

Automated soil classification and identification using Machine Vision and Artificial Neural Networks

**by
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Declaration

I, Mauritz van Rooyen (Identity Number: _____, Student Number _____) do hereby declare that this research project which has been submitted to the Central University of Technology for the degree Master Of Engineering: Electrical Engineering, is my own independent work; and complies with the Code of Academic Integrity, as well as other relevant policies, procedures, rules and regulations of the Central University of Technology; and has not been submitted before by any person in fulfilment (or partial fulfilment) of the requirements for the attainment of any qualification.

Signed: _____


Supervisor: _____


Date: _____2020/09/02_____

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Abstract

Introduction: In the construction industry, one of the major considerations when designing a superstructure is which foundation should be selected. Foundations provide support to superstructures by transferring the load of the structure evenly into the earth. An inappropriate foundation choice could result in damage to the superstructure, or even the collapse of such a structure. The clay content of soil is a major determining factor when selecting a foundation type. Soil containing clay, has the potential to shrink and swell as the water content changes. This heaving of the soil can cause damage to the superstructure built upon it. Determining the amount of clay in a soil sample, is one of the most important steps in the soil classification process. In South Africa, the Hydrometer method is commonly used to determine the clay content of soil samples. This method is a manual, time intensive soil classification method, with doubtful accuracy. This study was undertaken to develop an Automated Soil Classification System (ASCS) that will classify soil more accurately and more expeditiously, making it cost and time effective. This was achieved by applying a Machine Vision (MV) process to soil samples, to generate unique digital soil sample fingerprints for soil samples. This process was then combined with an Artificial Neural Network (ANN), to automatically classify the soil sample from the fingerprints.

Methods: Initially a Machine Vision Instrument (MVI) was constructed for the consistent capturing of high fidelity images during the sedimentation process of a soil sample. Software was then developed to process these captured images and generate unique Soil Sample (SS) fingerprints for different soil constitutions. Four investigations were preformed to validate the consistency of the SS fingerprints generated with the MVI. These investigations were: 1. Validation of the SS fingerprint generation process; 2. Validation of the soil sample preparation procedure; 3. Determination of the differentiation ability of the MVI; and 4. Validation of the MVI by generating SS fingerprints for coded

(unknown) soil samples. The generated SS fingerprints were then used to train an ANN to recognise and classify soil samples from their respective SS fingerprints. After the training of the ANN, a fifth investigation was undertaken to determine the accuracy of the trained ANN and a final, sixth investigation was undertaken to compare the performance of the ASCS to that of the Hydrometer method.

Results: The constructed MVI was able to acquire good quality greyscale images during the sedimentation process of soil samples in a consistent manner. Investigations 1 through 4 showed that correlation amongst SS fingerprints, generated from the same soil sample, was in the order of 97%, while the correlation amongst SS fingerprints, generated from multiple soil samples of the same constitution, was in the order of 95%. Investigation five showed that the training of the ANN was successful as the R values obtained after training were greater than 0,98. The sixth and final investigation showed that the accuracy of the ASCS was in the range of 95% and greatly outperformed the Hydrometer method, whose accuracy varied from approximately 49 to 89%. The ASCS also delivered these results in 28 hours while the Hydrometer method took approximately seven days.

Table of Contents

Declaration	i
Abstract	iii
Table of Contents.....	v
List of Tables.....	viii
List of Figures	ix
Chapter 1 Introduction	11
1.1 Background to the study	11
1.2 Hypothesis	13
1.3 Aim and objectives.....	13
1.4 Layout of the dissertation	15
Chapter 2 Study Design	18
2.1 Introduction	18
2.2 Study design	20
2.3 Chapter discussion and summary	23
Chapter 3 Literature Review.....	24
3.1 Introduction	24
3.2 Construction industry	25
3.2.1 History of foundations	25
3.2.2 Lessons from history	26
3.3 Types of building foundations	27
3.4 Soil classification.....	28
3.5 Soil classification methods.....	29
3.5.1 Sieving method	30
3.5.2 Pipette method.....	30
3.5.3 Hydrometer method	31
3.5.4 Modern methods	34
3.6 Machine Vision Systems	35
3.6.1 Image acquisition step	36
3.6.2 Camera selection for a Machine Vision system	36
3.6.3 Lens selection for a Machine Vision system.....	37
3.6.4 Illumination techniques for a Machine Vision system	38
3.6.5 Image processing step	40

