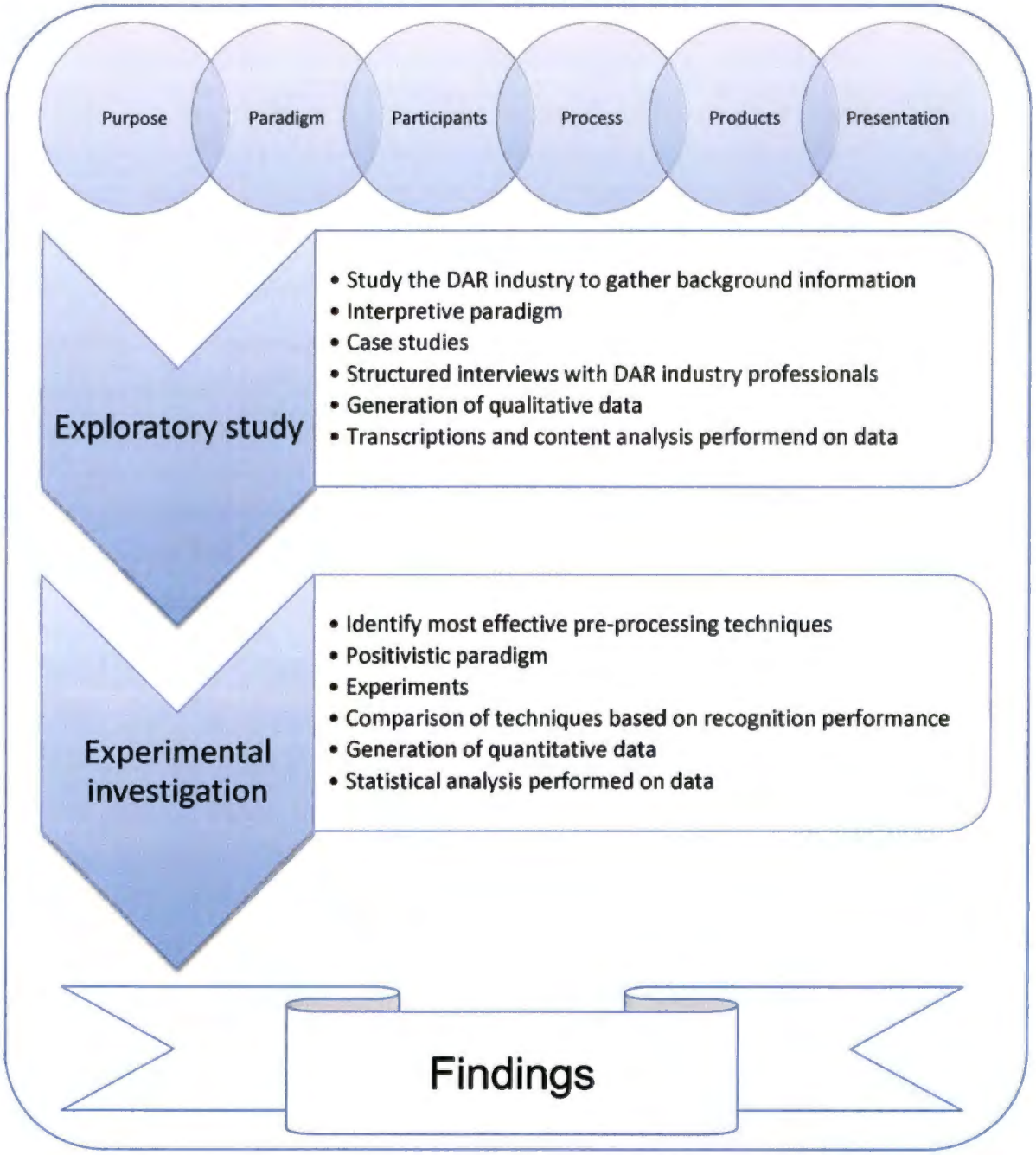


Figure 3-3 Research method summary

CHAPTER 4 – CURRENT STATE OF DAR IN SOUTH AFRICA

4.1 Introduction

Before the main research experiments could commence, an exploratory study was conducted in order to investigate the use of DAR technologies in South Africa.

The need for such a study was brought on by a lack of research regarding the current state of the South African DAR industry. It is clear that many companies could benefit greatly from the effective implementation of DAR technologies. Despite this, it is still unclear how these technologies are being implemented in South Africa.

In this chapter, the use of these technologies by the South African (SA) document solutions industry will be investigated and discussed. Questions that are addressed are:

- Is there a market for DAR to grow in SA?
- To which other industry(s) is DAR connected?
- The problems experienced with DAR compared to what could be achieved with DAR.
- Which business practices result in the effective implementation of DAR?
- What is the future of the industry?

In this chapter, the case studies will be elaborated upon by discussing the interview details in Section 4.2.1 and the participants in Section 4.2.2. The findings made regarding business process, software used, ICR, scanners, and the future of the industry will be revealed in Sections 4.3.1 - 4.3.5, respectively. The findings will then be discussed in Section 4.4.

4.2 Case studies

Case studies were conducted during which nine companies that are active in the document solutions industry in SA were identified. These companies were identified based on their involvement in the document solutions industry, the type of service they provide, and their involvement with DAR technology. The identified companies were contacted by email in order to arrange for interviews. Companies that did not respond to the emails were then contacted by telephone. Five of the identified companies agreed to do interviews while the others declined. The companies that declined closed down, were unwilling to cooperate, or gave references to other companies that agreed to do interviews.

4.2.1 Interview details

Semi-structured interviews lasting between 15 minutes to an hour were conducted in May 2014. The interviews were held at the premises of the participating companies. All but one of the

interviews were conducted with the owner or CEO of a company; the other interview was with an employee. The interviews were recorded with the interviewees' consent.

The topics of conversation during the interviews included an introduction of the interviewer, background of interviewee and company, main questions, and opinions on the industry. The following subjects were covered during the interviews:

- Service(s) that the company provides
- Explanation of the business process followed by the company
- DAR-related software issues
    - Which software products do they use, and their opinion thereof
    - Languages used on documents
    - Use of ICR (Intelligent Character Recognition)
    - Problems experienced with the software
- Scanners used
- Factors that have an effect on recognition accuracy
- The future of the industry

After the interviews were conducted, they were transcribed and content analysis was performed. This was done by searching for related points of interest within all the transcriptions. This allowed prevalent themes to emerge from the data.

4.2.2 Participants

To allow the participating companies to remain anonymous, they will be referred to as companies A, B, C, D, and E. Short descriptions of these companies are provided in Table 4-1.

Table 4-1 Participating companies

Company	Description
A	This company was started in 2002 by combining a passion for law and computer science. This company has about eight employees, depending on the type of project on which they are working. They started out by focusing solely on the law market, but later went commercial. They do most of their work for large auditing firms, lawyer firms, banks, and mining companies. They have done work for multiple companies across the world. This company provides paper-based

	information services for large court cases, forensic investigations, etc. based on its clients' needs.
B	This company was started in 2000 with the intention of helping other companies automate manual data capturing. This company has twenty employees. Their core focus is on automated data capturing, document management, and electronic signature solutions. They have done business with both local and international companies.
C	This company was established in 1993. It is a distributor of data capture, document conversion, document management, and enterprise content management software. Their products help organizations get the most from their business documents by optimizing the capture, conversion, storage, security, retrieval and management thereof with fast and accurate access to relevant information. They have business partners in a number of different countries.
D	This company was started in 2000. This company started out by selling and fixing scanners. They then expanded by scanning and indexing their clients' documents for them, and later branched out to provide training and technical maintenance services as well. This company has eleven franchises in SA. They have been involved in many projects in the rest of Africa.
E	This company was established in 1999 and focuses on electronic document imaging, management, and archiving, providing a comprehensive solution.

4.3 Findings

From the interviews, the following relevant information was obtained:

4.3.1 Business process

Companies B, C, and D agree that in this industry it is important to determine whether the product or service the company provides is what the client is actually looking for as a long term solution. Company A believes that it is important that documents be handled in such a way that there is always an audit trail. The scanned documents should always refer back to the original document. This includes information, such as where it came from, in what box it was stored, and a unique file number. According to companies A, B, and D, the following general process is followed for the development of an OCR-software based solution:

1. Demonstration – The company presents the clients with a demonstration so that they can understand what the company can help them with.

2. Define business case – Help clients define their business case; this includes an analysis of how the documents flow within their business.

3. Proof of concept – A trial run to prove to the client that the solution will work for them.

4. Purchase – The client buys the software.

5. Installation – The software is installed at the client's premises.

6. Maintenance – Continuous maintenance ensures that the system works effectively over a long period of time.

4.3.2 Software used

Company D claims that three main reasons for performing OCR is document indexing, connecting metadata to documents, and analysis of document content. Companies A and D both believe that when purchasing OCR software, it is important to search for something which is affordable, accurate, and simple to use. The companies were unanimous that when deciding which software to use, it is crucial to consider the type of document to be processed. Documents are normally classified into structured, semi-structured and unstructured, based on the format of their contents, as follows:

- **Structured** documents have the same structure and appearance. It is the easiest type for data capture, because every data field is located at the same place on all the documents. Examples include census forms, university registration forms, or multiple-choice cards.

- **Semi-structured** documents have the same structure but their appearance depends on a number of items and other parameters. Capturing data from these documents is a complex, but solvable task. Examples include invoices and purchase orders.

- **Unstructured** documents have a variety of structures and appearances. Examples include emails, letters, CVs, etc.

Companies B, C, and D make use of more than one OCR software package based on the application required. The other two companies only make use of one OCR software package because it is capable of doing everything they need. Companies A and E make use of ABBYY products, namely FineReader and Flexicapture. The only problem experienced with FineReader is the difficulty with which it recognizes complex documents that contain different texts, illustrations, various text directions, etc. However, this problem is not very common. Company A claims that FineReader allows one person to do the work of twenty when he/she knows how to

use it effectively. Other software used includes Captiva InputAccel, PSI:Capture, and FormStorm. Company A pointed out that no OCR software product is capable of doing everything perfectly.

4.3.3 Intelligent Character Recognition (ICR)

Companies A, B, C, and E agree that for ICR to work, the input form has to be very carefully structured, the user has to write in a clear print text, and the text should not be allowed to cross over into adjacent text blocks. It is clear that ICR mainly works with carefully structured forms. Furthermore, companies A and B state that form design is critical for ICR, in other words, people need to be forced to write in print by making use of constrained print boxes. The problem with this is that the input may be much larger than the boxes provided. For example, when an A4 page in portrait orientation has more than 35 boxes in a row, the boxes become too small to write in.

Company B provided an example of a client who used to have fourteen data capturers a few years ago. The number of data capturers have been reduced to four while the volume of documents received has doubled over the same period. This is as a result of successful ICR implemented on carefully designed forms.

4.3.4 Scanners

Companies A and C stated that while scanner classes mainly vary in their scanning speeds and reliability, the scanning quality is more or less the same. Company A also states that paper documents should be scanned to TIFF instead of PDF. This is because scanning to PDF makes use of a compressing method that causes the image to lose some of its quality. All the companies agree that documents should be scanned at a minimum of 200 DPI and a maximum of 300 DPI. When scanning at lower than 200 DPI the OCR recognition will become inaccurate, while scanning at higher than 300 DPI results in the file sizes of document images becoming too large. Company A said that the optimal DPI for OCR is 240, but some of the other companies disagreed and said that the benchmark for OCR is 300 DPI as 240 DPI is a little low for the recognition of small text. Companies A and B have a term when referring to the effects of input documents quality on recognition accuracy: Garbage in garbage out; meaning bad quality documents will lead to bad recognition accuracy.

4.3.5 The future of the industry

Companies B and C stated that the document management industry is still in its infancy. The global economy makes use of documents. Company A states that early in 2000 people said that everyone would start going paperless, but contrary to this, studies have shown that the volume of paper-based documents is only increasing. This is because many people prefer working with paper-based documents.

4.4 Discussion

From the results of the interviews it is clear that a market for DAR does exist in SA, even though it might be a niche market as company A describes it. The fact that most of these companies also do business internationally highlights the extent of the SA DAR industry.

The study also revealed that most of these companies' advertisement is via word of mouth. This could be because the companies form such a close relationship with their clients. It is also clear that these companies mostly deal with the same types of client who require more or less the same services.

One could also conclude that the DAR industry in SA is closely linked to the scanning solutions industry. Company B describes them as walking hand in hand. This is because scanning is the most efficient way of capturing digital images of physical documents.

It seems that the main problems experienced by the DAR industry include the following:

- Clients who are unsure about the capability of the solutions these companies provide, as explained by companies A, B, C, and D. This could be as a result of the little effort these companies put into advertising, causing potential clients to have a distorted impression of the services these companies are able to provide.

- Finding a software package which suits the clients' needs, as stated by companies A and C. This problem might be caused by each client requiring a different solution that is tailored specifically for them.

- Clients working with poor quality documents, as unanimously agreed upon by all the companies.

It is also clear that most of these companies make use of the same practices, such as the business process followed, the way they scan documents, and their approach to ICR. This shows that an effective process for providing DAR services has naturally emerged and has been adopted by most of the companies in the industry.

Lastly, it is impossible to tell what the future might hold, but the research has revealed that almost any business makes use of paper documents and this trend is not decreasing. As the use of paper-based information rises, the need for the digitization and processing of documents rises along with it. This confirms the need for DAR technologies in SA.

4.5 Summary

In this chapter, it was revealed that there is a lack of research concerning the use of DAR technologies in SA. Case studies were conducted in order to learn more about the situation. This

was done by conducting interviews with a handful of DAR-related companies in SA. The main findings revealed that a DAR industry in SA does exist. It was also revealed that many of these companies make use of the same business practices, get to deal with the same types of client, and face the same problems. These problems are clients who are unsure about what services they can provide, finding the right software for clients, and the use of poor quality documents.

Once the DAR industry, its practices, and use of OCR technologies were better understood, the experiments could commence. The exploratory study has revealed that poor quality documents are an actual problem that needs to be dealt with in the industry. Discovering which pre-processing techniques are the most effective for improving document image quality can lead to improvements in how companies in the DAR industry deal with these problems. The following chapter reveals how the platform on which the experiments were conducted was set up.

CHAPTER 5 – EXPERIMENTAL INVESTIGATION

5.1 Introduction

The purpose of this chapter is to explain the technical process of conducting experiments for this research study, as well as to reveal why experiments were chosen as research method.

As mentioned in Chapter 3, the aim of an experiment is to investigate cause and effect relationships. The original research question of this study asks for the comparison of pre-processing techniques for the processing of invoice documents. The reason for choosing experiments as research method for this study is because they allow for the investigation of various causes (application of different pre-processing techniques) and their related effects (resulting recognition accuracy of technique).

This research method was chosen because it was the most practical way of researching the effects of the various techniques. This research method also places a heavy emphasis on the generation of quantified data, which will allow for comparisons based on various statistics.

The experiment conducted involved taking a number of invoice document images, performing various pre-processing techniques on the images, and measuring the effect of the techniques on the recognition rates. By acquiring the recognition rates of the different techniques, it is possible to quantitatively compare the techniques with each other, as specified in the research question.

The rest of this chapter will describe and explain the experimental process. It is broken down into the following subsections, as illustrated in Figure 5-1:

- **Acquisition of images** – Explanation of how the original images, on which the experiments were conducted, had to be acquired.
- **Degradation of images** – Explanation of how the quality of some of the images was degraded in order to further test the effects of some of the techniques.
- **Coding of techniques** – Description of how the pre-processing techniques were coded in MATLAB and applied to the original document images.
- **Character recognition** – Shows how OCR was applied to the processed images.
- **Acquisition of ground truth text** – Explanation of how the true text within the original document images was obtained.

- **Development of comparison software** – Description of how a customized software application was developed, which allowed for the comparison of the original and resulting text files.

- **Comparisons** – Explanation of how the resulting OCR text files were compared with each other using the software developed. The final results were obtained from this step.

- **Summary** – A brief overview of the entire experiment process.

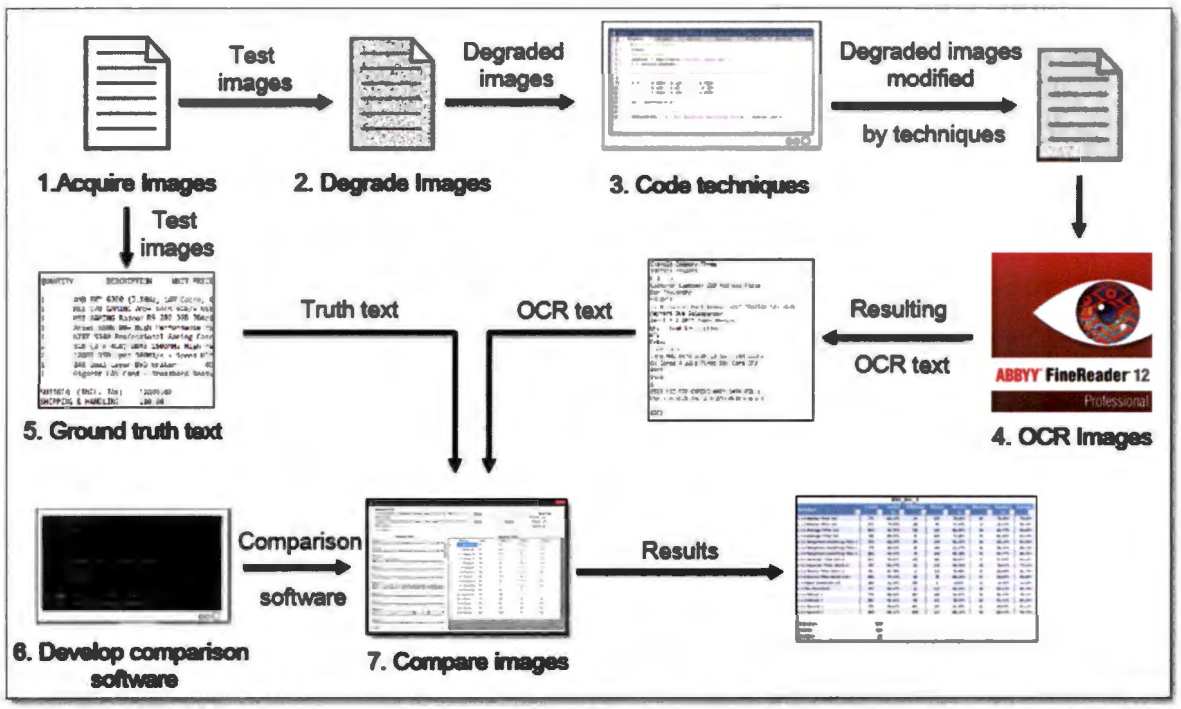


Figure 5-1 Experimental process overview

5.2 Acquisition of Images

Firstly, the images that were used for the experiments had to be acquired. The selection of images for experiments is an important step as this will greatly affect the outcome of the experiments. The reason for this is that if the quality of all the images is bad, the text will be more difficult to recognize. Therefore, it is important to use images that are of varying quality in order to get comprehensive results.

The flowing images were used for the experiments:

- **Three control invoices** – Named 'Control Invoice 1/2/3'. These are mock-up invoice documents that were created in Microsoft Word. They were then printed out and scanned in order to simulate degradation. These images would ultimately serve as the 'good quality' images for the experiments. These images are shown in Figure 5-2.