3.6.6	Data analysis step.....	41
3.6.7	Applications of Machine Vision systems	42
3.7	Artificial Neural Networks	42
3.7.1	ANN topologies	43
3.7.2	ANN training.....	45
3.8	Motivation for the use of Machine Vision and Artificial Neural Networks in soil classification	47
3.9	Chapter discussion and summary	49
Chapter 4 Development and construction of the Machine Vision Instrument.....		50
4.1	Introduction	50
4.2	Step1: Image acquisition.....	52
4.2.1	Component 1: Digital camera selection.....	52
4.2.2	Component 2: Soil sample illumination	54
4.2.3	Component 3: Soil sample preparation	57
4.3	Step 2: Image processing	59
4.3.1	Software development environment.....	59
4.3.2	Software development 1: Development of the Calibration software.....	65
4.3.3	Software development 2: Development of the soil sample fingerprint generation software	68
4.3.4	Software development 3: Development of the correlation software	71
4.4	Chapter discussion and summary	72
Chapter 5 Validation of the Machine Vision Instrument		74
5.1	Introduction	74
5.2	Materials and methods in preparation for investigations	75
5.2.1	Development of the soil sample preparation protocol	76
5.2.2	Development of SS fingerprint generation protocol.....	79
5.2.3	Visual interpretation of an SS fingerprint.....	80
5.3	Materials and methods: Investigations 1 to 4	83
5.4	Results of the four investigations	85
5.4.1	Results of Investigation 1: Validation of SS fingerprint generation	86
5.4.2	Results of Investigation 2: Validation of the soil sample preparation method.....	88
5.4.3	Results of Investigation 3: Application of the MVI to soil samples containing different amounts of clay	90

5.4.4	Results of Investigation 4: Correlation between coded Soil Sample fingerprints and pre-constituted Soil Sample fingerprints.....	92
5.5	Chapter discussion and summary	93
Chapter 6 Development of the Automated Soil Classification System		94
6.1	Introduction	94
6.2	Materials and methods in preparation for Investigations	95
6.2.1	Software environment selection for the development of the ANN	95
6.2.2	Importation of the SS fingerprint data into the MATLAB workspace.....	96
6.2.3	Preparation of the SS fingerprint data for training of the ANN.....	96
6.2.4	Development and training of the ANN.....	101
6.2.5	Integration of the ANN into the ASCS	105
6.3	Materials and methods for investigations 5 and 6	107
6.4	Results of investigations	109
6.4.1	Results of Investigation 5: Evaluation of the accuracy of the ASCS.....	109
6.4.2	Results of Investigation 6: Comparison of the accuracy as well as the test duration of the ASCS compared to that of the Hydrometer method.	109
6.5	Chapter discussion and summary	110
Chapter 7 Discussion and Conclusion.....		111
7.1	Introduction	111
7.2	The Automated Soil Classification System.....	112
7.3	Concluding remarks and future prospects.....	114

List of Tables

Table 2-1-1	Description and aims of the different investigations undertaken	21
Table 3-1	Guidelines for choosing a lens with the appropriate focal length.	38
Table 3-2	Selecting the appropriate illumination technique	38
Table 3-3	Features that should be considered when selecting software for a MV system.	41
Table 3-4	Examples of MV systems applications	42
Table 3-5	Common training algorithms used for the training of an ANN.	46
Table 3-6	<i>Applications for MV systems.</i>	47
Table 4-1	List and description of VIs used in software development	61
Table 5-1	Materials and methods for investigations 1 to 4.	83
Table 5-2	Correlation values of different SS fingerprint generated for the same soil sample.	86
Table 5-3	Correlation values of the SS fingerprints generated for the same soil sample prepared multiple times.	88
Table 5-4	Correlation values of the SS fingerprints generated for the soil samples with different constitutions.	90
Table 5-5	Correlations percentages between the SS fingerprints generated for the coded soil samples and the fingerprints generated for the pre-constituted soil samples.	92
Table 6-1	Steps to import and consolidate SS fingerprint data into the MATLAB environment.	96
Table 6-2	Example of ANN data format	97
Table 6-3	Script to generate extra data.	100
Table 6-4	Development steps of the ANN.	102
Table 6-5	Layout of steps for Investigations 5 and 6	108
Table 6-6	Soil classification results by the ASCS.	109
Table 6-7	Comparison of the soil classification results by the Hydrometer method and the ASCS.	110

List of Figures

Figure 2.1	Logic diagram of the ASCS showing the two major functional components.....	20
Figure 2.2	Flow diagram of the study design	21
Figure 3.1	Superstructure, substructure and foundation	24
Figure 3.2	Soil classification diagram.....	29
Figure 3.3	Sieving method apparatus	30
Figure 3.4	The Pipette method apparatus.....	31
Figure 3.5	The Hydrometer method apparatus	33
Figure 3.6	Logical diagram of a typical MV system	36
Figure 3.7	Examples of ANN topologies	44
Figure 4.1	Overall study design	50
Figure 4.2	Logical design of the MVI.....	51
Figure 4.3	Light sources tested.....	55
Figure 4.4	Light-proof box specifications.....	56
Figure 4.5	Windows of the LabVIEW development environment	60
Figure 4.6	Block diagram of calibration program.....	66
Figure 4.7	Calibration program User Interface window	68
Figure 4.8	The BD window for the SS Fingerprint generation program.....	69
Figure 4.9.	UI for the SS fingerprint generation program	70
Figure 4.10	BD window for the correlation program.....	71
Figure 4.11	The UI for the correlation program	72
Figure 5.1	Positioning Phase 3 in the overall study design	74
Figure 5.2	Logical design for the establishment of a functional MVI	75
Figure 5.3	Mixing apparatus built to mix soil samples consistently	77
Figure 5.4	Greyscale spectrum representing opaqueness in a grayscale image	80
Figure 5.5	Histogram snapshots at specified time intervals and histogram superimposition.....	81
Figure 5.6	SS fingerprint consisting of superimposed snapshot histograms	82
Figure 5.7	Three dimensional surface plot of an SS fingerprint.....	83
Figure 5.8	Visual representation of the five SS fingerprints generated for the same pre-constituted soil sample.....	87
Figure 5.9	Visual representation of the five SS fingerprints generated for the five separately prepared soil samples	89

Figure 5.10	SS fingerprints and their corresponding 3D surface plots	91
Figure 6.1	Positioning Phase 4 and 5 in the overall study design	94
Figure 6.2	Logical layout for the preparations for Investigations 5 and 6	95
Figure 6.3	Training matrices for the ANN Toolbox	100
Figure 6.4	Linear plot of the ANN training results.....	105
Figure 6.5	Deploy Solution window of the ANN Toolbox.....	106
Figure 6.6	Automatically generated program displayed as a Simulink diagram	106
Figure 6.7	Modified Simulink program.....	107

Chapter 1

Introduction

1.1 Background to the study

Civil Engineering at its core, is an engineering profession that deals with, but is not limited to, the design, construction and maintenance of the physical and naturally built environment (Das, 2011). This environment includes structures, such as roads, bridges, canals, airports, sewerage systems, pipelines, houses and large office buildings (Rogers, Olshansky and Rogers, 1993; Das, 2018). The construction of such a structure starts with its foundation. Therefore, choosing the appropriate foundation type is crucial to any civil engineering construction project (Monye, 2018).