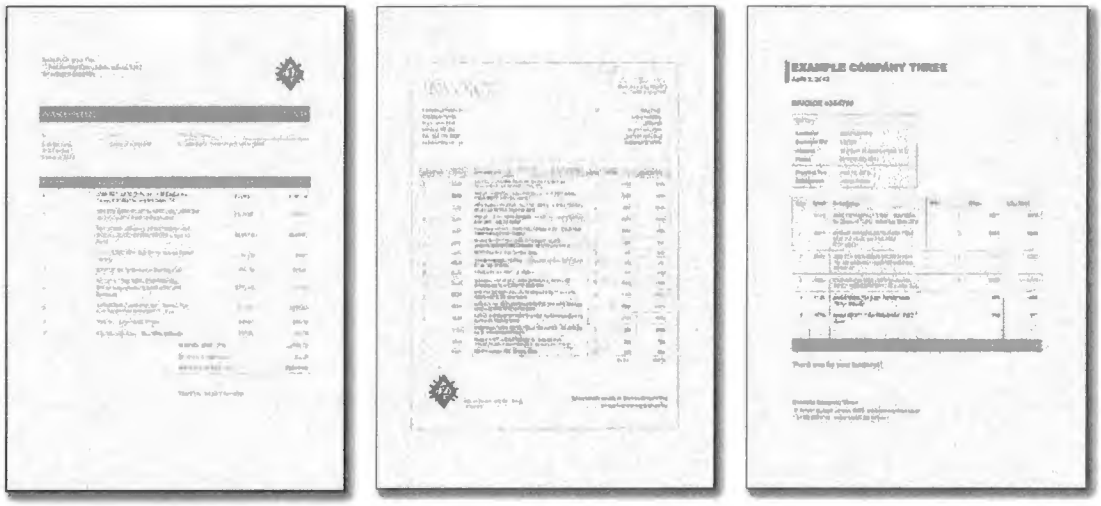


Figure 5-2 Control invoices

- **Three real invoices** - Named 'Real Invoice 1/2/3'. These are real invoice documents which were obtained from a local company. The documents selected were chosen to represent 'real world' invoices with greater complexities than those of the control invoice documents. The complexity of these invoices could easily be seen in their structure, content, and quality. These invoices are illustrated in Figure 5-3.

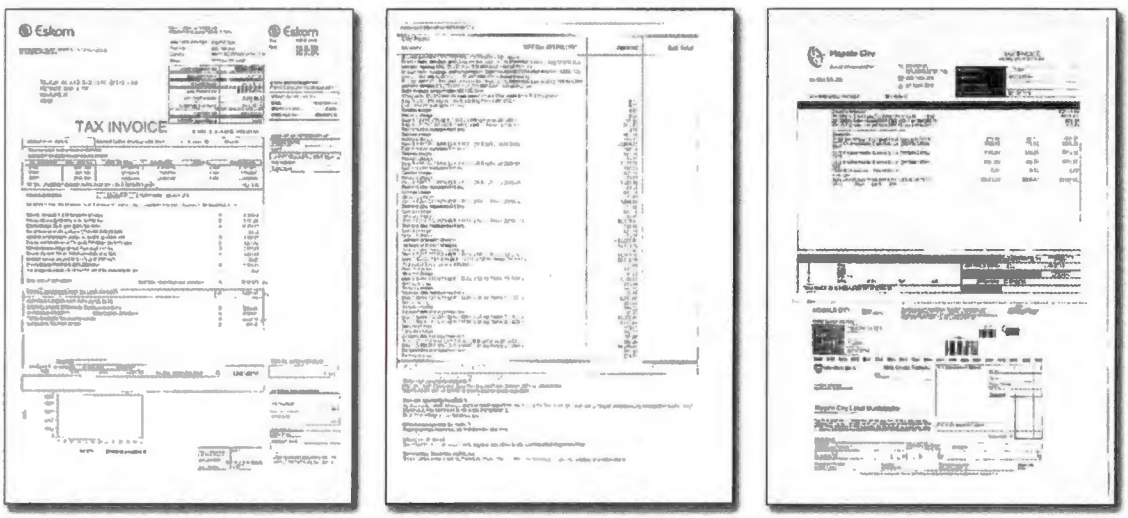


Figure 5-3 Real Invoices

- **Four invoices with noise** - Named 'Noisy Invoice 1/2/3/4'. These are four 'real world' invoice documents with similar structure and content. Noise was digitally added to these images, as explained in Section 5.3, specifically to determine how well the noise reduction techniques work. The format of the noisy invoices is illustrated in Figure 5-4.

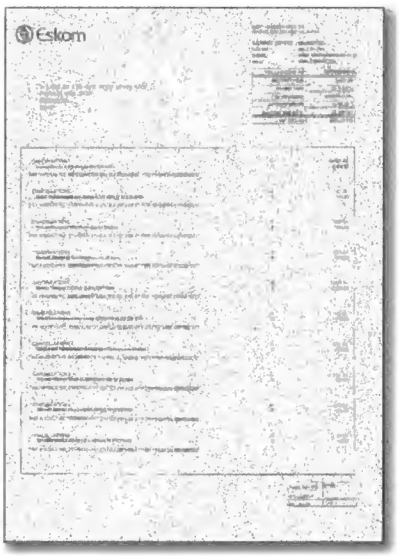


Figure 5-4 Noisy invoices' format

It is important to point out that due to the fact that some of these documents contain confidential information, they cannot be fully displayed. Therefore, only thumbnail images of all the documents are shown. The high resolution images with confidential information filtered out can be found in Annexure C.

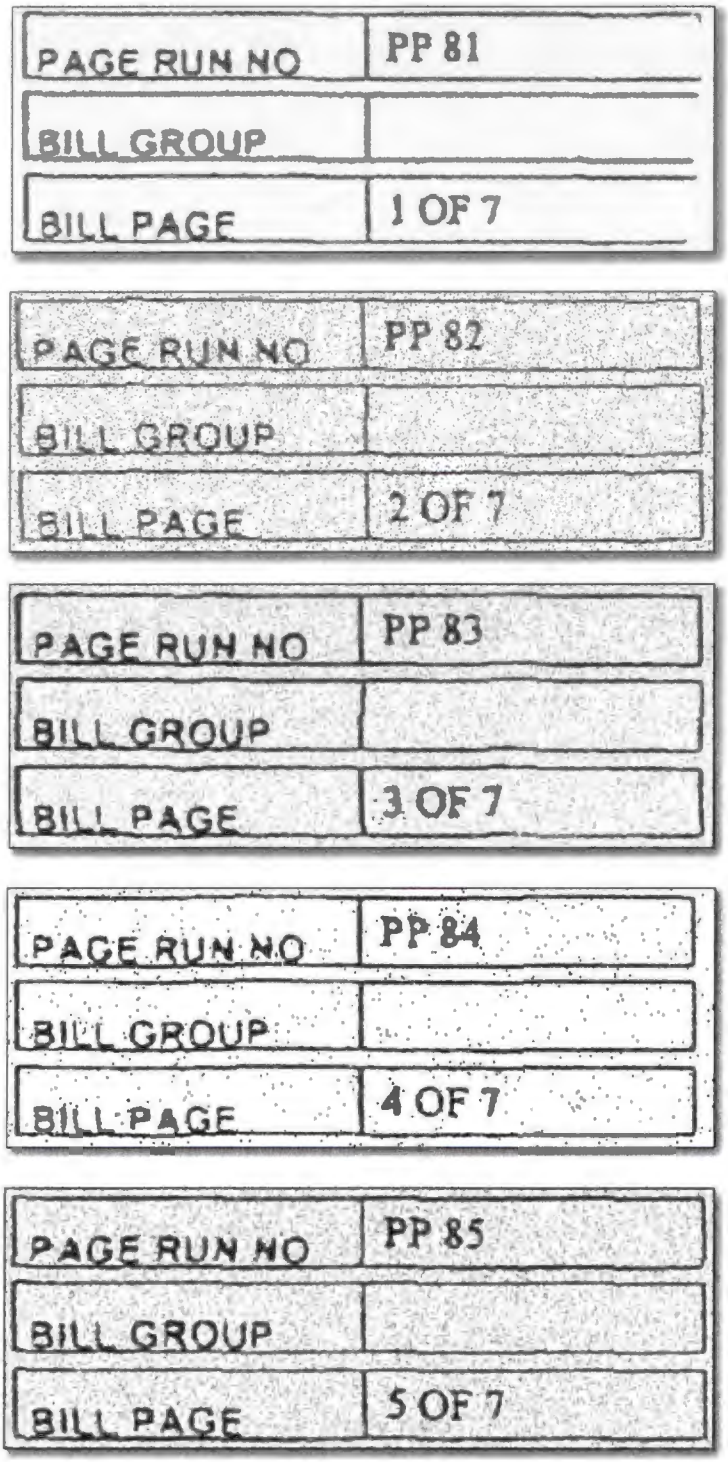
5.3 Degradation of images

As previously explained, four document images were selected specifically to test the effectiveness of noise reduction techniques. Before the noise reduction techniques could be tested, however, noise had to be digitally added to the images. MATLAB was used to digitally add various types of noise to these four documents using the '*imnoise*' function. The following noise was added to the document images:

- **Noisy Invoice 1** – Gaussian noise with 0.1 mean and a variance of 0.01. The reason for adding 0.1 mean instead of 0 is to increase the intensity values of the noise to more realistically mimic the natural effects of noise (Lim, 2006:216).
- **Noisy Invoice 2** – Poisson noise.
- **Noisy Invoice 3** – Salt-and-pepper noise with a noise density of 0.02.
- **Noisy Invoice 4** – Speckle noise, which is random noise with 0 mean and a variance of 0.01.

Explanations of these types of noise can be found in subsection 2.3.1.2, p. 13. Gaussian, Poisson, salt-and-pepper, and speckle noise are some of the most common noise types in images. The selection of these four types of noise was based on the classification of the types of noise in a different study, which researched noise removal techniques (Verma & Ali, 2013:617).

Figure 5-5 shows the original unaltered image, as well as the addition of Gaussian noise, Poisson noise, salt-and-pepper noise, and speckle noise respectively.



Original Image

Image corrupted by **Gaussian noise**

Image corrupted by **Poisson noise**

Image corrupted by **Salt-and-pepper noise**

Image corrupted by **Speckle noise**

Figure 5-5 Effects of various noise types on image

5.4 Coding of techniques

The next step was to code the pre-processing techniques, which would be used to alter the document images for the experiments. MATLAB was used for this step as well. The code for all the techniques have the same format in order to keep them uniform and to avoid confusion. This format is revealed in Figure 5-6.

```
%%# Clear workspace
clear;
%%# Read image
imgName = importdata('Current_Image.mat');
I = imread(imgName);

%Apply transformation : [TRANSFORMATION NAME]
%
%       Apply transformation here
%

%Save resulting file
imwrite(I,'1.1.1 #1 Median filter 3x3 Result.tif');

%   File Name Format:
% [Transformation type].
% [Transformation number].
% [Transformation variation]
% #[Document image number]
% [Transformation name]
% Result.tif
```

Figure 5-6 MATLAB technique template

It is important to note that this study focuses on the comparison of noise reduction and binarization techniques independently. Therefore there are no noise reduction techniques that make use of binarization, or binarization techniques that make use of noise reduction in this study.

The techniques used for the experiments in this study are:

1. **Noise reduction**
   - 1.1. Median filter
     - 1.1.1. 3 × 3 mask
     - 1.1.2. 5 × 5 mask
   - 1.2. Average filter
     - 1.2.1. 3 × 3 mask
     - 1.2.2. 5 × 5 mask
   - 1.3. Weighted smoothing filter
     - 1.3.1. 3 × 3 mask:

$$\frac{1}{8}\times\begin{bmatrix}0&1&0\\1&4&1\\0&1&0\end{bmatrix}$$

1.3.2. 3 × 3 mask:

$$\frac{1}{16}\times\begin{bmatrix}1&2&1\\2&4&2\\1&2&1\end{bmatrix}$$

1.3.3. 5 × 5 mask:

$$\frac{1}{20}\times\begin{bmatrix}0&0&1&0&0\\0&1&2&1&0\\1&2&4&2&1\\0&1&2&1&0\\0&0&1&0&0\end{bmatrix}$$

1.4. Gaussian filter

1.4.1. 5 × 5 mask, $\sigma = 1$

1.4.2. 10 × 10 mask, $\sigma = 2$

1.5. Wiener filter

1.5.1. 5 × 5 mask, additive noise estimation = 0.1

1.5.2. 10 × 10 mask, additive noise estimation = 0.01

2. Binarization

2.1. Global threshold 128

2.2. Otsu threshold

2.3. Niblack

2.3.1. 25 × 25 mask, padding size = 10

2.3.2. 10 × 10 mask, padding size = 25

2.4. Sauvola

2.4.1. 25 × 25 mask, threshold = 0.2

2.4.2. 10 × 10 mask, threshold = 0.1

Various mask sizes or technique settings were used where it was possible, therefore most of the techniques appear more than once in the experiments. These techniques were then applied to each document image, resulting in the creation of 170 different processed document images.

The technical descriptions of each of these techniques can be found in Section 2.4, p. 19. The effects of each of these techniques, with its various mask sizes and settings on the same piece of text, are shown in the following three pages.

1. Noise reduction techniques' effects on text image

1.1.1 Median filter 3x3

1.1.2 Median filter 5x5

1.2.1 Average filter 3x3

1.2.2 Average filter 5x5

1.3.2 Weighted smoothing filter 1

1.3.1 Weighted smoothing filter 2

1.3.3 Weighted smoothing filter 3

1.4.1 Gaussian filter 5x5 s1

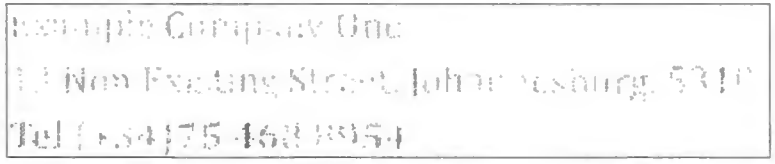
1.4.2 Gaussian filter 10x10 s2

1.5.1 Wiener filter 5x5 0.1v

1.5.2 Wiener filter 10x10 0.01v

2. Binarization techniques' effects on text image

2.1 Global threshold 128



2.2 Otsu threshold

2.3.1 Niblack 1

2.3.2 Niblack 2

2.4.1 Sauvola 1

2.4.2 Sauvola 2

5.5 Character recognition

ABBYY FineReader 12 was used in order to perform OCR on the processed document images. The reason ABBYY FineReader was chosen is because it allows the user to disable the pre-processing functions. This is important otherwise the application will apply its own pre-processing effects on top of the effects already applied on the document images.

When performing OCR on the images, it is important to take the following steps:

- Deselect 'Automatically process pages' – This disables the automatic pre-processing of the images by the software.
- Select text regions for each page – This helps the software to better understand what text it should recognize and the format of the document image. Figure 5-7 and Figure 5-8 show this being implemented. The green areas represent normal text areas, whereas the blue areas represent tables.

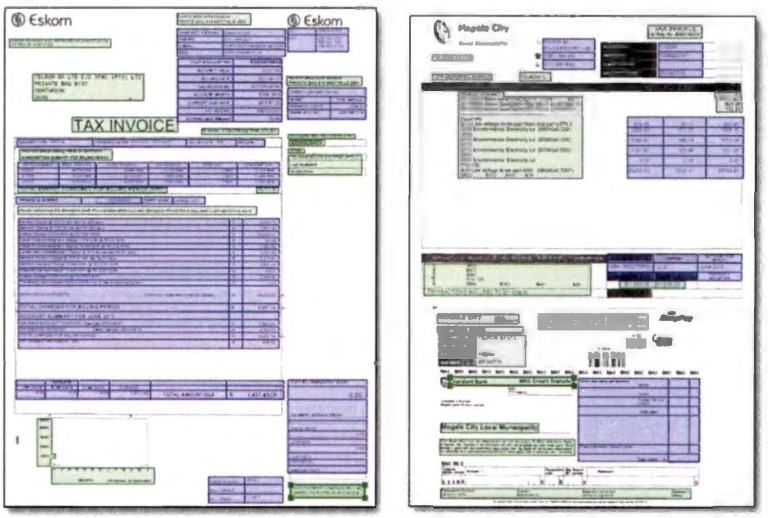


Figure 5-7 Selection of text regions

- Under 'Document layout' in the toolbar, select 'Plain text' – This will structure the resulting text as a normal text file. This can be seen in the right-hand panel in Figure 5-8.
- Under the 'Save' dropdown menu, choose 'Save as TXT' – This allows the user to save the results as a .txt file. This is important for the comparisons as the ground truth text is also in a .txt file (see Section 5.6, p. 60).
- Under the 'File options' setting, select 'Create a separate file for each page' – This creates a single .txt file for each page's OCR results. This simplifies the comparison process as the results for each technique will be in its own .txt file instead of having all the results in a single file.

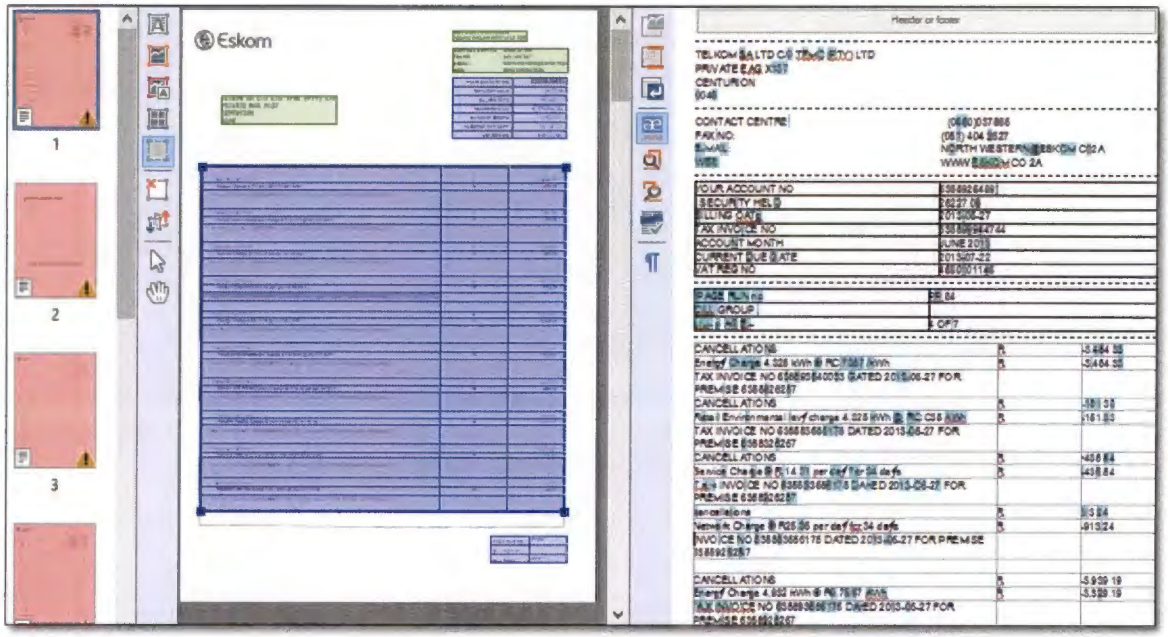


Figure 5-8 Text recognition using ABBYY FineReader

Figure 5-9 reveals a sample of the resulting recognized text. By scanning through the text, it is clear that some characters are misrecognized and some characters were recognized where there were none.

```
Example Company Three
INVOICE #354796
Bill To
Customer Customer ID# Address Phone
Dan Foxworthy
9324511
31 B Ison St Fast London 521" *♦27)32 423 6631
Payment Due Salesperson
April * 2 2012 James Harvey
Qty. Item# Description
WTY
Price
Line Total
5448 AMD FX'W 6300 ,3 5GHz 14M Cache
6x Cores 4 1GHz Turbo Six Core CPU
1578
1578
6523 MSI 970 GAMING AM3* SATA 6Gb s
USB 3 0 SU/XFire ATX AMD Motherboard
1399
139
/> V t
a
«CQ7
Z DO /
8GB >2 * 4GR DDR3 '600MHz High Performance Gaming RAM with Heat Spreader
```

Figure 5-9 Resulting OCR text

It is important to note that OCR can only be performed on the noisy invoice documents that have had noise reduction techniques applied to them. In other words, OCR cannot be performed on the noisy invoice documents that have only been binarized. This is because the binarization of a noisy document would lead to noise being interpreted as foreground objects as illustrated in Figure 5-10. ABBYY FineReader would then attempt to recognize the noise as text characters. This would take a very long time and produce a resulting text file containing mostly nonsense.