The foundation of any structure, large or small, should be built to withstand forces exhibited on the structure (Rogers, Olshansky and Rogers, 1993). These forces include forces of nature, such as wind, water and seismic activities but also include heaving forces caused by the expansion of clay rich soil (Rogers, Olshansky and Rogers, 1993; Morales and Morales, 2004). In instances where an appropriate foundation was not constructed for a building built upon clay-rich soil; such a building will crack and is at risk of collapsing (Das, 2011; Peduto *et al.*, 2016; Monye, 2018).

The design of a foundation is mainly determined by the type of soil upon which the foundation will be constructed (Monye, 2018). To obtain insight into what type of foundation should be used for the construction of a building, soil classification should be performed as the first step in the construction planning process (Department of the Army, 1983; Peduto *et al.*, 2016). Various soil classification tests are available which can be performed to determine the composition of the soil for proper foundation selection (Das, 2018). On rocky surfaces, such as limestone or granite, shallow foundation types are typically selected for superstructures, while foundations constructed on soils

containing high amounts of clay and softer soil types, will be deeper foundation types for better support of the superstructure (Peduto et al., 2016).

Soil classification is a crucial part in civil construction projects. Soil classification involves the separation of soil into different groups and classes, of which each class or group has similar characteristics, and therefore have potentially similar behaviour (Reale et al., 2018). If soil contains active soil components, such as different types of clay, standard foundation types cannot be used (Rogers, Olshansky and Rogers, 1993; Peduto *et al.*, 2016). Using standard or shallow foundation types will result in the uneven displacement of the foundation as the clay in the soil expands when the soil's moisture content is high and then contracts again when this moisture levels are reduced (Bell, Cripps and Culshaw, 1986; Fondjo, 2018). This uneven displacement of the foundation may cause cracks in the structure, resulting in an unstable structure which subsequently could collapse (Rogers, Olshansky and Rogers, 1993; Peduto *et al.*, 2016).

In South Africa, commonly used soil classification methods are manual in nature (Tromp and Watermeyer, 1992). Mechanical soil analysis is performed on coarse soils by means of the sieving method. For soils containing particles smaller than 0,002um particles, sedimentation methods have to be performed due to the physical grain-size limit of sieves used in the sieving method. Both the Hydrometer and the Pipette methods analyse soil samples according to their sedimentation characteristics. From these methods, the Hydrometer method is one of the most commonly used (Monye, 2018). This method can be time intensive and is inaccurate (Stott and Theron, 2016; Monye, 2018). The inaccurate classification of a soil sample can result in choosing an inappropriate foundation type for the construction of a building (Tromp and Watermeyer, 1992). More accurate results can be achieved by using expensive methods of classification, for instance laser diffraction or electron microscopes (Department of Public Works, 2007). There is thus an urgent need for an automated system that produces soil classification results, more cheaply, accurately and

expeditiously (Chanasyk and Naeth, 1996). Such an automated system could be more affordable to smaller construction companies and should limit human error, thereby resulting in more accurate soil samples classifications. More accurate soil classification should reduce the number of unsuitable foundation types being selected for superstructures and result in safer superstructures being constructed (Rogers, Olshansky and Rogers, 1993; Monye, 2018).

1.2 Hypothesis

The purpose of this study was to demonstrate that by automating the soil classification process by means of a constructed MVI and a trained ANN, it might be possible to speed up the soil classification process of fine-grained soils tremendously as well as minimize human error, resulting in more accurate soil classifications.

An automated soil classification process by means of a constructed MVI and a trained ANN, could be the solution to speed up the soil classification process of fine-grained soils as well as minimize human error, resulting in more accurate soil classifications.

1.3 Aim and objectives

The Hydrometer method is based on Stokes' law which describes the sedimentation rate of soil particles in a viscous fluid (Monye, 2018). Focus was put on the Hydrometer method as elements applied in this method has the potential to be automated. The Hydrometer analyses soil samples according to the sedimentation rate of particles in a fluid. This sedimentation process of the soil samples could be captured digitally and analysed mathematically in an attempt to classify the soil samples. The automation of these elements will require an analysis of the digitally captured sedimentation process, as well as a mechanism to classify the soil samples from this analysis.