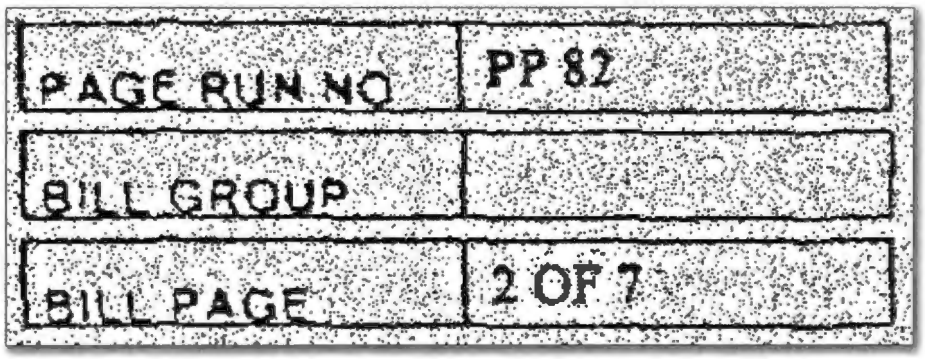


Figure 5-10 Binarization of noisy image

5.6 Acquisition of ground truth text

This step involved the acquisition of the actual text contained in the original document images in .txt format. This is because most of the original documents are real-world documents that were scanned, therefore the text contained in them could not simply be copied. It is essential that these text files represent the document images' text 100% accurately or else it would negatively impact the final results.

The ground truth text was acquired by manually rewriting all the text contained in the invoice documents into a simple .txt file. After this was done, the text was manually verified twice for quality control purposes to ensure that the ground truth text is as accurate as possible.

The resulting ground truth text for Control Invoice 1 follows in Figure 5-11.

```
Example Company One
13 Non Existing Street, Johannesburg, 5310
Tel (+34)75 468 8954

INVOICE 0086521 7.12.2013
BILL TO          SHIP TO              INSTRUCTIONS
Jack Peterson    Same as recipient    No additional instructions were given
253 Fox Ave
Pretoria, 2331

QUANTITY    DESCRIPTION UNIT PRICE  TOTAL

1    AMD FX™ 6300 (3.5GHz, 14M Cache, 6x Cores, 4.1GHz Turbo) Six Core CPU
1299.00 1299.00
1    MSI 970 GAMING AM3+ SATA 6Gb/s USB 3.0 SLI/XFire ATX AMD Motherboard
1599.00 1599.00
1   MSI GAMING Radeon R9 280 3GB 384bit OVERCLOCKED EDITION DDR5 Graphics Card
4549.00 4549.00
1   Antec 500W 80+ High Performance Power Supply    449.00  449.00
1   NZXT S340 Professional Gaming Case  399.00  399.00
2   8GB (2 x 4GB) DDR3 1600MHz High Performance Gaming RAM with Heat Spreader
1299.00 2598.00
2    128GB SSD Upto 500MB/s + Speed Ultra-Fast Solid State Drive (OS DRIVE)
649.00  1298.00
1   24X Dual Layer DVD Writer   499.00  499.00
1   Gigabit LAN Card - Broadband Ready  199.00  199.00

SUBTOTAL (INCL. TAX)    12889.00
SHIPPING & HANDLING 110.00
TOTAL DUE BY 7.15.2013  12999.00

Thank you for your business!
```

Figure 5-11 Control Invoice 1 ground truth text

5.7 Development of comparison software

In order to be able to compare the contents of the resulting OCR text files with the ground truth text files, the best approach was to develop a simple C# application. The need for a custom built application was brought on by the lack of an effective method or existing software that can effectively compare the text files' contents. Manual comparison methods were out of the question as comparisons had to be made for each character in 170 different documents. There was also no available software that could do these comparisons. Most of the software that was considered for the experiment, was plagiarism checkers and other applications that compared full words and sentences to each other. These applications did not focus on the comparison of individual characters. This caused the applications to be wildly inaccurate as a single misread character would lead to the misrecognition of a whole word.

A custom-built application, on the other hand, was able to compare the resulting OCR text files to the ground truth text files on the following three grounds:

- **Characters recognized** – The application looks at all the characters contained in the ground truth text file, and sees how many of those characters are contained in the OCR text files. It

also looks at how many additional characters (that were not matched to any in the ground truth text) are contained in the OCR text files. These numbers are identified as 'Correct' and 'Additional' respectively.

- **Phrases recognized** – The application splits the files' contents up into phrases of text, which are separated by spaces or line separations. The application then checks how many of the phrases recognized are the same as the phrases in the ground truth text files.

- **Numbers recognized** – The application removes all the nonnumeric text from the files. It then checks to see how many of the numbers contained in the ground truth text file are also in the OCR result text files.

In order to avoid inaccurate recognitions because of the case of a character, the case of the following characters are not taken into consideration for the comparisons since both the upper and lower cases look similar:

- C, F, J, K, M, O, P, S, U, V, W, X, Y, Z

The cases of all the other characters were, however, still taken into consideration.

Three random samples were selected from the application's results and then manually verified in order to ensure that the software was working effectively. This was done by manually comparing the characters in the ground truth text file with the characters in the resulting OCR text file and crossing off characters that exist in both documents one by one. The resulting documents' text was then classified into '*missing*' and '*additional*' characters, just as the application does. The resulting '*missing*' and '*additional*' characters obtained contained the same characters, and number of characters, as that of the application, meaning that it was working as intended. This was quite a time consuming process, which is the reason why only three samples could be tested.

The user interface of the comparison application is shown in Figure 5-12.

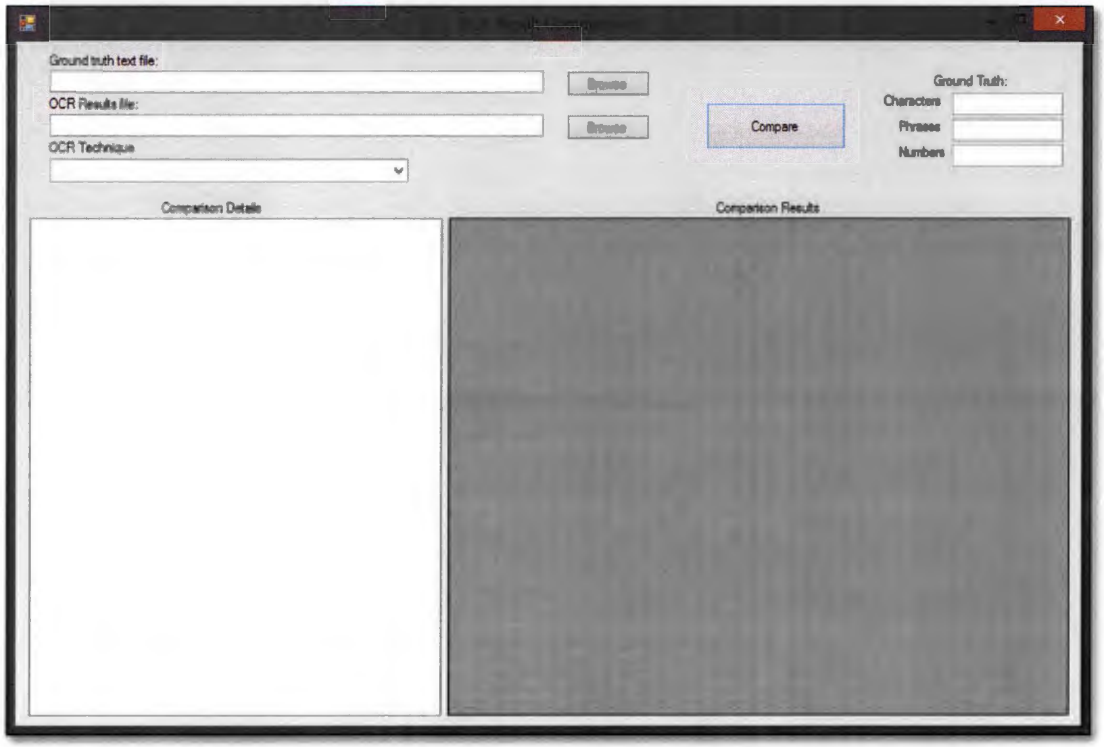


Figure 5-12 Comparison application UI

5.8 Comparisons

The executions of the comparisons involved the following steps:

1. Open the comparison application
2. Select the ground truth text file for the comparison
3. For each technique, do the following:
    a. Select the OCR result text file under 'OCR Result file'
    b. Select the technique name under 'OCR Technique'
    c. Click 'Compare'

This resulted in a table being created, which had the following values for each technique for the selected ground truth document:

- Technique name
- Number of characters correctly recognized
- Additional characters recognized
- Phrases correctly recognized
- Numbers correctly recognized

The application also revealed the total number of characters, phrases, and numbers in the ground truth text file. The comparison application containing the results of the comparisons for Control Invoice 1 is shown in Figure 5-13.

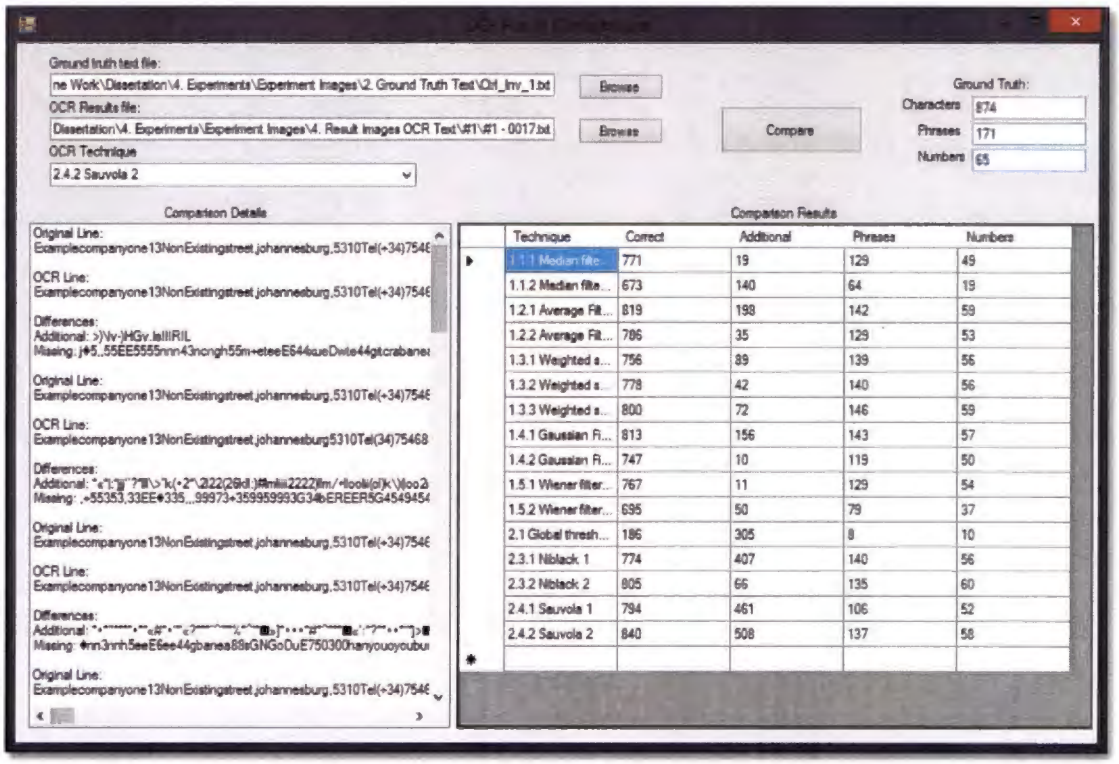


Figure 5-13 Comparison application results

5.9 Summary

In this chapter, experiments were used for this research study as they allowed for the systematic observation of the cause and effect relationship between the various pre-processing techniques and the resulting recognition accuracy of each technique.

This chapter also discussed the process of comparing these techniques in great detail. Firstly, the original images on which the experiments would be done were obtained. The quality of some of these images was then degraded to be able to later test the effects of the noise reduction techniques. The various pre-processing techniques were then coded in MATLAB, whereafter each technique was applied to each original image, resulting in the creation of 170 different processed images. The text within these document images was then recognized using ABBYY FineReader. After this was done, the actual text contained in the original images was manually acquired to allow for comparisons between the processed text and the actual text. A custom software application was then developed in order to allow for comparisons based on the text contained in the processed and the original images. The comparisons were executed

successfully, and the results were obtained. This entire process is illustrated clearly in Figure 5-1, p. 48.

The results obtained can be found in Annexure A - Results, and the analysis thereof in Annexure B - Analysis. The following chapter will be used to analyse and discuss the findings of the experimental investigation results.

CHAPTER 6 – EXPERIMENT RESULTS AND DISCUSSION

6.1 Introduction

In this chapter, the results of the experimental investigation will be discussed and analysed. The figures and statistics discussed in this chapter can be found in Annexure A – Results, and Annexure B – Analysis.

The analysis and discussion of the results aims to answer the following questions:

- Which techniques were the best/worst at recognizing individual characters?
- Which techniques were the best/worst at recognizing whole phrases?
- Which techniques were the best/worst at recognizing numbers?
- Which techniques were the best/worst on average?
- Which document image was the easiest/most difficult to recognize?
- Which results stood out from the norm, and why?

This rest of this chapter will be dedicated to discussing the results found concerning the characters, phrases, and numbers recognized in Sections 6.2 - 6.4. Following that, the average recognition performance, document performance, and unaltered document performance will be looked at in Sections 6.5 - 6.7 respectively. Lastly, the findings will be summarized in Section 6.8 before moving on to the conclusions.

6.2 Characters

In the first instance it is important to note how the performance of the techniques on character recognition has been measured since the number of characters correctly recognized as well as the additional characters incorrectly recognized had to be taken into consideration.

When looking at the results tables in Annexure A – Results, there are three dividing columns; the first column contains the character recognition statistics, which includes True Positive, False Positive, and F-factor. The second column reveals the number of phrases recognized, and what percentage of the total phrases have been recognized. The third column reveals the same as the second, but for numbers recognized.

Character recognition makes use of the F-factor to score the performance of the techniques. The F-factor can be determined as follows:

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (14)$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (15)$$

$$F\text{-}factor = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (16)$$

To put it in other words, precision is the fraction of retrieved characters that are relevant and recall is the fraction of relevant characters that are retrieved. This concept is illustrated in Figure 6-1.

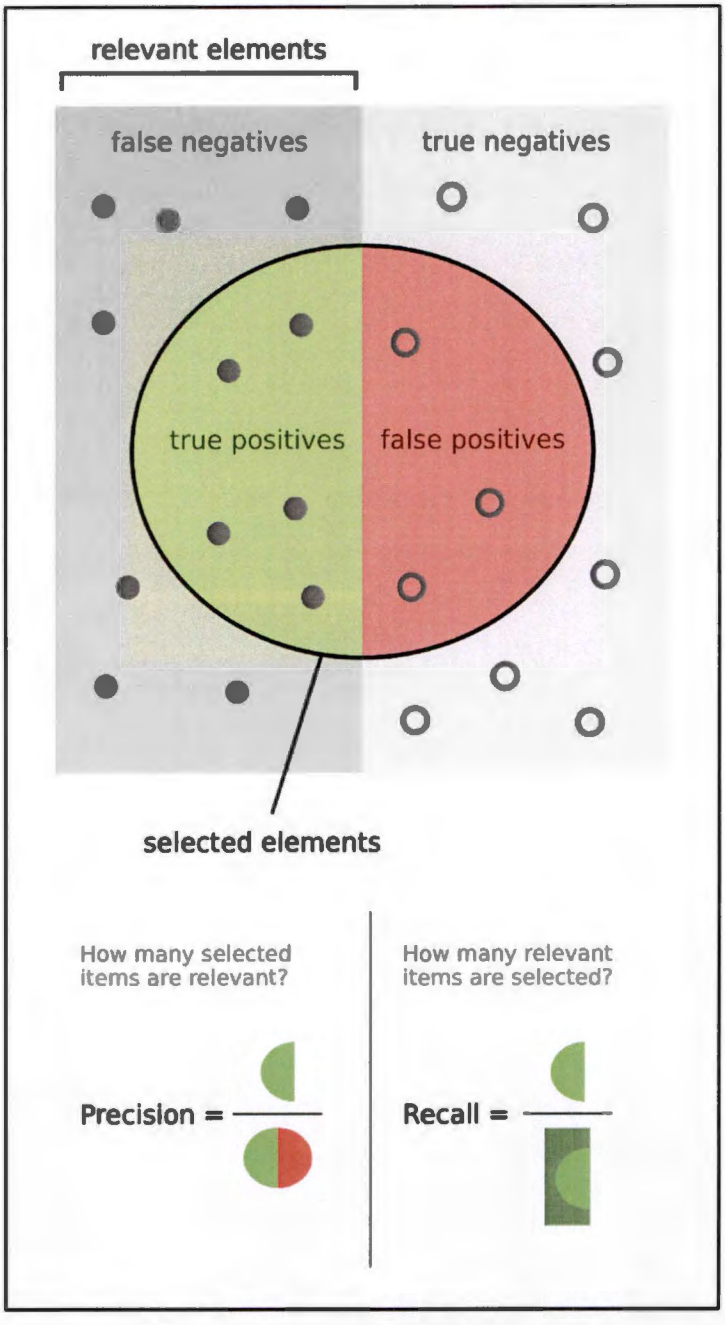


Figure 6-1 Precision and recall (Wikipedia, 2015)

The F-factor makes use of precision and recall to accurately score the performance of the techniques by considering both the characters correctly recognized and the characters incorrectly recognized.

Secondly, when looking at the techniques' scores in terms of characters recognized, it is clear that the character recognition rates are much higher than phrases and numbers recognition rates for all noise reduction techniques. Average character recognition rates for noise reduction techniques range from 75.2% to 92.2% while phrase recognition rates range from 31.5% to 76.7% and numbers recognition rates range from 33.5% to 76.1%. These rates are much more balanced out for binarization, with the average character recognition rates ranging from 78% to 91.7%, phrase recognition rates ranging from 50.6% to 80.8%, and number recognition rates ranging from 54.5% to 88%. This difference is clearly illustrated in Figure 6-2.

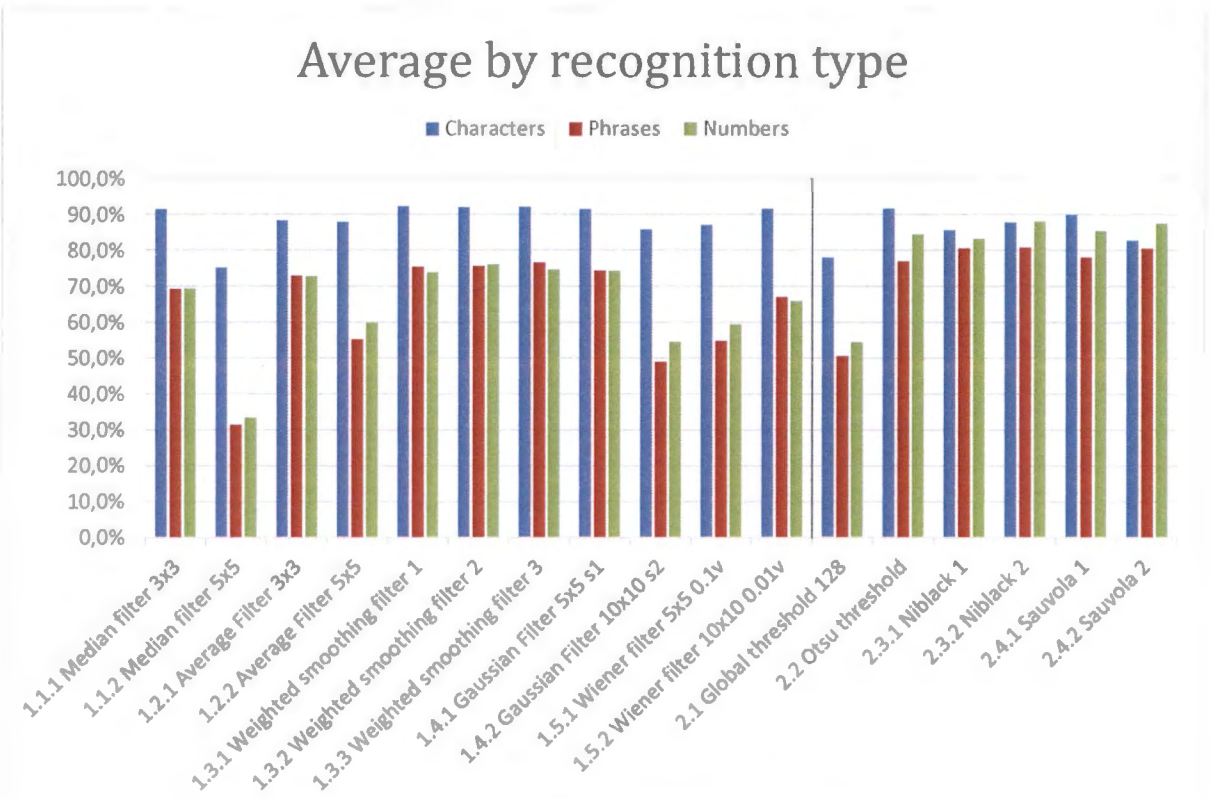


Figure 6-2 Average by recognition type

This is because the document images have far more characters than they have phrases or numbers. Another contributing factor is the fact that a character can be recognized regardless of its position on the document image or the phrase in which it is. In other words, the rules for recognizing characters are not as strict as they are for phrases and numbers, where the text is required to contain exactly the same sequence of characters as the ground truth text.

The next interesting observation about the characters recognized is the performance of the techniques on the noisy document images. Unsurprisingly, the weighted smoothing filters got the best recognition rates for Noisy Invoices 1, 2, and 4 (Gaussian, Poisson, and speckle noise). The results for Noisy Invoice 3 (salt-and-pepper noise) are interesting, however. The technique that performed the best here was the median filter 3x3 with 92.6%, and the technique that performed the worst was the average filter 3x3 with 57.3%, while all the other techniques lay between 70.2% and 88.8%.

The reason for this is that the small median filter 3x3 effectively gets rid of salt-and-pepper noise without degrading the quality of the document image too much. The small average filter 3x3, on the other hand, creates a light grey patch on all the salt pixels. These patches are then incorrectly identified as characters by the OCR software, resulting in a massive number of additional characters recognized.

The effects of these techniques are shown in the following three figures. Figure 6-3 shows a part of the original image. Figure 6-4 shows the application of a median filter 3x3, which is much clearer, and Figure 6-5 shows the application of an average filter 3x3, which created lots of grey patches.

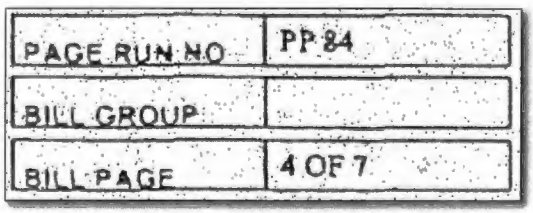


Figure 6-3 Image with no filter

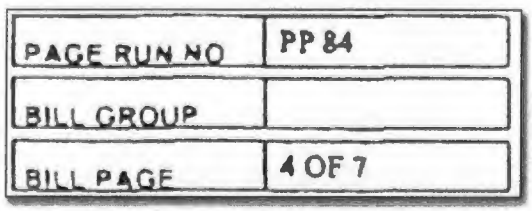


Figure 6-4 Application of median filter 3x3

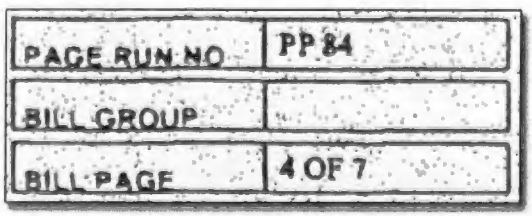


Figure 6-5 Application of average filter 3x3

The noise reduction techniques that performed the best for character recognition were weighted smoothing filters 1, 2, and 3, with an insignificant performance difference between the three at ±92.1%. The noise reduction technique that performed the worst for character recognition was median filter 5x5 with 75.2%.

The binarization technique that performed the best for character recognition was Otsu threshold with 91.7% and the technique that performed the worst was global threshold 128 with 78%. Global threshold 128 would actually have performed much better if its performance on Control Invoice 1 was not taken into account. This implies that the rest of the test documents' text was dark enough to be binarized sufficiently by a subpar technique.

6.3 Phrases

The noise reduction techniques that performed the best for the recognition of phrases, are weighted smoothing filter 3 with 76.7%, weighted smoothing filter 2 with 75.7%, and weighted smoothing filter 1 with 75.5%. Gaussian filter 5x5 s1 follows closely with 74.3%. These four noise reduction techniques outperformed most of the other techniques effortlessly.

When looking at the binarization techniques in terms of phrases recognized, Niblack 1, Niblack 2, and Sauvola 2 performed the best with ±80.6%, while global threshold 128 performed the worst with 50.6%.

What stands out the most in the phrases results is the score of global threshold 128 on Control Invoice 1 with only 4.7%. This is because only eight out of the possible 171 phrases were recognized correctly. The reason for this is the light intensity of the text in the image. The resulting text is a collection of nonsense characters. This is illustrated in Figure 6-6 with a piece of Control Invoice 1 processed by global threshold 128, and its resulting text in Figure 6-7.

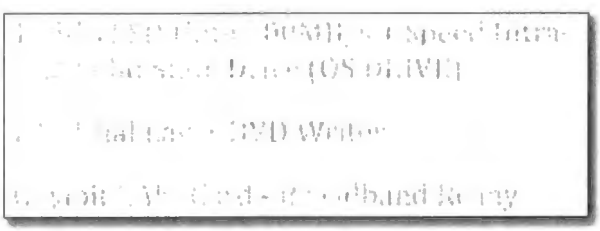


Figure 6-6 Application of global threshold 128

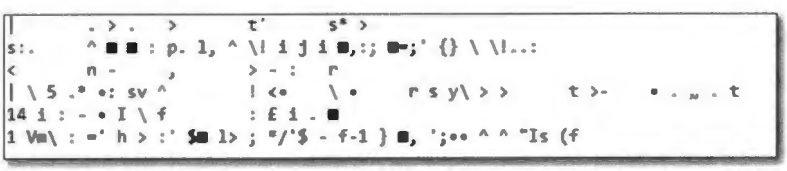


Figure 6-7 Global threshold 128 resulting text

6.4 Numbers

The accurate recognition of numbers could be seen as the most important measurement for the processing of invoice documents as numbers are extremely important in these documents, e.g. account numbers, dates, or payment amounts.

It is common for different techniques to recognize the same amount of numbers for the same document as there is not a large amount of numbers to recognize. Some documents have more techniques that recognize the same amount of numbers because they contain less numbers. On the other hand, some documents have many more numbers to recognize and therefore no duplicates are found in their results.

When looking at the noise reduction results of numbers recognized, weighted smoothing filter 2 has the highest recognition accuracy with 76.1%, followed by weighted smoothing filter 3 with 74.7%, then Gaussian filter 5x5 s1 with 74.2%. The effects of these three techniques are illustrated in the following three figures. Figure 6-8 shows the application of weighted smoothing filter 2, Figure 6-9 shows the application of weighted smoothing filter 3, and Figure 6-10 the application of Gaussian filter 5x5 s1, all on the same piece of Control Invoice 3.

Figure 6-8 Application of weighted smoothing filter 2

Figure 6-9 Application of weighted smoothing filter 3

Figure 6-10 Application of Gaussian filter 5x5 s1

Unsurprisingly, median filter 5x5 performed the worst of all the noise reduction techniques for number recognition with an average recognition percentage of 33.5%. The technique closest to that is Gaussian filter 10x10 s2 with 54.6%, a difference of 21.1%. The effects of these techniques are illustrated in Figure 6-11 with median filter 5x5 and in Figure 6-12 with Gaussian filter 10x10 s2 applied on Real Invoice 2. It is clear that the text in the first image is sharper, but the characters

are broken and unclear, while the text in the second image is very blurred, but the characters are still whole and recognizable.

Figure 6-11 Median filter 5x5

Figure 6-12 Gaussian filter 10x10 s2

Concerning the binarization techniques for numbers recognized, Niblack 2 performed the best with 88%, with Sauvola 2 close behind, scoring 87.5%. The binarization technique that performed the worst was once again global threshold 128 with 54.6%.

6.5 Averages

The first matter to notice when looking at the noise reduction statistics is that weighted smoothing filters 1, 2, and 3 had the best recognition rates for characters, and phrases, and were all in the top four for numbers. When looking at the total averages, weighted smoothing filter 2 is only 0.07% higher than weighted smoothing filter 3, with weighted smoothing filter 1 only 0.66% behind. This means that essentially, the three most effective techniques are weighted smoothing filter 2, with an average performance of 81.24%, weighted smoothing filter 3, with an average performance of 81.17%, and weighted smoothing filter 1, with an average performance of 80.51% respectively.

The next key element to point out is how poorly the median filter 5x5 did, compared to how well median filter 3x3 performed. The reason for this is that the 3x3 filter is effective at removing noise from an image while still maintaining the quality of small text characters. The larger 5x5 filter also effectively removes the noise, but it fails to preserve the quality of the text characters. This is illustrated in Figure 6-13 with the effects of median filter 3x3 and Figure 6-14 with the effects of median filter 5x5 on the same piece of text. This is an important observation since this small difference in median filter size would not have such a significant impact on most other image processing applications, but for OCR it makes a massive difference.

Figure 6-13 Effects of median filter 3x3

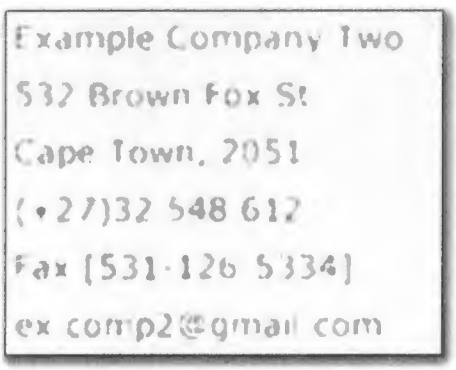


Figure 6-14 Effects of median filter 5x5

When looking at the average statistics for binarization techniques, it is clear that global threshold 128 does extremely poorly on Control Invoice 1 with only 15.8% compared to its performance on the other document images where it scored between 64.2% and 84.7%. The reason for this is, as previously mentioned, because the text in the original Control Invoice 1 is really light compared to the text from other original invoice document images. This is illustrated in the following three figures, with Figure 6-15 showing a piece of light text from Control Invoice 1, Figure 6-16 with a similar piece of text from Control Invoice 2, and Figure 6-17 with a piece from Control Invoice 3.

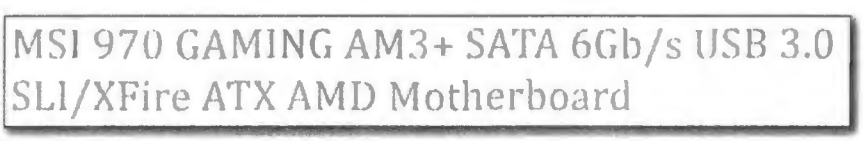


Figure 6-15 Text from Control Invoice 1

Figure 6-16 Text from Control Invoice 2

Figure 6-17 Text from Control Invoice 3

This low intensity means that most of the pixels will get cut off by the technique, resulting in a processed image where half of the necessary pixels are missing, as illustrated in Figure 6-18.

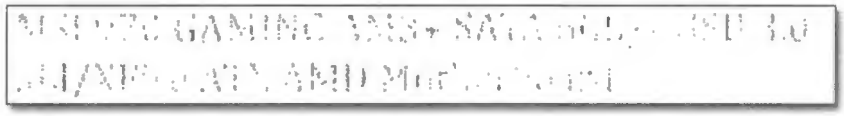


Figure 6-18 Application of global threshold 128 on low intensity text

By looking at the average performance of the binarization techniques, it becomes clear that all the techniques except global threshold 128 performed really well. The technique that performed the best was Niblack 2 with 85.5%. It is also worth noting that Niblack 2 had the highest recognition rate for phrases and numbers, and Otsu threshold had the highest recognition rate for characters.

The information discussed above is summarised in Figure 6-2, p. 68, which reveals the performance of each technique based on its average recognition rate for **characters** (represented by blue), **phrases** (represented by red), and (**numbers** represented by green).

The following chart, Figure 6-19, reveals the total average performance of each technique. These scores were obtained by averaging the characters, phrases, and numbers recognition performance. Figure 6-20 shows the box plot of the average accuracy of each technique.

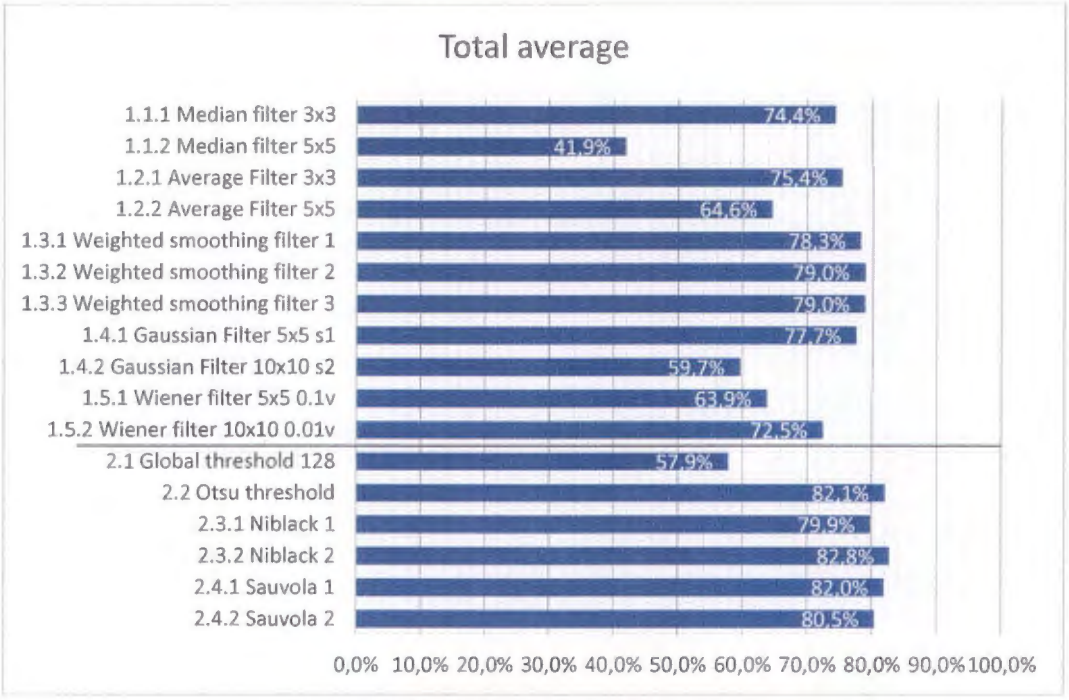


Figure 6-19 Technique total average

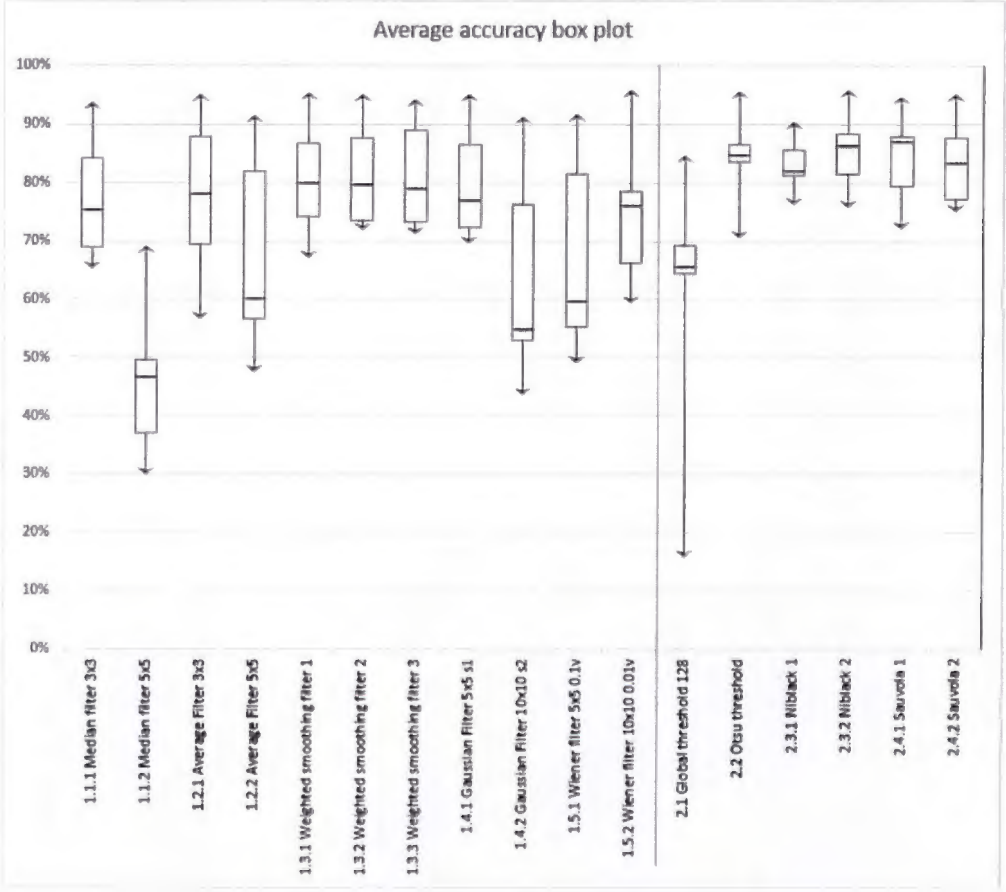


Figure 6-20 Average accuracy box plot

6.6 Document Performance

The purpose of the document performance statistics is to reveal how difficult the document images were to recognize correctly. By looking at the statistics, it is clear that the Control Invoices were the easiest to recognize, as intended, with an average recognition rate of 82.8%. The Real Invoices were a bit more difficult to recognize, with an average recognition rate of 75.9%. The Noisy Invoices were the most difficult to recognize with an average recognition rate of 63.4%.

The following chart reveals the average performance of each document image.

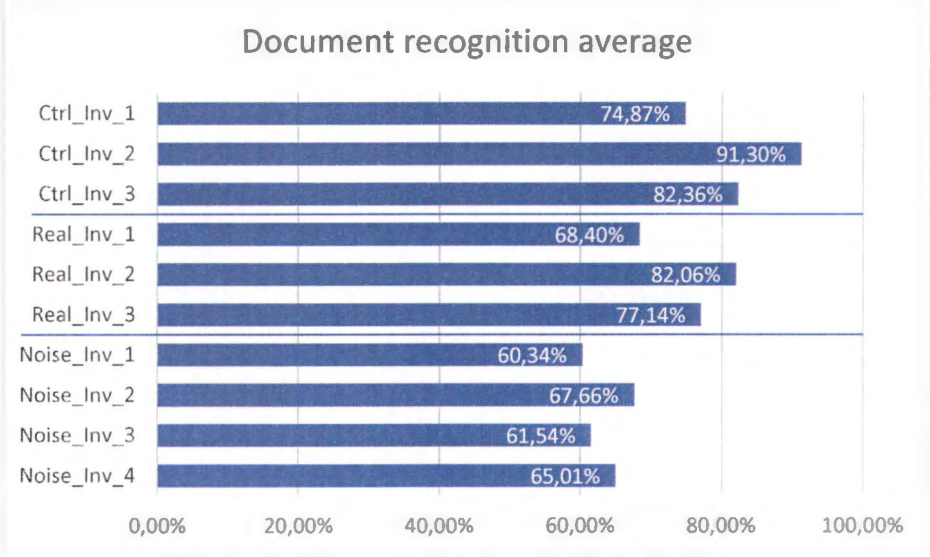


Figure 6-21 Document recognition average

6.7 Unaltered document performance

When comparing the average recognition rates of the techniques with the recognition rates of the unaltered documents, as seen in Figure 6-22, it becomes clear that the techniques struggled to get higher performance than the unaltered recognition rates on the Control Invoices. This is because the Control Invoices are already more or less noise free and the application of a noise reduction technique might unnecessarily degrade the quality of the image. The application of noise reduction techniques on the Real and Noisy Invoices had a significant effect as these documents did contain either natural or digital noise.