Digital analysis was accomplished by means of a developed and constructed Machine Vision Instrument (MVI). The MVI digitally captured the sedimentation process of soil samples, mixed with water, in sedimentation cylinders. The digitally captured data could then be used to train a developed Artificial Neural Network (ANN) for training and analysis. Because different types of soil particles have different sedimentation characteristics (Weil and Brady, 2016), an Automated Soil Classification System (ASCS) should be able to identify soil compositions from the different characteristics displayed in the sedimentation process of different types of particles. These different characteristics should be identifiable by means of the trained ANN.

The purpose of this study was to demonstrate that by automating the soil classification process by means of a constructed MVI and a trained ANN, it might be possible to speed up the soil classification process of fine-grained soils tremendously as well as minimize human error, resulting in more accurate soil classifications. The constructed MVI is shown in Figure 4.4. The full functionality of the MVI as well as the soil sample preparation method is discussed in Chapter 4.

Therefore, the aim of this study was to construct and develop an Automated Soil Classification System using Machine Vision and an Artificial Neural Network. To achieve this aim, the following objectives were devised:

- To undertake a literature review that will underpin the study;
- To construct an MVI system to inspect and capture the sedimentation process of a soil sample through Machine Vision (MV);
- To generate data from the sedimentation process of a soil sample by means of the constructed MVI, process this data with a trained ANN and
- To determine the accuracy of the complete ASCS system compared to that of the Hydrometer method.

1.4 Layout of the dissertation

This thesis has been partitioned into seven chapters covering the following topics:

Chapter 1: Introduction

Chapter 1 contains a brief synopsis, problem statement, motivation, as well as the aim and the objectives for this study.

Chapter 2: Study design

In Chapter 2, the study design and a description of the different components of this research project are presented.

Chapter 3: Literature review

Chapter 3 contains literature reviews of the construction industry and the foundations used to construct superstructures. Soil classification methods focusing on the Hydrometer method are also presented. Furthermore, Machine Vision systems, Artificial Neural Networks and how these technologies are applied are also reviewed in this chapter

Chapter 4: Development and construction of the Machine Vision Instrument

The construction of the Machine Vision Instrument is presented in this chapter. It covers the selection and implementation of the hardware used for image acquisition, illumination and soil sample preparation. Chapter 4 also includes the methods and results of the software development for the calibration of the MVI, the SS fingerprint generation software and the data correlation software.

Chapter 5: Validation of the Machine Vision Instrument

In Chapter 5, the validation process of the developed MVI is presented. The following four investigations were undertaken in this chapter to validate the MVI:

- **Investigation 1:** Validation of the SS fingerprint generation process,
- **Investigation 2:** Validation of the soil sample preparation method,
- **Investigation 3:** Determination of the differentiation ability of the MVI and
- **Investigation 4:** Validation of the SS fingerprint generation process by means of coded soil samples.

The materials and methods together with the results of all four investigations are presented in this chapter.

Chapter 6: Development of the Automated Soil Classification System

This chapter presents the development of the ANN that was implemented as part of the Automated Soil Classification System. Two investigations were undertaken in this chapter:

- **Investigation 5:** Evaluation of the accuracy of the ASCS and
- **Investigation 6:** Comparison of the accuracy as well as the test duration of the ASCS compared to that of the Hydrometer method.

The materials and methods together with the results for the development of the ANN as well as the two investigations are presented in this chapter.

Chapter 7: Discussion and conclusions

In this concluding chapter, the key findings of this study are presented. It is shown how these findings are integrated into existing knowledge and it also contains a discussion on the challenges and further development of the ASCS.

References: The references of this thesis were generated with the reference manager Mendeley.