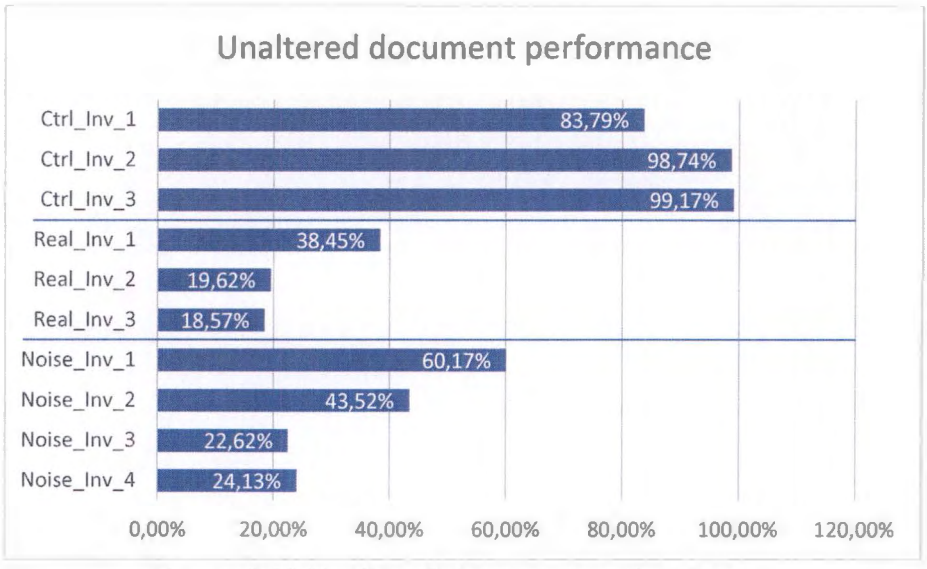


Figure 6-22 Unaltered document performance

The following three figures illustrate this by showing a part of the essentially noiseless image Control Invoice 2 in Figure 6-23, a part of image Noisy Invoice 1 with added noise in Figure 6-24, and a naturally noisy part of image Real Invoice 2 in Figure 6-25.

Figure 6-23 Noiseless image Control Invoice 2

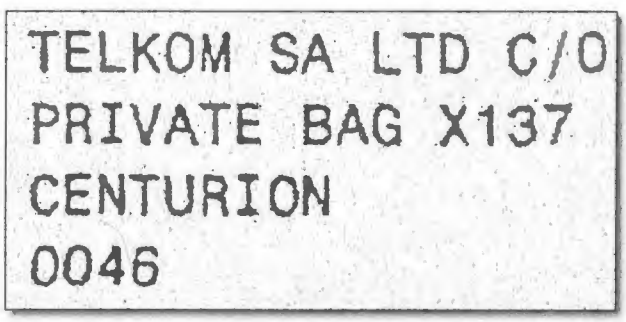


Figure 6-24 Added noise in Noisy Invoice 1

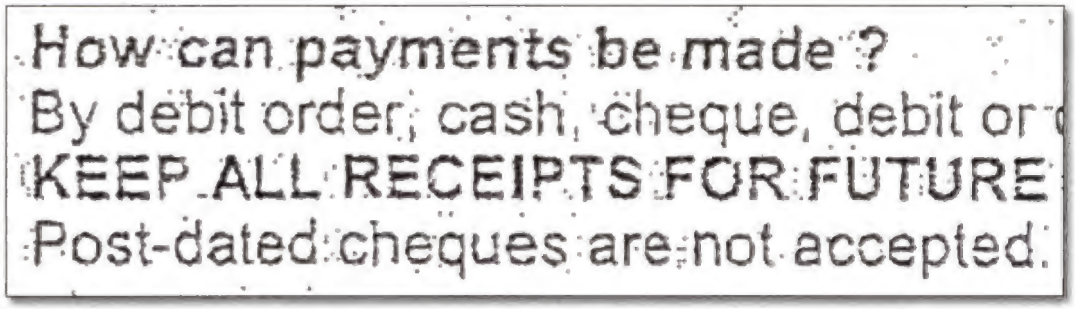


Figure 6-25 Noisy part of Real Invoice 2

6.8 Summary

In this chapter, the results of the experiments were revealed and discussed. The techniques that were the most effective and the least effective were revealed, as summarized in Table 6-1.

Table 6-1 Results summary

	Noise reduction				Binarization			
	Best	Score	Worst	Score	Best	Score	Worst	Score
Characters	1.3.1 Weighted smoothing filter 1	**92,20%**	1.1.2 Median filter 5x5	**75,18%**	2.2 Otsu threshold	**91,66%**	2.1 Global threshold 128	**78%**
Phrases	1.3.3 Weighted smoothing filter 3	**76,71%**	1.1.2 Median filter 5x5	**31,49%**	2.3.2 Niblack 2	**80,78%**	2.1 Global threshold 128	**50,64%**
Numbers	1.3.2 Weighted smoothing filter 2	**76,08%**	1.1.2 Median filter 5x5	**33,46%**	2.3.2 Niblack 2	**88,03%**	2.1 Global threshold 128	**54,55%**
Average	1.3.2 Weighted smoothing filter 2	**81,24%**	1.1.2 Median filter 5x5	**46,71%**	2.3.2 Niblack 2	**85,52%**	2.1 Global threshold 128	**61,06%**

It was also revealed that the Control Invoices were the easiest to recognize, the Real Invoices were quite difficult to recognize, and the Noisy Invoices were the most difficult to recognize. Lastly, it was shown that without altering the original images, the Control Invoices still achieved high recognition accuracies, but the Real and Noisy Invoices had very low recognition accuracies, confirming that the techniques have a significant effect on the invoice images.

The research study will be concluded in Chapter 7, where the main findings will be summarized and elaborated upon. Suggestions for further research will also be discussed and final conclusions will be drawn.

CHAPTER 7 – CONCLUSIONS

7.1 Introduction and thesis summary

In **Chapter 1 – Introduction**, it was pointed out that physical and electronic documents are extremely important for the preservation of information, and the conversion from physical document to machine-understandable electronic document is a very complex task (Shafait, 2009:1). It was revealed that DAR is the process whereby useful information on physical documents is extracted, and it consists of four phases, namely pre-processing, layout analysis, text recognition, and post-processing (Marinai, 2008:1). The importance of the pre-processing phase was highlighted by revealing how big the impact was that it has on the successful recognition of a document (2009:72). It was also revealed that there is a lack of studies that compare pre-processing techniques with one another specifically for the optimization of invoice or semi-structured documents.

This brought forward the main objective of this study, which was to compare various pre-processing techniques with one another in order to determine the most effective techniques to be used for invoice processing. In order to achieve this the following objectives were accomplished: (1) an understanding was gained regarding the functioning of the document management and OCR industry, (2) the most common pre-processing techniques were identified and studied, (3) invoice documents were distinguished from other documents, (4) an experiment process was created in which various techniques could be compared to one another based on their performance, (5) the techniques were compared and results were obtained, (6) the experiment results were analysed and discussed to reveal important findings, and (7) techniques that are the most likely to be effective were revealed.

In **Chapter 2 – Literature review**, the literature on the topic was investigated in order to gain a comprehensive understanding of the subject material. This was done by first looking at what OCR is, which includes its history, applications, and recent trends and movements. Following this, the DAR process was broken down and each of its steps was discussed. This included pre-processing, layout analysis, text recognition, and post-processing. All the key concepts discussed in this chapter are summed up in Figure 2-1, p. 7.

In **Chapter 3 – Research method**, the research studies were explained by making use of the six P's of research. It was explained that an exploratory study was conducted by making use of case studies to interview people involved in the DAR industry. Following that, an explanation was given of how an experimental investigation was conducted to compare pre-processing techniques to each other. A summary of the research method is illustrated in Figure 3-3, p. 39.

In **Chapter 4 – Current state of DAR in South Africa**, the exploratory study was discussed in detail. The chapter started out by motivating the need for such a study, whereafter an explanation of the case studies that were conducted followed. This included details of the interviews and the participants. The findings regarding business process, software, ICR, scanners, and the future of the industry were then revealed and discussed.

In **Chapter 5 – Experimental investigation**, the technical process of conducting the experiments was described and explained. This process started out with the acquisition of the original images. The quality of some of those images was then degraded in order to later test the effects of the noise reduction techniques. The techniques were then coded in MATLAB and applied to the original images. Following that, the processed documents were recognized using ABBYY FineReader. The ground truth text was then manually taken from the original document images. A software application was then developed, which allowed for comparisons of the processed images in order to measure their performance. All the processed images were fed into the application and the final results were obtained.

In **Chapter 6 – Results and discussion**, the results obtained from the experiments were analysed and explained. The results were discussed in terms of the recognition rates for characters, phrases, and numbers. The average recognition performance of each document was also discussed as well as the performance of the unaltered documents. A summary of the most significant findings can be found in Table 6-1, p. 78.

The rest of this chapter will be used to effectively summarize the results of the experiments in Section 7.2. The contribution of the work is then summarized in Section 7.3, suggestions for future work are given in Section 7.4, and the final conclusions are drawn in Section 7.5.

7.2 Summary of findings

The exploratory study has revealed many relevant findings regarding the DAR industry. Concerning the software used in the industry, it was learned that there are three main reasons for using OCR, namely document indexing, connecting metadata to documents, and to analyse document content. It was also revealed that affordability, accuracy, and simplicity are things to look for when purchasing OCR software. In addition to this, it is important to consider the type of document which has to be processed by categorizing it into structured, semi-structured, or unstructured.

The exploratory study showed that carefully structured forms have to be used for the implementation of ICR, as the users are required to write in clear print text which should not cross over into adjacent text boxes. The professionals also believe that the way in which documents

are scanned is also important. The optimal DPI to scan documents at for the use of OCR is between 240 and 300.

The last important thing revealed by the exploratory study, was the problems experienced by the professionals in the DAR industry. This includes clients which are unsure about what the companies can help them with, finding the right software packages for each of the clients, and the use of poor quality documents. The use of poor quality documents is an actual problem which can be addressed by using the findings of the experimental investigation.

In the experimental investigation, the most prominent noise reduction and binarization techniques have been identified and explained. These techniques were successfully compared with one another through the experiments conducted in Chapter 5.

Regarding the noise reduction techniques, it was discovered that the three weighted smoothing filters had the highest average recognition accuracies, suggesting that they are the three most effective noise reduction techniques for the recognition of invoice documents.

It was revealed in this study that the two main relevant elements that make invoice documents unique from other documents are their typical structure, and the strong focus on accurate numbers. Invoice documents are typically semi-structured documents. This means that they have more or less the same structure, but their appearance depends on various parameters, such as the number of items contained in the document.

The strong focus on numbers means that for invoice document processing, the accurate recognition of numbers is very important. Considering the performance of techniques on the recognition of numbers, weighted smoothing filter 2 performed the best.

It was also revealed that when working with salt-and-pepper noise, an average filter 3x3 is very inefficient as a grey patch is created for each piece of noise, which is then incorrectly read as a character. A median filter 3x3 on the other hand, is very effective at removing this type of noise as it does not degrade the quality of the original text too much.

The last observation concerning the noise reduction techniques is how poorly the median filter 5x5 performed all around. This is because the size of the filter is too big, causing it to degrade the image of the text significantly as it attempts to remove the noise.

Regarding the binarization techniques, the first observation to point out is the extremely poor performance of the global threshold 128. This is as a result of the technique separating the foreground and background pixels at a pre-set intensity value. By contrast, the Otsu threshold

separates the foreground and background at the optimum intensity, and therefore performs better in most instances.

From this study, one is able to conclude that of the binarization techniques tested, Niblack 2 and Otsu threshold are the most effective for the processing of invoice documents. The results have also revealed that Niblack 2 excelled at the recognition of numbers, while Otsu threshold had the highest recognition rate for characters. This would suggest that for the processing of invoice documents, Niblack 2 would be preferred.

Unfortunately, this study was limited by some factors. One of the limiting factors is the fact that only single techniques were compared with one another, and no combinations of techniques were tested. Combinations of techniques would possibly lead to even better results and could be considered for future research.

Another limiting factor is the timeframe for this study. Given more time, more conclusive results could be obtained using the same experiments. These possibilities are further discussed in Section 7.4.

7.3 Summary of contributions

One of the main contributions of this study was the creation of a method that allows for the comparison of pre-processing techniques, which is based on the recognition performance of the resulting text. This method can be used to test and compare any pre-processing techniques, independent from the rest of the recognition process. This method could also be used to test different types of document and is not in any way limited to invoice documents.

Furthermore, the most effective techniques for noise reduction and for binarization have been identified, based on their recognition performance on invoice documents. This allows businesses who process invoice documents through DAR to potentially improve their recognition rates by making use of the suggested techniques.

It was revealed that in the DAR industry, a general business process is followed by most companies. This process includes a demonstration during which the business shows its clients what it is able to help them with. Subsequently, a business case is defined, and a proof of concept trial run is used to show that the proposed solution will work for the client. The client then purchases the software, it is installed, and the software is continually maintained to ensure that it works effectively over a long period.

The exploratory study for this research also revealed many interesting elements regarding the document solutions industry. Findings regarding the software used revealed that most companies make use of ABBYY software. Other software used includes Captiva InputAccel, PSI:Capture,

and FormStorm. It was also learned that ICR and invoice documents do not really work together, as ICR works best when carefully structured forms are used so that the users can be forced to write in constrained print boxes. Since invoice documents are mainly semi-structured, ICR for invoice documents can be tricky. Lastly, it was revealed that the preferred DPI to scan documents at for OCR, is between 240 and 300.

7.4 Suggestions for further research

When considering future work that may emanate from this study, there are a number of possible research directions that could make use of the experiment method used, such as

- Additional techniques could be added to the experiment.
- Combinations of techniques could be tested, and more complex techniques could be incorporated.
- Processing time could be taken into account when comparing the techniques. Processing time could apply to the time taken to apply the technique to the document image, or the time taken to recognize the text of the processed document image.

This would allow for more comprehensive results. Another possibility involving the experiment method would be to modify and improve the software application used to compare the recognised text. This would potentially allow the comparisons to be made based on more than just characters, numbers, and phrases. It would be very valuable if the application was able to identify and compare key words or phrases in the recognized text. This would allow weights of importance to be added to some of the characters, numbers, or phrases in the documents.

Moving away from the experiment method, other possible research directions could involve the analysis and comparison of techniques for the other three phases of the DAR process, namely layout analysis, text recognition, and post-processing. This could possibly lead to a complete optimization of the combination of techniques used for DAR.

7.5 Conclusions

The aims and objectives of this study have been achieved. This research has tested and revealed some of the most effective pre-processing techniques to be used for the processing of invoice documents. In addition to this, some insight into the current state of affairs in the South African DAR industry was gained.

This study has shown that a couple of noise reduction and binarization techniques stand out from the rest for the processing of invoice documents. It has also revealed something about the

functioning of some of these techniques when applied to invoice documents, which aids in the understanding of why these techniques should or should not be used for invoice processing.

The findings of this study could be implemented by DAR-related businesses in order to improve their recognition accuracy. This can easily be done by making use of the most effective techniques revealed in this study, and staying away from the least effective techniques. Business can also learn from the findings of this study regarding the business practices, software used, ICR implementation, and scanners.

Regarding the future of the DAR industry, many consider it to be in its infancy. Information is the most valuable asset to any organization and DAR technologies could be incorporated by most companies to support their business processes. The automated processing of invoice documents could save companies time and resources.

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ANNEXURE A – RESULTS

The following ten tables contain the comparison test results of all the techniques applied to the test document images as well as the number of characters, phrases, and numbers in the associated ground truth text files.

1. Control Invoice 1

Ground truth text totals:

Characters	**874**
Phrases	**171**
Numbers	**65**

Technique	True Positive	False Positive	F-factor	Phrases	Phrases %	Numbers	Numbers %
1.1.1 Median filter 3x3	771	19	**92,67%**	129	**75,44%**	49	**75,38%**
1.1.2 Median filter 5x5	673	140	**79,79%**	64	**37,43%**	19	**29,23%**
1.2.1 Average filter 3x3	819	198	**86,62%**	142	**83,04%**	59	**90,77%**
1.2.2 Average filter 5x5	786	35	**92,74%**	129	**75,44%**	53	**81,54%**
1.3.1 Weighted smoothing filter 1	756	89	**87,96%**	139	**81,29%**	56	**86,15%**
1.3.2 Weighted smoothing filter 2	778	42	**91,85%**	140	**81,87%**	56	**86,15%**
1.3.3 Weighted smoothing filter 3	800	72	**91,64%**	146	**85,38%**	59	**90,77%**
1.4.1 Gaussian filter 5x5 s1	813	156	**88,23%**	143	**83,63%**	57	**87,69%**
1.4.2 Gaussian filter 10x10 s2	747	10	**91,60%**	119	**69,59%**	50	**76,92%**
1.5.1 Wiener filter 5x5 0.1v	767	11	**92,86%**	129	**75,44%**	54	**83,08%**
1.5.2 Wiener filter 10x10 0.01v	695	50	**85,86%**	79	**46,20%**	37	**56,92%**
2.1 Global threshold 128	186	305	**27,25%**	8	**4,68%**	10	**15,38%**
2.2 Otsu threshold	747	21	**90,99%**	119	**69,59%**	58	**89,23%**
2.3.1 Niblack 1	774	407	**75,33%**	140	**81,87%**	56	**86,15%**
2.3.2 Niblack 2	805	66	**92,26%**	135	**78,95%**	60	**92,31%**
2.4.1 Sauvola 1	794	461	**74,59%**	106	**61,99%**	52	**80,00%**
2.4.2 Sauvola 2	840	508	**75,61%**	137	**80,12%**	58	**89,23%**

Table A-1 Control Invoice 1 results

2. Control Invoice 2

Ground truth text totals:

Characters	**1489**
Phrases	**347**
Numbers	**162**

Technique	True Positive	False Positive	F-factor	Phrases	Phrases %	Numbers	Numbers %
1.1.1 Median filter 3x3	1417	14	**97,05%**	309	**89,05%**	154	**95,06%**
1.1.2 Median filter 5x5	1230	190	**84,57%**	176	**50,72%**	96	**59,26%**
1.2.1 Average filter 3x3	1388	1	**96,46%**	320	**92,22%**	157	**96,91%**
1.2.2 Average filter 5x5	1334	7	**94,28%**	298	**85,88%**	153	**94,44%**
1.3.1 Weighted smoothing filter 1	1392	1	**96,60%**	321	**92,51%**	157	**96,91%**
1.3.2 Weighted smoothing filter 2	1388	1	**96,46%**	320	**92,22%**	157	**96,91%**
1.3.3 Weighted smoothing filter 3	1387	2	**96,39%**	314	**90,49%**	156	**96,30%**
1.4.1 Gaussian filter 5x5 s1	1388	1	**96,46%**	321	**92,51%**	157	**96,91%**
1.4.2 Gaussian filter 10x10 s2	1358	17	**94,83%**	294	**84,73%**	153	**94,44%**
1.5.1 Wiener filter 5x5 0.1v	1331	8	**94,13%**	298	**85,88%**	154	**95,06%**
1.5.2 Wiener filter 10x10 0.01v	1416	5	**97,32%**	324	**93,37%**	157	**96,91%**
2.1 Global threshold 128	1396	65	**94,64%**	268	**77,23%**	133	**82,10%**
2.2 Otsu threshold	1415	4	**97,32%**	322	**92,80%**	157	**96,91%**
2.3.1 Niblack 1	1395	322	**87,02%**	282	**81,27%**	124	**76,54%**
2.3.2 Niblack 2	1454	100	**95,56%**	330	**95,10%**	157	**96,91%**
2.4.1 Sauvola 1	1389	0	**96,53%**	315	**90,78%**	157	**96,91%**
2.4.2 Sauvola 2	1429	89	**95,04%**	325	**93,66%**	157	**96,91%**

Table A-2 Control Invoice 2 results

3. Control Invoice 3

Ground truth text totals:

Characters	**742**
Phrases	**159**
Numbers	**70**

Technique	True Positive	False Positive	F-factor	Phrases	Phrases %	Numbers	Numbers %
1.1.1 Median filter 3x3	651	100	**87,21%**	130	**81,76%**	61	**87,14%**
1.1.2 Median filter 5x5	589	21	**87,13%**	94	**59,12%**	43	**61,43%**
1.2.1 Average filter 3x3	629	4	**91,49%**	137	**86,16%**	61	**87,14%**
1.2.2 Average filter 5x5	621	2	**90,99%**	130	**81,76%**	61	**87,14%**
1.3.1 Weighted smoothing filter 1	655	21	**92,38%**	139	**87,42%**	60	**85,71%**
1.3.2 Weighted smoothing filter 2	652	66	**89,32%**	137	**86,16%**	62	**88,57%**
1.3.3 Weighted smoothing filter 3	628	3	**91,48%**	137	**86,16%**	61	**87,14%**
1.4.1 Gaussian filter 5x5 s1	628	1	**91,61%**	131	**82,39%**	60	**85,71%**
1.4.2 Gaussian filter 10x10 s2	615	7	**90,18%**	126	**79,25%**	60	**85,71%**
1.5.1 Wiener filter 5x5 0.1v	621	2	**90,99%**	130	**81,76%**	61	**87,14%**
1.5.2 Wiener filter 10x10 0.01v	609	10	**89,49%**	121	**76,10%**	59	**84,29%**
2.1 Global threshold 128	636	167	**82,33%**	81	**50,94%**	44	**62,86%**
2.2 Otsu threshold	651	122	**85,94%**	134	**84,28%**	63	**90,00%**
2.3.1 Niblack 1	698	476	**72,86%**	138	**86,79%**	62	**88,57%**
2.3.2 Niblack 2	696	731	**64,18%**	138	**86,79%**	63	**90,00%**
2.4.1 Sauvola 1	655	67	**89,48%**	134	**84,28%**	62	**88,57%**
2.4.2 Sauvola 2	714	1502	**48,28%**	139	**87,42%**	63	**90,00%**

Table A-3 Control Invoice 3 results

4. Real Invoice 1

Ground truth text totals:

Characters	**2368**
Phrases	**453**
Numbers	**130**

Technique	True Positive	False Positive	F-factor	Phrases	Phrases %	Numbers	Numbers %
1.1.1 Median filter 3x3	2049	157	**89,59%**	252	**55,63%**	66	**50,77%**
1.1.2 Median filter 5x5	1779	546	**75,82%**	131	**28,92%**	40	**30,77%**
1.2.1 Average filter 3x3	2095	260	**88,71%**	282	**62,25%**	68	**52,31%**
1.2.2 Average filter 5x5	1975	310	**84,89%**	188	**41,50%**	56	**43,08%**
1.3.1 Weighted smoothing filter 1	2096	180	**90,27%**	296	**65,34%**	73	**56,15%**
1.3.2 Weighted smoothing filter 2	2086	186	**89,91%**	299	**66,00%**	78	**60,00%**
1.3.3 Weighted smoothing filter 3	2110	184	**90,52%**	300	**66,23%**	77	**59,23%**
1.4.1 Gaussian filter 5x5 s1	2063	261	**87,94%**	284	**62,69%**	76	**58,46%**
1.4.2 Gaussian filter 10x10 s2	1804	296	**80,75%**	142	**31,35%**	42	**32,31%**
1.5.1 Wiener filter 5x5 0.1v	1960	293	**84,83%**	190	**41,94%**	54	**41,54%**
1.5.2 Wiener filter 10x10 0.01v	2128	184	**90,94%**	304	**67,11%**	78	**60,00%**
2.1 Global threshold 128	2075	189	**89,59%**	276	**60,93%**	62	**47,69%**
2.2 Otsu threshold	2103	214	**89,78%**	299	**66,00%**	73	**56,15%**
2.3.1 Niblack 1	2176	196	**91,81%**	336	**74,17%**	82	**63,08%**
2.3.2 Niblack 2	2143	182	**91,33%**	321	**70,86%**	85	**65,38%**
2.4.1 Sauvola 1	2140	168	**91,53%**	325	**71,74%**	87	**66,92%**
2.4.2 Sauvola 2	2118	171	**90,96%**	319	**70,42%**	85	**65,38%**

Table A-4 Real Invoice 1 results

5. Real Invoice 2

Ground truth text totals:

Characters	**2956**
Phrases	**585**
Numbers	**139**

Technique	True Positive	False Positive	F-factor	Phrases	Phrases %	Numbers	Numbers %
1.1.1 Median filter 3x3	2783	87	**95,54%**	472	**80,68%**	112	**80,58%**
1.1.2 Median filter 5x5	2283	712	**76,73%**	262	**44,79%**	31	**22,30%**
1.2.1 Average filter 3x3	2811	134	**95,27%**	491	**83,93%**	122	**87,77%**
1.2.2 Average filter 5x5	2672	88	**93,49%**	426	**72,82%**	93	**66,91%**
1.3.1 Weighted smoothing filter 1	2819	143	**95,27%**	473	**80,85%**	119	**85,61%**
1.3.2 Weighted smoothing filter 2	2818	159	**94,99%**	490	**83,76%**	126	**90,65%**
1.3.3 Weighted smoothing filter 3	2849	148	**95,72%**	508	**86,84%**	125	**89,93%**
1.4.1 Gaussian filter 5x5 s1	2855	164	**95,56%**	503	**85,98%**	124	**89,21%**
1.4.2 Gaussian filter 10x10 s2	2488	61	**90,39%**	358	**61,20%**	68	**48,92%**
1.5.1 Wiener filter 5x5 0.1v	2665	74	**93,59%**	414	**70,77%**	84	**60,43%**
1.5.2 Wiener filter 10x10 0.01v	2778	52	**96,02%**	462	**78,97%**	85	**61,15%**
2.1 Global threshold 128	2586	362	**87,60%**	315	**53,85%**	71	**51,08%**
2.2 Otsu threshold	2754	77	**95,18%**	427	**72,99%**	124	**89,21%**
2.3.1 Niblack 1	2935	246	**95,65%**	466	**79,66%**	133	**95,68%**
2.3.2 Niblack 2	2830	240	**93,93%**	444	**75,90%**	133	**95,68%**
2.4.1 Sauvola 1	2903	192	**95,95%**	453	**77,44%**	126	**90,65%**
2.4.2 Sauvola 2	2831	159	**95,22%**	437	**74,70%**	133	**95,68%**

Table A-5 Real Invoice 2 results

6. Real Invoice 3

Ground truth text totals:

Characters	**1425**
Phrases	**249**
Numbers	**66**

Technique	True Positive	False Positive	F-factor	Phrases	Phrases %	Numbers	Numbers %
1.1.1 Median filter 3x3	1356	257	**89,27%**	171	**68,67%**	56	**84,85%**
1.1.2 Median filter 5x5	1057	325	**75,31%**	72	**28,92%**	30	**45,45%**
1.2.1 Average filter 3x3	1332	152	**91,58%**	173	**69,48%**	54	**81,82%**
1.2.2 Average filter 5x5	1143	262	**80,78%**	87	**34,94%**	37	**56,06%**
1.3.1 Weighted smoothing filter 1	1287	72	**92,46%**	172	**69,08%**	48	**72,73%**
1.3.2 Weighted smoothing filter 2	1314	215	**88,96%**	175	**70,28%**	55	**83,33%**
1.3.3 Weighted smoothing filter 3	1359	137	**93,05%**	175	**70,28%**	52	**78,79%**
1.4.1 Gaussian filter 5x5 s1	1348	160	**91,92%**	177	**71,08%**	53	**80,30%**
1.4.2 Gaussian filter 10x10 s2	993	162	**76,98%**	77	**30,92%**	41	**62,12%**
1.5.1 Wiener filter 5x5 0.1v	1197	301	**81,90%**	101	**40,56%**	41	**62,12%**
1.5.2 Wiener filter 10x10 0.01v	1344	222	**89,87%**	167	**67,07%**	44	**66,67%**
2.1 Global threshold 128	1326	312	**86,58%**	140	**56,22%**	45	**68,18%**
2.2 Otsu threshold	1346	196	**90,73%**	191	**76,71%**	56	**84,85%**
2.3.1 Niblack 1	1333	166	**91,18%**	198	**79,52%**	59	**89,39%**
2.3.2 Niblack 2	1414	330	**89,24%**	192	**77,11%**	58	**87,88%**
2.4.1 Sauvola 1	1346	169	**91,56%**	204	**81,93%**	59	**89,39%**
2.4.2 Sauvola 2	1360	206	**90,94%**	192	**77,11%**	58	**87,88%**

Table A-6 Real Invoice 3 results

7. Noisy Invoice 1

Ground truth text totals:

Characters	**1620**
Phrases	**304**
Numbers	**97**

Technique	True Positive	False Positive	F-factor	Phrases	Phrases %	Numbers	Numbers %
1.1.1 Median filter 3x3	1453	150	**90,16%**	169	**55,59%**	52	**53,61%**
1.1.2 Median filter 5x5	1138	433	**71,33%**	58	**19,08%**	21	**21,65%**
1.2.1 Average filter 3x3	1434	138	**89,85%**	179	**58,88%**	47	**48,45%**
1.2.2 Average filter 5x5	1329	247	**83,17%**	93	**30,59%**	28	**28,87%**
1.3.1 Weighted smoothing filter 1	1477	99	**92,43%**	198	**65,13%**	59	**60,82%**
1.3.2 Weighted smoothing filter 2	1467	99	**92,09%**	196	**64,47%**	61	**62,89%**
1.3.3 Weighted smoothing filter 3	1482	103	**92,48%**	197	**64,80%**	55	**56,70%**
1.4.1 Gaussian filter 5x5 s1	1460	119	**91,28%**	189	**62,17%**	62	**63,92%**
1.4.2 Gaussian filter 10x10 s2	1237	278	**78,92%**	79	**25,99%**	25	**25,77%**
1.5.1 Wiener filter 5x5 0.1v	1269	276	**80,19%**	101	**33,22%**	33	**34,02%**
1.5.2 Wiener filter 10x10 0.01v	1430	142	**89,60%**	160	**52,63%**	49	**50,52%**

Table A-7 Noisy Invoice 1 results

8. Noisy Invoice 2

Ground truth text totals:

Characters	**1622**
Phrases	**307**
Numbers	**99**

Technique	True Positive	False Positive	F-factor	Phrases	Phrases %	Numbers	Numbers %
1.1.1 Median filter 3x3	1440	116	**90,62%**	188	**61,24%**	58	**58,59%**
1.1.2 Median filter 5x5	1106	527	**67,96%**	49	**15,96%**	27	**27,27%**
1.2.1 Average filter 3x3	1484	82	**93,10%**	217	**70,68%**	62	**62,63%**
1.2.2 Average filter 5x5	1370	169	**86,68%**	131	**42,67%**	49	**49,49%**
1.3.1 Weighted smoothing filter 1	1502	75	**93,90%**	234	**76,22%**	74	**74,75%**
1.3.2 Weighted smoothing filter 2	1536	60	**95,46%**	227	**73,94%**	67	**67,68%**
1.3.3 Weighted smoothing filter 3	1504	87	**93,62%**	221	**71,99%**	67	**67,68%**
1.4.1 Gaussian filter 5x5 s1	1480	87	**92,82%**	205	**66,78%**	60	**60,61%**
1.4.2 Gaussian filter 10x10 s2	1332	203	**84,38%**	107	**34,85%**	42	**42,42%**
1.5.1 Wiener filter 5x5 0.1v	1343	212	**84,55%**	125	**40,72%**	48	**48,48%**
1.5.2 Wiener filter 10x10 0.01v	1489	65	**93,77%**	217	**70,68%**	70	**70,71%**

Table A-8 Noisy Invoice 2 results

9. Noisy Invoice 3

Ground truth text totals:

Characters	**1655**
Phrases	**308**
Numbers	**99**

Technique	True Positive	False Positive	F-factor	Phrases	Phrases %	Numbers	Numbers %
1.1.1 Median filter 3x3	1511	98	**92,59%**	201	**65,26%**	51	**51,52%**
1.1.2 Median filter 5x5	1176	521	**70,17%**	52	**16,88%**	23	**23,23%**
1.2.1 Average filter 3x3	1554	2216	**57,29%**	170	**55,19%**	57	**57,58%**
1.2.2 Average filter 5x5	1412	178	**87,03%**	136	**44,16%**	51	**51,52%**
1.3.1 Weighted smoothing filter 1	1544	372	**86,47%**	186	**60,39%**	54	**54,55%**
1.3.2 Weighted smoothing filter 2	1557	375	**86,81%**	205	**66,56%**	66	**66,67%**
1.3.3 Weighted smoothing filter 3	1568	607	**81,88%**	224	**72,73%**	64	**64,65%**
1.4.1 Gaussian filter 5x5 s1	1539	372	**86,32%**	212	**68,83%**	61	**61,62%**
1.4.2 Gaussian filter 10x10 s2	1400	162	**87,04%**	101	**32,79%**	38	**38,38%**
1.5.1 Wiener filter 5x5 0.1v	1381	280	**83,29%**	111	**36,04%**	45	**45,45%**
1.5.2 Wiener filter 10x10 0.01v	1461	175	**88,79%**	138	**44,81%**	44	**44,44%**

Table A-9 Noisy Invoice 3 results

10. Noisy Invoice 4

Ground truth text totals:

Characters	**1620**
Phrases	**306**
Numbers	**100**

Technique	True Positive	False Positive	F-factor	Phrases	Phrases %	Numbers	Numbers %
1.1.1 Median filter 3x3	1432	122	**90,23%**	183	**59,80%**	56	**56,00%**
1.1.2 Median filter 5x5	993	539	**63,01%**	40	**13,07%**	14	**14,00%**
1.2.1 Average filter 3x3	1475	98	**92,39%**	209	**68,30%**	63	**63,00%**
1.2.2 Average filter 5x5	1350	231	**84,35%**	133	**43,46%**	40	**40,00%**
1.3.1 Weighted smoothing filter 1	1499	63	**94,22%**	235	**76,80%**	65	**65,00%**
1.3.2 Weighted smoothing filter 2	1488	66	**93,76%**	219	**71,57%**	58	**58,00%**
1.3.3 Weighted smoothing filter 3	1521	90	**94,15%**	221	**72,22%**	56	**56,00%**
1.4.1 Gaussian filter 5x5 s1	1472	89	**92,55%**	206	**67,32%**	58	**58,00%**
1.4.2 Gaussian filter 10x10 s2	1304	210	**83,22%**	120	**39,22%**	39	**39,00%**
1.5.1 Wiener filter 5x5 0.1v	1333	230	**83,76%**	128	**41,83%**	37	**37,00%**
1.5.2 Wiener filter 10x10 0.01v	1492	76	**93,60%**	225	**73,53%**	67	**67,00%**

Table A-10 Noisy Invoice 4 results

ANNEXURE B – ANALYSIS

When looking at the tables in this Annexure, it is important to notice that the cells are different colours. For Tables B-1 – B-8, the colour of the cell highlights the techniques' performance compared to the other techniques for each document image on a scale of 1 to 10. A red cell indicates that for the specific document image (indicated by the column), the associated technique's recognition performance is worse than that of most of the other techniques. A yellow cell indicates that the technique's performance was average, and a green cell indicates that the technique outperformed the rest of the techniques.

The colours of the cells in Tables B-9 – B-10 highlight the techniques' performance for the associated document image compared to the performance on the other document images. In other words, a green cell reveals that the technique performed the best for the associated document image, while a red cell reveals that the technique performed the worst on that associated document image.

Lastly, the colours of the cells in Table B-11 are used to highlight the performance of the techniques on the associated document image for characters, phrases, numbers, and averages respectively.

The scale used for the colouring of the cells is perfectly illustrated in Figure B-1, with the red cell performing the worst and the green cell performing the best on a scale from 1 to 10.

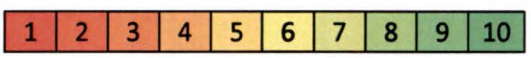


Figure B-1 Cell colour scale

1. Characters

Table B-1 Average by characters recognized – Noise reduction

Technique	Ctrl Inv 1	Ctrl Inv 2	Ctrl Inv 3	Real Inv 1	Real Inv 2	Real Inv 3	Noise Inv 1	Noise Inv 2	Noise Inv 3	Noise Inv 4	Average
1.1.1 Median filter 3x3	92,67%	97,05%	87,21%	89,59%	95,54%	89,27%	90,16%	90,62%	92,59%	90,23%	**91,49%**
1.1.2 Median filter 5x5	79,79%	84,57%	87,13%	75,82%	76,73%	75,31%	71,33%	67,96%	70,17%	63,01%	**75,18%**
1.2.1 Average filter 3x3	86,62%	96,46%	91,49%	88,71%	95,27%	91,58%	89,85%	93,10%	57,29%	92,39%	**88,28%**
1.2.2 Average filter 5x5	92,74%	94,28%	90,99%	84,89%	93,49%	80,78%	83,17%	86,68%	87,03%	84,35%	**87,84%**
1.3.1 Weighted smoothing filter 1	87,96%	96,60%	92,38%	90,27%	95,27%	92,46%	92,43%	93,90%	86,47%	94,22%	**92,20%**
1.3.2 Weighted smoothing filter 2	91,85%	96,46%	89,32%	89,91%	94,99%	88,96%	92,09%	95,46%	86,81%	93,76%	**91,96%**
1.3.3 Weighted smoothing filter 3	91,64%	96,39%	91,48%	90,52%	95,72%	93,05%	92,48%	93,62%	81,88%	94,15%	**92,09%**
1.4.1 Gaussian filter 5x5 s1	88,23%	96,46%	91,61%	87,94%	95,56%	91,92%	91,28%	92,82%	86,32%	92,55%	**91,47%**
1.4.2 Gaussian filter 10x10 s2	91,60%	94,83%	90,18%	80,75%	90,39%	76,98%	78,92%	84,38%	87,04%	83,22%	**85,83%**
1.5.1 Wiener filter 5x5 0.1v	92,86%	94,13%	90,99%	84,83%	93,59%	81,90%	80,19%	84,55%	83,29%	83,76%	**87,01%**
1.5.2 Wiener filter 10x10 0.01v	85,86%	97,32%	89,49%	90,94%	96,02%	89,87%	89,60%	93,77%	88,79%	93,60%	**91,53%**

Table B-2 Average by characters recognized – Binarization

Technique	Ctrl Inv 1	Ctrl Inv 2	Ctrl Inv 3	Real Inv 1	Real Inv 2	Real Inv 3	Average
2.1 Global threshold 128	27,25%	94,64%	82,33%	89,59%	87,60%	86,58%	**78,00%**
2.2 Otsu threshold	90,99%	97,32%	85,94%	89,78%	95,18%	90,73%	**91,66%**
2.3.1 Niblack 1	75,33%	87,02%	72,86%	91,81%	95,65%	91,18%	**85,64%**
2.3.2 Niblack 2	92,26%	95,56%	64,18%	91,33%	93,93%	89,24%	**87,75%**
2.4.1 Sauvola 1	74,59%	96,53%	89,48%	91,53%	95,95%	91,56%	**89,94%**
2.4.2 Sauvola 2	75,61%	95,04%	48,28%	90,96%	95,22%	90,94%	**82,68%**

2. Phrases

Table B-3 Average by phrases recognized - Noise reduction

Technique	Ctrl Inv 1	Ctrl Inv 2	Ctrl Inv 3	Real Inv 1	Real Inv 2	Real Inv 3	Noise Inv 1	Noise Inv 2	Noise Inv 3	Noise Inv 4	Average
1.1.1 Median filter 3x3	75,44%	89,05%	81,76%	55,63%	80,68%	68,67%	55,59%	61,24%	65,26%	59,80%	**69,31%**
1.1.2 Median filter 5x5	37,43%	50,72%	59,12%	28,92%	44,79%	28,92%	19,08%	15,96%	16,88%	13,07%	**31,49%**
1.2.1 Average filter 3x3	83,04%	92,22%	86,16%	62,25%	83,93%	69,48%	58,88%	70,68%	55,19%	68,30%	**73,01%**
1.2.2 Average filter 5x5	75,44%	85,88%	81,76%	41,50%	72,82%	34,94%	30,59%	42,67%	44,16%	43,46%	**55,32%**
1.3.1 Weighted smoothing filter 1	81,29%	92,51%	87,42%	65,34%	80,85%	69,08%	65,13%	76,22%	60,39%	76,80%	**75,50%**
1.3.2 Weighted smoothing filter 2	81,87%	92,22%	86,16%	66,00%	83,76%	70,28%	64,47%	73,94%	66,56%	71,57%	**75,68%**
1.3.3 Weighted smoothing filter 3	85,38%	90,49%	86,16%	66,23%	86,84%	70,28%	64,80%	71,99%	72,73%	72,22%	**76,71%**
1.4.1 Gaussian filter 5x5 s1	83,63%	92,51%	82,39%	62,69%	85,98%	71,08%	62,17%	66,78%	68,83%	67,32%	**74,34%**
1.4.2 Gaussian filter 10x10 s2	69,59%	84,73%	79,25%	31,35%	61,20%	30,92%	25,99%	34,85%	32,79%	39,22%	**48,99%**
1.5.1 Wiener filter 5x5 0.1v	75,44%	85,88%	81,76%	41,94%	70,77%	40,56%	33,22%	40,72%	36,04%	41,83%	**54,82%**
1.5.2 Wiener filter 10x10 0.01v	46,20%	93,37%	76,10%	67,11%	78,97%	67,07%	52,63%	70,68%	44,81%	73,53%	**67,05%**