Chapter 2

Study Design

2.1 Introduction

Soil classification plays a determining role in the selection of the foundation type used when constructing a building of any type (Jones and Jefferson, 2012; Kaur and Fanourakis, 2016). When clay is present in the soil, the foundation type needs to compensate for the movement in the soil caused by clay particles expanding during rainy seasons and contracting during dry seasons (Fondjo, 2018). Large percentages of clay in the soil may result in the shifting of a building caused by heave in the soil, which could lead to instability and consequently an unsafe building (Department of the Army, 1983; Przewlocki and Zielinska, 2016).

There are many methods to determine the amount of clay in a soil sample. Most of these methods are time consuming; however, those that produce results relatively quickly, use expensive testing equipment which are not accessible to smaller construction companies (Sudarsan *et al.*, 2018). A commonly used method in many countries to determine the clay content in a soil sample is the Hydrometer method (Stott and Theron, 2016). The Hydrometer method uses the sedimentation rate of the particles in a soil sample to determine the percentage of clay in a soil sample by applying Stokes' law which states that:

“The velocity of a small sphere moving through a viscous fluid is directly proportional to diameter of the sphere.” (Bedaiwy and Naguib, 2012).

The problem with Stokes' law is that the law can only be accurately applied to small spherical particles that are moving through a viscous fluid (Stott and Theron, 2016). This is not the case when real world soil samples are used, as clay particles tend to be flaky, rather than spherical in nature.

For this reason, the accuracy of the measurements of the clay percentages in real world soil samples may be compromised when the Hydrometer method is used. Furthermore, human interaction and the lengthy process can influence the accuracy of the Hydrometer negatively and are therefore distinct disadvantages of this method (Stott and Theron, 2016; Monye, 2018).

The aim of this study was to produce an Automated Soil Classification System (ASCS) that improves on the accuracy and speed of the Hydrometer when classifying soil samples. Two steps were needed to create an ASCS. The first step was to create a Machine Vision Instrument (MVI) to acquire and process images during the sedimentation process of a pre-constituted soil samples. The acquired images were then processed to generate unique Soil Sample (SS) fingerprints for different soil sample constitutions. In step two, these SS fingerprints were used to train an Artificial Neural Network (ANN) to identify the percentage of clay in a soil sample from its SS fingerprint. It was envisaged that this two-step ASCS would also produce more accurate clay percentage predictions in unknown soil samples more rapidly than the Hydrometer method. The ASCS thus comprises of two functional components; the MVI that is responsible for the generation of a SS fingerprint and a trained ANN to classify soil samples from the generated SS fingerprints (Figure 1.1).

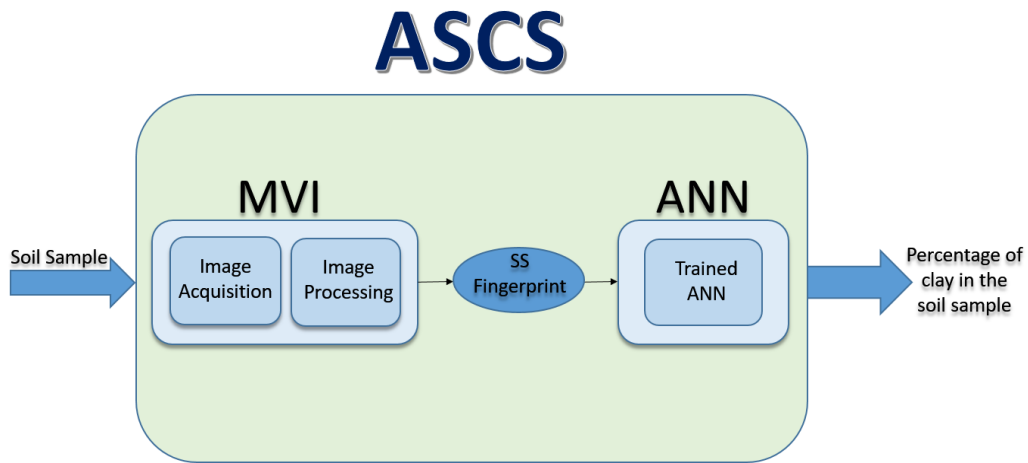


Figure 1.1 Logic diagram of the ASCS showing the two major functional components.