Table B-4 Average by phrases recognized - Binarization

Technique	Ctrl Inv 1	Ctrl Inv 2	Ctrl Inv 3	Real Inv 1	Real Inv 2	Real Inv 3	Average
2.1 Global threshold 128	4,68%	77,23%	50,94%	60,93%	53,85%	56,22%	**50,64%**
2.2 Otsu threshold	69,59%	92,80%	84,28%	66,00%	72,99%	76,71%	**77,06%**
2.3.1 Niblack 1	81,87%	81,27%	86,79%	74,17%	79,66%	79,52%	**80,55%**
2.3.2 Niblack 2	78,95%	95,10%	86,79%	70,86%	75,90%	77,11%	**80,78%**
2.4.1 Sauvola 1	61,99%	90,78%	84,28%	71,74%	77,44%	81,93%	**78,03%**
2.4.2 Sauvola 2	80,12%	93,66%	87,42%	70,42%	74,70%	77,11%	**80,57%**

3. Numbers

Table B-5 Average by numbers recognized - Noise reduction

Technique	Ctrl Inv 1	Ctrl Inv 2	Ctrl Inv 3	Real Inv 1	Real Inv 2	Real Inv 3	Noise Inv 1	Noise Inv 2	Noise Inv 3	Noise Inv 4	Average
1.1.1 Median filter 3x3	75,38%	95,06%	87,14%	50,77%	80,58%	84,85%	53,61%	58,59%	51,52%	56,00%	**69,35%**
1.1.2 Median filter 5x5	29,23%	59,26%	61,43%	30,77%	22,30%	45,45%	21,65%	27,27%	23,23%	14,00%	**33,46%**
1.2.1 Average filter 3x3	90,77%	96,91%	87,14%	52,31%	87,77%	81,82%	48,45%	62,63%	57,58%	63,00%	**72,84%**
1.2.2 Average filter 5x5	81,54%	94,44%	87,14%	43,08%	66,91%	56,06%	28,87%	49,49%	51,52%	40,00%	**59,90%**
1.3.1 Weighted smoothing filter 1	86,15%	96,91%	85,71%	56,15%	85,61%	72,73%	60,82%	74,75%	54,55%	65,00%	**73,84%**
1.3.2 Weighted smoothing filter 2	86,15%	96,91%	88,57%	60,00%	90,65%	83,33%	62,89%	67,68%	66,67%	58,00%	**76,08%**
1.3.3 Weighted smoothing filter 3	90,77%	96,30%	87,14%	59,23%	89,93%	78,79%	56,70%	67,68%	64,65%	56,00%	**74,72%**
1.4.1 Gaussian filter 5x5 s1	87,69%	96,91%	85,71%	58,46%	89,21%	80,30%	63,92%	60,61%	61,62%	58,00%	**74,24%**
1.4.2 Gaussian filter 10x10 s2	76,92%	94,44%	85,71%	32,31%	48,92%	62,12%	25,77%	42,42%	38,38%	39,00%	**54,60%**
1.5.1 Wiener filter 5x5 0.1v	83,08%	95,06%	87,14%	41,54%	60,43%	62,12%	34,02%	48,48%	45,45%	37,00%	**59,43%**
1.5.2 Wiener filter 10x10 0.01v	56,92%	96,91%	84,29%	60,00%	61,15%	66,67%	50,52%	70,71%	44,44%	67,00%	**65,86%**

Table B-6 Average by numbers recognized - Binarization

Technique	Ctrl Inv 1	Ctrl Inv 2	Ctrl Inv 3	Real Inv 1	Real Inv 2	Real Inv 3	Average
2.1 Global threshold 128	15,38%	82,10%	62,86%	47,69%	51,08%	68,18%	**54,55%**
2.2 Otsu threshold	89,23%	96,91%	90,00%	56,15%	89,21%	84,85%	**84,39%**
2.3.1 Niblack 1	86,15%	76,54%	88,57%	63,08%	95,68%	89,39%	**83,24%**
2.3.2 Niblack 2	92,31%	96,91%	90,00%	65,38%	95,68%	87,88%	**88,03%**
2.4.1 Sauvola 1	80,00%	96,91%	88,57%	66,92%	90,65%	89,39%	**85,41%**
2.4.2 Sauvola 2	89,23%	96,91%	90,00%	65,38%	95,68%	87,88%	**87,52%**

4. Averages

Table B-7 Total average - Noise reduction

Technique	Ctrl Inv 1	Ctrl Inv 2	Ctrl Inv 3	Real Inv 1	Real Inv 2	Real Inv 3	Noise Inv 1	Noise Inv 2	Noise Inv 3	Noise Inv 4	Average
1.1.1 Median filter 3x3	81,16%	93,72%	85,37%	65,33%	85,60%	80,93%	66,45%	70,15%	69,79%	68,68%	**76,72%**
1.1.2 Median filter 5x5	48,81%	64,85%	69,23%	45,17%	47,94%	49,89%	37,35%	37,06%	36,76%	30,03%	**46,71%**
1.2.1 Average filter 3x3	86,81%	95,20%	88,27%	67,76%	88,99%	80,96%	65,73%	75,47%	56,69%	74,56%	**78,04%**
1.2.2 Average filter 5x5	83,24%	91,53%	86,63%	56,49%	77,74%	57,26%	47,54%	59,62%	60,90%	55,94%	**67,69%**
1.3.1 Weighted smoothing filter 1	85,13%	95,34%	88,51%	70,59%	87,24%	78,09%	72,79%	81,62%	67,14%	78,67%	**80,51%**
1.3.2 Weighted smoothing filter 2	86,63%	95,20%	88,02%	71,97%	89,80%	80,86%	73,15%	79,03%	73,35%	74,44%	**81,24%**
1.3.3 Weighted smoothing filter 3	89,26%	94,39%	88,26%	71,99%	90,83%	80,71%	71,33%	77,76%	73,08%	74,12%	**81,17%**
1.4.1 Gaussian filter 5x5 s1	86,51%	95,29%	86,57%	69,70%	90,25%	81,10%	72,46%	73,40%	72,25%	72,62%	**80,02%**
1.4.2 Gaussian filter 10x10 s2	79,37%	91,33%	85,05%	48,14%	66,84%	56,67%	43,56%	53,89%	52,74%	53,81%	**63,14%**
1.5.1 Wiener filter 5x5 0.1v	83,79%	91,69%	86,63%	56,10%	74,93%	61,53%	49,14%	57,92%	54,93%	54,20%	**67,09%**
1.5.2 Wiener filter 10x10 0.01v	62,99%	95,87%	83,29%	72,68%	78,72%	74,53%	64,25%	78,39%	59,35%	78,04%	**74,81%**

Table B-8 Total average - Binarization

Technique	Ctrl Inv 1	Ctrl Inv 2	Ctrl Inv 3	Real Inv 1	Real Inv 2	Real Inv 3	Average
2.1 Global threshold 128	15,77%	84,66%	65,38%	66,07%	64,18%	70,33%	**61,06%**
2.2 Otsu threshold	83,27%	95,68%	86,74%	70,64%	85,79%	84,10%	**84,37%**
2.3.1 Niblack 1	81,12%	81,61%	82,74%	76,35%	90,33%	86,70%	**83,14%**
2.3.2 Niblack 2	87,84%	95,86%	80,32%	75,86%	88,50%	84,74%	**85,52%**
2.4.1 Sauvola 1	72,19%	94,74%	87,44%	76,73%	88,01%	87,63%	**84,46%**
2.4.2 Sauvola 2	81,65%	95,21%	75,23%	75,59%	88,54%	85,31%	**83,59%**

5. Document performance

Table B-9 Document performance - Noise reduction

Technique	Ctrl Inv 1	Ctrl Inv 2	Ctrl Inv 3	Real Inv 1	Real Inv 2	Real Inv 3	Noise Inv 1	Noise Inv 2	Noise Inv 3	Noise Inv 4
1.1.1 Median filter 3x3	81,16%	93,72%	85,37%	65,33%	85,60%	80,93%	66,45%	70,15%	69,79%	68,68%
1.1.2 Median filter 5x5	48,81%	64,85%	69,23%	45,17%	47,94%	49,89%	37,35%	37,06%	36,76%	30,03%
1.2.1 Average filter 3x3	86,81%	95,20%	88,27%	67,76%	88,99%	80,96%	65,73%	75,47%	56,69%	74,56%
1.2.2 Average filter 5x5	83,24%	91,53%	86,63%	56,49%	77,74%	57,26%	47,54%	59,62%	60,90%	55,94%
1.3.1 Weighted smoothing filter 1	85,13%	95,34%	88,51%	70,59%	87,24%	78,09%	72,79%	81,62%	67,14%	78,67%
1.3.2 Weighted smoothing filter 2	86,63%	95,20%	88,02%	71,97%	89,80%	80,86%	73,15%	79,03%	73,35%	74,44%
1.3.3 Weighted smoothing filter 3	89,26%	94,39%	88,26%	71,99%	90,83%	80,71%	71,33%	77,76%	73,08%	74,12%
1.4.1 Gaussian filter 5x5 s1	86,51%	95,29%	86,57%	69,70%	90,25%	81,10%	72,46%	73,40%	72,25%	72,62%
1.4.2 Gaussian filter 10x10 s2	79,37%	91,33%	85,05%	48,14%	66,84%	56,67%	43,56%	53,89%	52,74%	53,81%
1.5.1 Wiener filter 5x5 0.1v	83,79%	91,69%	86,63%	56,10%	74,93%	61,53%	49,14%	57,92%	54,93%	54,20%
1.5.2 Wiener filter 10x10 0.01v	62,99%	95,87%	83,29%	72,68%	78,72%	74,53%	64,25%	78,39%	59,35%	78,04%
Average	**79,43%**	**91,31%**	**85,07%**	**63,27%**	**79,90%**	**71,14%**	**60,34%**	**67,66%**	**61,54%**	**65,01%**

Table B-10 Document performance - Binarization

Technique	Ctrl Inv 1	Ctrl Inv 2	Ctrl Inv 3	Real Inv 1	Real Inv 2	Real Inv 3
2.1 Global threshold 128	15,77%	84,66%	65,38%	66,07%	64,18%	70,33%
2.2 Otsu threshold	83,27%	95,68%	86,74%	70,64%	85,79%	84,10%
2.3.1 Niblack 1	81,12%	81,61%	82,74%	76,35%	90,33%	86,70%
2.3.2 Niblack 2	87,84%	95,86%	80,32%	75,86%	88,50%	84,74%
2.4.1 Sauvola 1	72,19%	94,74%	87,44%	76,73%	88,01%	87,63%
2.4.2 Sauvola 2	81,65%	95,21%	75,23%	75,59%	88,54%	85,31%
Average	**70,31%**	**91,29%**	**79,64%**	**73,54%**	**84,22%**	**83,13%**

6. Unaltered document performance

Table B-11 Unaltered document performance

Document	True Positive	False Positive	Total Characters	Characters %	Phrases	Total Phrases	Phrases %	Numbers	Total Numbers	Numbers %	Average %
Ctrl_Inv_1	96,04%	91,53%	874	93,73%	138	171	80,70%	50	65	76,92%	83,79%
Ctrl_Inv_2	99,87%	99,46%	1489	99,66%	335	347	96,54%	162	162	100,00%	98,74%
Ctrl_Inv_3	99,19%	99,60%	742	99,39%	156	159	98,11%	70	70	100,00%	99,17%
Real_Inv_1	90,54%	61,02%	2368	72,91%	126	453	27,81%	19	130	14,62%	38,45%
Real_Inv_2	70,07%	38,33%	2956	49,55%	46	585	7,86%	2	139	1,44%	19,62%
Real_Inv_3	35,65%	76,56%	1425	48,65%	10	249	4,02%	2	66	3,03%	18,57%
Noise_Inv_1	94,01%	93,09%	1620	93,55%	186	304	61,18%	25	97	25,77%	60,17%
Noise_Inv_2	61,15%	91,62%	1622	73,35%	126	307	41,04%	16	99	16,16%	43,52%
Noise_Inv_3	40,24%	73,23%	1655	51,94%	49	308	15,91%	0	99	0,00%	22,62%
Noise_Inv_4	61,74%	70,43%	1620	65,80%	14	306	4,58%	2	100	2,00%	24,13%
Average				**74,85%**			**43,78%**			**33,99%**	

7. Box plot

If all the average results achieved (taken from Section 4) by each technique were arranged in ascending order of magnitude for each technique, the following necessary information could be acquired:

- **Min**: The lowest value of the given data set.
- **Q1**: The first quartile (or lower quartile) is the middle value of the lower half of the data set.
- **Median**: The middle value of the entire data set.
- **Q3**: The third quartile (or upper quartile) is the middle value of the upper half of the data set.
- **Max**: The highest value of the given data set.

The following table contains the statistics used to create the box plot chart shown in Figure 6-20, p. 75.

Table B-12 Average box plot statistics

Technique	Min	Q1	Median	Q3	Max	Average
1.1.1 Median filter 3x3	65,3%	69,0%	75,5%	84,3%	93,7%	76,7%
1.1.2 Median filter 5x5	30,0%	37,1%	46,6%	49,6%	69,2%	46,7%
1.2.1 Average filter 3x3	56,7%	69,5%	78,2%	87,9%	95,2%	78,0%
1.2.2 Average filter 5x5	47,5%	56,7%	60,3%	81,9%	91,5%	67,7%
1.3.1 Weighted smoothing filter 1	67,1%	74,1%	80,1%	86,7%	95,3%	80,5%
1.3.2 Weighted smoothing filter 2	72,0%	73,6%	79,9%	87,7%	95,2%	81,2%
1.3.3 Weighted smoothing filter 3	71,3%	73,3%	79,2%	89,0%	94,4%	81,2%
1.4.1 Gaussian filter 5x5 s1	69,7%	72,5%	77,3%	86,6%	95,3%	80,0%
1.4.2 Gaussian filter 10x10 s2	43,6%	53,0%	55,3%	76,2%	91,3%	63,1%
1.5.1 Wiener filter 5x5 0.1v	49,1%	55,2%	59,7%	81,6%	91,7%	67,1%
1.5.2 Wiener filter 10x10 0.01v	59,3%	66,4%	76,3%	78,6%	95,9%	74,8%
2.1 Global threshold 128	15,8%	64,5%	65,7%	69,3%	84,7%	61,1%
2.2 Otsu threshold	70,6%	83,5%	84,9%	86,5%	95,7%	84,4%
2.3.1 Niblack 1	76,4%	81,2%	82,2%	85,7%	90,3%	83,1%
2.3.2 Niblack 2	75,9%	81,4%	86,3%	88,3%	95,9%	85,5%
2.4.1 Sauvola 1	72,2%	79,4%	87,5%	87,9%	94,7%	84,5%
2.4.2 Sauvola 2	75,2%	77,1%	83,5%	87,7%	95,2%	83,6%

ANNEXURE C – IMAGES USED FOR EXPERIMENTS

Control Invoice 1

Example Company One
13 Non Existing Street, Johannesburg, 5310
Tel (+34)75 468 8954

INVOICE 0086521 **7.12.2013**

BILL TO	SHIP TO	INSTRUCTIONS
Jack Peterson 253 Fox Ave Pretoria, 2331	Same as recipient	No additional instructions were given

QUANTITY	DESCRIPTION	UNIT PRICE	TOTAL
1	AMD FX™ 6300 (3.5GHz, 14M Cache, 6x Cores, 4.1GHz Turbo) Six Core CPU	1299.00	1299.00
1	MSI 970 GAMING AM3+ SATA 6Gb/s USB 3.0 SLI/XFire ATX AMD Motherboard	1599.00	1599.00
1	MSI GAMING Radeon R9 280 3GB 384bit OVERCLOCKED EDITION DDR5 Graphics Card	4549.00	4549.00
1	Antec 500W 80+ High Performance Power Supply	449.00	449.00
1	NZXT S340 Professional Gaming Case	399.00	399.00
2	8GB (2 x 4GB) DDR3 1600MHz High Performance Gaming RAM with Heat Spreader	1299.00	2598.00
2	128GB SSD Upto 500MB/s + Speed Ultra-Fast Solid State Drive (OS DRIVE)	649.00	1298.00
1	24X Dual Layer DVD Writer	499.00	499.00
1	Gigabit LAN Card - Broadband Ready	199.00	199.00
		SUBTOTAL (INCL TAX)	12889.00
		SHIPPING & HANDLING	110.00
		TOTAL DUE BY 7.15.2013	**12999.00**

Thank you for your business!

Control Invoice 2

Date: February 27, 2015
Invoice # 325441

Example Company Two
532 Brown Fox St
Cape Town, 2051
(+27)32 548 612
Fax [531-126-5334]
ex.comp2@gmail.com

TO:
Jake Zeelie
Drake Company
12 Dog St
Cape Town, 2051
(+27)82 353 1245]
Customer ID 35248

QUANTITY	ITEM #	DESCRIPTION	WTY	PRICE	LINE TOTAL
1	6542	Intel Core i7-4790K (4.0GHz, 8M Cache, 8x Cores) Overclocked to 4.6GHz Per Core CPU	1	4499	4499
1	2245	MSI Z97 GAMING 7 Intel Z97 Chipset LGA 1150 SATA 6Gb/s USB 3.0 Motherboard	1	3499	3499
1	6651	AMD Radeon R9 295X2 Dual GPU 8GB (2 x 4GB) 1024bits (512 x 2) GDDR5 Graphics Card	2	5800	5800
2	2147	8GB (2 x 4GB) DDR3 1600MHz High Performance Gaming RAM with Heat Spreader	3	1199	2398
1	5514	EVGA SuperNOVA 1300W FULLY Modular 80+ GOLD High Performance Power Supply	1	1350	1350
1	0214	Noctua NH-D14 Dual Radiator 6 Heatpipe with 140mm/120mm Dual SSO Bearing Fans CPU Cooler	1	582	582
1	2995	NZXT Phantom 530 Gaming Case	1	599	599
1	4413	128GB SSD Upto 500MB/s + Speed Ultra-Fast Solid State Drive (OS DRIVE)	1	354	354
2	5001	24x Dual Layer DVD +/- Writer	1	499	998
1	2114	Intel Core i7-4790K (4.0GHz, 8M Cache, 8x Cores) Overclocked to 4.6GHz Per Core CPU	1	3598	3598
1	5587	MSI Z97 GAMING 7 Intel Z97 Chipset LGA 1150 SATA 6Gb/s USB 3.0 Motherboard	1	1594	1594
1	4389	AMD Radeon R9 295X2 Dual GPU 8GB (2 x 4GB) 1024bits (512 x 2) GDDR5 Graphics Card	2	6189	6189
2	4522	8GB (2 x 4GB) DDR3 1600MHz High Performance Gaming RAM with Heat Spreader	2	2115	4230
1	1105	EVGA SuperNOVA 1300W FULLY Modular 80+ GOLD High Performance Power Supply	1	1580	1580
1	4456	Noctua NH-D14 Dual Radiator 6 Heatpipe with 140mm/120mm Dual SSO Bearing Fans CPU Cooler	3	985	985
1	5474	NZXT Phantom 530 Gaming Case	3	561	561
				Total	38816

Where dreams come true, today, tomorrow.

Make all checks payable to Example Company Two

THANK YOU FOR YOUR BUSINESS!

Control Invoice 3

EXAMPLE COMPANY THREE

April 3, 2012

INVOICE #354796

Bill To	
Customer	Dan Foxworthy
Customer ID#	9324511
Address	31 Bilson St, East London, 5211
Phone	(+27)32 423 6631
Payment Due	April 12, 2012
Salesperson	James Harvey

Qty.	Item#	Description	WTY	Price	Line Total
1	5448	AMD FX™ 6300 (3.5GHz, 14M Cache, 6x Cores, 4 1GHz Turbo) Six Core CPU	1	1578	1578
1	6523	MSI 970 GAMING AM3+ SATA 6Gb/s USB 3.0 SLI/XFire ATX AMD Motherboard	3	1399	1399
3	2587	8GB (2 x 4GB) DDR3 1600MHz High Performance Gaming RAM with Heat Spreader	2	1100	3300
2	7889	MSI GeForce GTX 750 Overclocked Edition 1GB DDR5 DX11 Graphics Card	2	2899	5798
1	1124	Antec 500W 80+ High Performance Power Supply	1	499	499
1	2658	Antec GX300 Clear Side Panel USB3.0 Case	1	380	380
				Total	**12954**

Thank you for your business!

Example Company Three

18 Jonson St, East London, 4123 | www.excompthree.co.za

(+27)32 122 5180 | excompany3@gmail.com

Real Invoice 1

Eskom

ESKOM HOLDINGS SOC LIMITED REG NO 2002/015527/06
VAT REG NO 4740101508

NORTH WESTERN REGION
PRIVATE BAG X16 WESTVILLE 2000

CONTACT CENTRE: (0860) 037566
FAX NO: (051) 404 2627
E-MAIL: NORTH WESTERN@ESKOM CO.ZA
WEB: WWW ESKOM CO ZA

YOUR ACCOUNT NO	[redacted]
SECURITY HELD	
BILLING DATE	
TAX INVOICE NO	
ACCOUNT MONTH	
CURRENT DUE DATE	
VAT REG NO	
NOTIFIED MAX DEMAND	

TELKOM SA LTD C/O TFMC (PTY) LTD
PRIVATE BAG X137
CENTURION
0046

TAX INVOICE

E-MAIL: UTILITIES@TFMC.CO.ZA

READING TYPE: ACTUAL	READING DATES: 2012/06/21 - 2013/06/20	NO OF DAYS 364	SEASON:

Your next actual reading will be on 22/07/2013

CONSUMPTION SUMMARY FOR BILLING PERIOD

METER NUMBER	PREV READING	CURR READING	DIFFERENCE	CONSTANT	CONSUMPTION
139295	40974.0000	62086 0000	21112.0000	1.0000	21,112 0000
139384	10144.0000	25750.0000	15606.0000	1.0000	15,606.0000
140375	55704.0000	67699 0000	11995 0000	1 0000	11,995.0000

TOTAL ENERGY CONSUMED FOR BILLING PERIOD (kWh) 48,713.00

PREMISE ID NUMBER [redacted] TARIFF NAME: Landrate 1,2,3

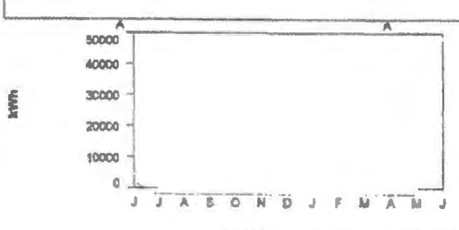
[redacted]

Service Charge @ R14.31 per day for 283 days	R	4,049.73
Network Charge @ R25.86 per day for 283 days	R	7,801.38
Energy Charge 37,873 kWh @ R0.7987 /kWh	R	30,249.17
Retail Environmental levy charge 1,204 kWh @ R0.02 /kWh	R	24.08
Retail Environmental levy charge 36,688 kWh @ R0.035 /kWh	R	1,283.42
Service and Administration Charge @ R15.45 per day for 81 days	R	1,251.45
Network Access Charge @ R28.61 per day for 81 days	R	2,317.41
Network Demand Charge 10,840 kWh @ R0.1741 /kWh	R	1,887.24
Reliability service charge 10,840 kWh @ R0.0027 /kWh	R	29.27
Energy Charge 10,840 kWh @ R0.5969 /kWh	R	7,554.40
The energy rate includes the 3.5 c/kWh cost of the environmental levy	R	0.00
REBILLED ADJUSTMENTS (Summary - See attachment for details)	R	-59,504.89
TOTAL CHARGES FOR BILLING PERIOD	R	- 3,257 14

ACCOUNT SUMMARY FOR JUNE 2013

BALANCE BROUGHT FORWARD (Due Date 2013-06-27)	R	7,982.23
PAYMENT(S) RECEIVED Direct Deposit - 2013-06-14	R	-6,108.51
TOTAL CHARGES FOR BILLING PERIOD	R	-3,257.14
VAT RAISED ON ITEMS AT 14%	R	- 456.00

ARREARS					
>90 DAYS	61-90 DAYS	31-60 DAYS	CURRENT	TOTAL AMOUNT DUE	R
0.00	0.00	0.00	1,837.42-		1,837.42CR



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Eskom

TEL: 08600 37566
SMS: 082 941 3707
083 847 1951
084 655 5778

NORTH WESTERN REGION
PRIVATE BAG X16 WESTVILLE 2000

DIRECT DEPOSIT DETAIL
BANK: [redacted]
BRANCH CODE:
BANK ACC NO:

ACCOUNT NO / REFERENCE NO
[redacted]

NAME
TELKOM SA LTD C/O TFMC (PTY) L

FAX NUMBER
[redacted]

TOTAL AMOUNT DUE
0.00

PAYMENT ARRANGEMENT

INSTALMENT
0.00

ARREARS
0.00

DUE DATE
2013-07-22

AMOUNT PAID

LATE PAYMENT CHARGES WILL BE ADDED TO OVERDUE ACCOUNTS

Real Invoice 2

Account Number [redacted]

City Power Electricity VAT No. [redacted]	Amount	Sub Total
(Reading period = 2012/06/30 to 2013/06/12 = 348 days)		
Energy meter readings and consumption: Meter no ALS0609802 start reading 89,576.000 and end reading 111,635.000 = 22,059.000 kWh - Actual Reading		
Energy meter readings and consumption: Meter no ALS0609803 start reading 14,206.000 and end reading 27,975.000 = 13,769.000 kWh - Actual Reading		
Energy meter readings and consumption: Meter no ALS0609804 start reading 105,544.000 and end reading 136,065.000 = 30,521.000 kWh - Actual Reading		
Daily average consumption 190.658 kWh		
Charges for 66,349.000 kWh are based on a sliding scale for a 348 day period		
Step 1 0.000 kWh @ R 1.9906 (Billing Period 2013/06)	0.00	
Demand side management levy	0.00	
Service charge	0.00	
Network charge	0.00	
Step 1 13.214 kWh @ R 1.3030 (Billing Period 2013/06)	17.22	
Step 1 171.786 kWh @ R 1.9906 (Billing Period 2013/06)	341.96	
Demand side management levy	3.70	
Service charge	331.74	
Network charge	146.22	
Step 1 8,387.000 kWh @ R 1.3030 (Billing Period 2013/05)	10,928.26	
Demand side management levy	167.74	
Service charge	331.74	
Network charge	146.22	
Step 1 6,997.000 kWh @ R 1.3030 (Billing Period 2013/04)	9,117.09	
Demand side management levy	139.94	
Service charge	331.74	
Network charge	146.22	
Step 1 4,697.000 kWh @ R 1.3030 (Billing Period 2013/03)	6,120.19	
Demand side management levy	93.94	
Service charge	331.74	
Network charge	146.22	
Step 1 5,564.000 kWh @ R 1.3030 (Billing Period 2013/02)	7,249.89	
Demand side management levy	111.28	
Service charge	331.74	
Network charge	146.22	
Step 1 8,148.000 kWh @ R 1.3030 (Billing Period 2013/01)	10,616.84	
Demand side management levy	162.96	
Service charge	331.74	
Network charge	146.22	
Reversal of interim charges	- 13,075.66	
Reversal of interim charges	- 14,873.99	
Demand side management levy	173.67	
Step 1 7,235.233 kWh @ R 1.9906 (Billing Period 2012/12)	14,402.45	
Step 1 19,431.767 kWh @ R 1.3030 (Billing Period 2012/12)	25,319.59	
Registered Social Landlord Rebate	0.00	
Service charge	331.74	
Network charge	146.22	
Step 1 5,464.719 kWh @ R 1.3030 (Billing Period 2012/11)	7,120.53	
Service charge	331.74	
Network charge	146.22	
Demand side management levy	109.29	
Step 1 4,636.731 kWh @ R 1.3030 (Billing Period 2012/10)	6,041.66	
Service charge	331.74	
Network charge	146.22	
Demand side management levy	92.73	
Step 1 6,568.702 kWh @ R 1.9906 (Billing Period 2012/09)	13,075.66	
Step 1 1,313.740 kWh @ R 1.3030 (Billing Period 2012/09)	1,711.80	
Service charge	331.74	
Network charge	146.22	
Demand side management levy	157.65	
Step 1 203.714 kWh @ R 1.7780 (Billing Period 2012/08)	362.20	
Step 1 5,500.286 kWh @ R 1.9906 (Billing Period 2012/08)	10,948.87	
Demand side management levy	114.08	
Service charge	331.74	

Where can payments be made ?
Any CoJ Cash Office; any Easy Pay site; any bank (branch, ATM or internet site).
YOUR ACCOUNT NUMBER IS YOUR REFERENCE NUMBER

How can payments be made ?
By debit order, cash, cheque, debit or credit card. Cheques paid to the CoJ are to be made out to 'City of Johannesburg Metropolitan Municipality'.
KEEP ALL RECEIPTS FOR FUTURE REFERENCE
Post-dated cheques are not accepted.

When can payments be made ?
Payments must reach CoJ on or before the due date.

Change of Address
This must be done timeously, in writing and submitted to any CoJ Municipal Regional Office.

Terminating Electricity and Water.
This must be done in writing, 7 working days before the date you wantyour services terminated and submitted to

Real Invoice 3

Mogale City
Local Municipality

PO BOX 94,
KRUGERSDORP 1740
(0861) 664 253
(011) 660 4043

TELKOM SA LTD

[redacted]

ACCOUNT No.	[redacted]
INVOICE No.	
CLIENT'S VAT No.	
DATE OF ACCOUNT	

[redacted] TELKOM C

Balance b/forward			135111.48
20130614 Bank trans [redacted] KEY			10231.42-
20130625 Admin feeADMIN FEE WD-1 on 20130515			825.36
20130625 Admin feeADMIN FEE FD on 21/06/2013			132.24
Electricity			
BULK low voltage three part fixed charge(1x379.3	379.36	53.11	432.47
0272 Environmental Electricity Le (35040x0.035)	1226.40	171.70	1398.10
3856			
0272 Environmental Electricity Le (30560x0.035)	1069.60	149.74	1219.34
6372			
0272 Environmental Electricity Le (33360x0.035)	1167.60	163.46	1331.06
6390			
0291 Environmental Electricity Le	0.00	0.00	0.00
KVA 120			
Bulk Low Voltage three part kWh (35040x0.7207)	25253.33	3535.47	26788.80
3856 8053 8491 438			

SERVICE	METER	PRE READING	NOW READING	CONSUMPTION	DEPOSIT	ACCOUNT FOR PERIOD
E	3856				1984 / REDITORS- 0.00	June 2013
E	6372					
E	6390				[redacted]	PROPERTY VALUATION
E	KVA 120					
E	3856	8053	8491	438	2013/05/30 - 2013/06/28	
TRANSACTIONS INCLUDED TO 2013/06/30					[redacted]	

MOGALE CITY LOCAL MUNICIPALITY

THIS STUB MUST ACCOMPANY PAYMENT PLEASE DO NOT DETACH IF PAYING AT THE POST OFFICE CHEQUES PAYABLE TO MOGALE CITY MUNICIPALITY AND TO BE RECEIVED BEFORE DUE DATE POST DATED CHEQUES ARE NOT ACCEPTABLE

EasyPay

REMITTANCE ADVICE

ACCOUNT FOR:	TELKOM SA LTD
AMOUNT DUE	
ACCOUNT NO	112294
DUE DATE	2013/07/31

0726

112294

M65 M65 M65 M65 M65 M65 M65 M65 M65 M65 M65 M65 M65 M65 M65 M65 M65 M65

Standard Bank **M65 Credit Transfer**

Date (YYYY/MM/DD)

Complete in duplicate
Shaded areas for bank use only

Teller's date stamp and signature	Notes
	Coins
	Postal / Money orders
	Total cash
Cheque deposited (Drawer's name)	
	Total credit R

Mogale City Local Municipality

The Bank shall not be responsible for the accuracy of data reference fields. Cheques, etc. handed in for collection will only be available as cash when paid. While acting in good faith and exercising reasonable care the Bank will not accept responsibility for ensuring that depositors/account holders have lawful title to cheques, etc. collected

M65 (M) E

Customer identity number	Amount *	Transaction code	Dep Branch BT number	Reference
0.9.6 N E	E	E	E	E

Depositor's/Contact person's name | Contact telephone no | Depositor's/Contact person's signature | Operator's initials

Noisy Invoice1

Eskom

NORTH WESTERN REGION
PRIVATE BAG X16 WESTVILLE 2000

CONTACT CENTRE: (0860) 037566
FAX NO: (031) 404 2627
E-MAIL: NORTHWESTERN@ESKOM.CO.ZA
WEB: WWW.ESKOM.CO.ZA

2013-07-09

TELKOM SA LTD C/O TFMC (PTY) LTD
PRIVATE BAG X137
CENTURION
0046

YOUR ACCOUNT NO
SECURITY HELD
BILLING DATE
TAX INVOICE NO
ACCOUNT MONTH
CURRENT DUE DATE
VAT REG NO
NOTIFIED MAX DEMAND

[redacted]

REBILLED ADJUSTMENTS R -59,504.69

TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS	R	-443.81
Service Charge @ R14.31 per day for 31 days	R	-443.81

TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS	R	-832.66
Network Charge @ R26.86 per day for 31 days	R	-832.66

TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS	R	-3,967.14
Energy Charge 4,967 kWh @ R0.7987 /kWh	R	-3,967.14

TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS	R	-173.85
Retail Environmental levy charge 4,967 kWh @ R0.035 /kWh	R	-173.85

TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS	R	-457.92
Service Charge @ R14.31 per day for 32 days	R	-457.92

TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS	R	-859.52
Network Charge @ R26.86 per day for 32 days	R	-859.52

TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS	R	-4,307.39
Energy Charge 5,393 kWh @ R0.7987 /kWh	R	-4,307.39

TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS	R	-30.34
Retail Environmental levy charge 1,517 kWh @ R0.02 /kWh	R	-30.34

TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS	R	-135.66
Retail Environmental levy charge 3,876 kWh @ R0.035 /kWh	R	-135.66

TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

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BILL PAGE	2 OF 7

Noisy Invoice 2

Eskom

NORTH WESTERN REGION
PRIVATE BAG X16 WESTVILLE 2000

CONTACT CENTRE: (0860) 037566
FAX NO: (051) 404 3627
E-MAIL: NORTH WESTERN@ESKOM.CO.ZA
WEB: WWW.ESKOM.CO.ZA

YOUR ACCOUNT NO	[redacted]
SECURITY HELD	
BILLING DATE	
TAX INVOICE NO	
ACCOUNT MONTH	
CURRENT DUE DATE	
VAT REG NO	

TELKOM SA LTD C/O TFMC (PTY) LTD
PRIVATE BAG X137
CENTURION
0046

2013 -07- 0 9

CANCELLATIONS	R	-400 66
Service Charge @ R14.31 per day for 28 days	R	-400.66
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-752.08
Network Charge @ R26.86 per day for 28 days	R	-752.08
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-3 157 26
Energy Charge 3,953 kWh @ R0.7987 /kWh	R	-3,157.26
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	138 36
Retail Environmental levy charge 3,953 kWh @ R0.035 /kWh	R	-138.36
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-386 37
Service Charge @ R14.31 per day for 27 days	R	-386.37
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-725 22
Network Charge @ R26.86 per day for 27 days	R	-725.22
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-3,595 75
Energy Charge 4,502 kWh @ R0.7987 /kWh	R	-3,595.75
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-157 57
Retail Environmental levy charge 4,502 kWh @ R0.035 /kWh	R	-157.57
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-386 37
Service Charge @ R14.31 per day for 27 days	R	-386.37
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-725 22
Network Charge @ R26.86 per day for 27 days	R	-725.22
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		

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Noisy Invoice 3

Eskom

NORTH WESTERN REGION
PRIVATE BAG X16 WESTVILLE 3000

CONTACT CENTRE: (0860) 037566
FAX NO: (031) 464 3637
E-MAIL: NORTH.WESTERN@ESKOM.CO.ZA
WEB: WWW.ESKOM.CO.ZA

2013 -07- 0 9

TELKOM SA LTD C/O TFMC (PTY) LTD
PRIVATE BAG X137
CENTURION
0046

2013 -07- 0 9

YOUR ACCOUNT NO	[redacted]
SECURITY HELD	
BILLING DATE	
TAX INVOICE NO	
ACCOUNT MONTH	
CURRENT DUE DATE	
VAT REG NO	

CANCELLATIONS	R	-3,454.38
Energy Charge 4,325 kWh @ R0.7987 /kWh	R	-3,454.38
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-151.38
Retail Environmental levy charge 4,325 kWh @ R0.035 /kWh	R	-151.38
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-486.54
Service Charge @ R14.31 per day for 34 days	R	-486.54
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-913.24
Network Charge @ R26.86 per day for 34 days	R	-913.24
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-3,939.19
Energy Charge 4,932 kWh @ R0.7987 /kWh	R	-3,939.19
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-172.62
Retail Environmental levy charge 4,932 kWh @ R0.035 /kWh	R	-172.62
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-483.50
Service and Administration Charge @ R16.45 per day for 30 d	R	-483.50
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-858.30
Network Access Charge @ R28.61 per day for 30 days	R	-858.30
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-842.82
Network Demand Charge 4,841 kWh @ R0.1741 /kWh	R	-842.82
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		
CANCELLATIONS	R	-13.07
Reliability service charge 4,841 kWh @ R0.0027 /kWh	R	-13.07
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]		

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BILL GROUP	
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Noisy Invoice 4

Eskom

NORTH WESTERN REGION
PRIVATE BAG X16 WESTVILLE 2000

CONTACT CENTRE: (0860) 037566
FAX NO: (031) 464 2027
E-MAIL: NORTH WESTERN@ESKOM.CO.ZA
WEB: WWW.ESKOM.CO.ZA

YOUR ACCOUNT NO	[redacted]
SECURITY HELD	
BILLING DATE	
TAX INVOICE NO	
ACCOUNT MONTH	
CURRENT DUE DATE	
VAT REG NO	

TELKOM SA LTD C/O TFMC (PTY) LTD
PRIVATE BAG X137
CENTURION
0046

2013 -07- 0 9

CANCELLATIONS
Energy Charge 4,841 kWh @ R0.6969 /kWh — R -3,373 80 / R -3,373.80
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS
Service Charge @ R14.31 per day for 30 days — R -429 30 / R -429.30
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS
Network Charge @ R26.86 per day for 30 days — R -805 80 / R -805.80
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS
Energy Charge 4,236 kWh @ R0.7987 /kWh — R 3 383 29 / R -3,383.29
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS
Retail Environmental levy charge 4,236 kWh @ R0.035 /kWh — R 148 26 / R -148.26
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS
Service Charge @ R14.31 per day for 35 days — R -500 85 / R -500.85
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS
Network Charge @ R26.86 per day for 35 days — R -940 10 / R -940.10
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS
Energy Charge 6,847 kWh @ R0.7987 /kWh — R -5,488 70 / R -5,488.70
TAX INVOICE NO. [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS
Retail Environmental levy charge 6,847 kWh @ R0.035 /kWh — R -239 65 / R -239.65
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

CANCELLATIONS
Service Charge @ R14.31 per day for 30 days — R 429 30 / R -429.30
TAX INVOICE NO [redacted] DATED 2013-06-27 FOR PREMISE [redacted]

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BILL PAGE	5 OF 7

PLAGIARISM REPORT

22290680:Disseration_v5_-_Petrie_van_Zyl.docx

ORIGINALITY REPORT

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This serves to confirm that I, Isabella Johanna Swart, registered with and accredited as translator by the South African Translators' Institute, registration no. 1001128, language edited the Title page, Acknowledgements, Abstract and Samevatting, Key terms, Chapters 1-7, p. 85 of Annexure A, p. 95 of Annexure B and the Box plot on p. 102 of Annexure B of the following dissertation.

Evaluation of pre-processing techniques for the analysis and recognition of invoice documents

by

PA van Zyl

22290680

Date: 16 November 2015

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