2.2 Study design

To simplify the design of the ASCS, it was decided to separate this research project into 5 phases. In the first phase, a comprehensive review of the literature was undertaken to underpin this study. Literature was sourced on topics such as soil sample classification, machine vision and artificial neural networks. In Phase 2 of the project, a Machine Vision Instrument (MVI) was designed and constructed to generate SS fingerprints that uniquely identified pre-constituted soil samples. Phase 2 comprised of two separate steps addressing image acquisition and image processing. In the 3rd phase, the MVI was tested for its ability to generate accurate SS fingerprints from several pre-constituted soil samples containing different percentages of clay. This phase comprised of four sequential investigations. The SS fingerprints that were generated in Phase 3 were then used to train an ANN in Phase 4 so that the ANN could identify the amount of clay in a soil sample from its SS fingerprint. In the final phase, Phase 5, the completed ASCS system was tested using blind pre-constituted soil samples, after which its accuracy was compared to that of the Hydrometer method. The flow diagram of the overall study design is shown in Figure 1.2.

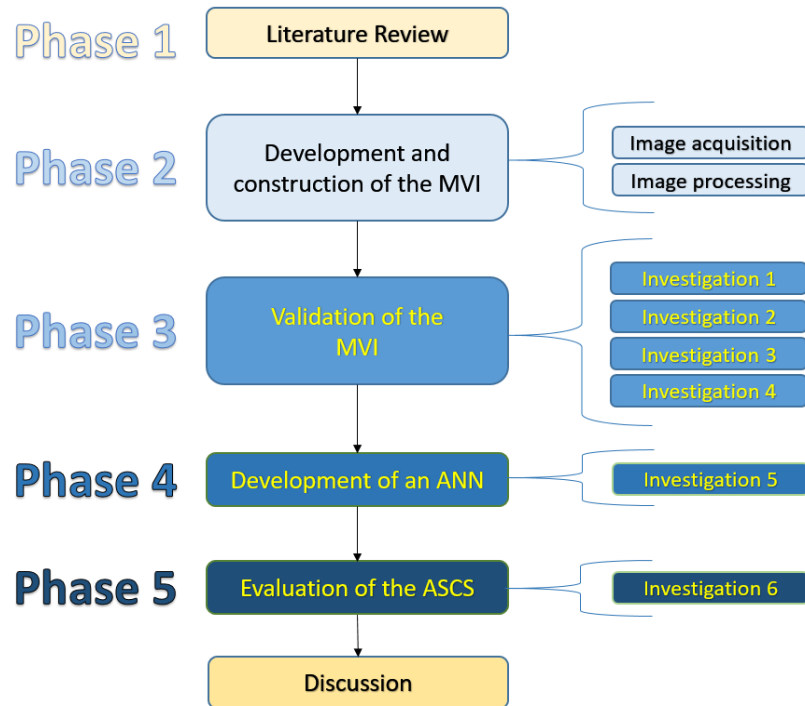


Figure 1.2 Flow diagram of the study design.

Overall, phase 3 to phase 5 were broken down into six individual investigations. Phase 3 covered four investigations to ascertain if the SS fingerprints were generated in a reliable manner and would be fit for use as training data for a developed ANN in Phases 4. Phase 4 contained Investigation 5, where the training of the ANN was validated, while Phase 5 contained Investigation 6, where the accuracy of the completed ASCS system was compared to that of the Hydrometer method. Table 2-1-1 provides a descriptive summary of the investigations undertaken in Phase 3 to Phase 5.

Table 2-1-1 Description and aims of the different investigations undertaken in Phase 3 to Phase 5.

Phase 3: Implementation of the MVI to generate SS fingerprints	
Investigation	Description
Investigation 1: Validation of the SS fingerprint generation process	The aim of this investigation was to determine if MVI could be used to generate SS fingerprints reliably and consistently. To meet this aim, a single pre-constituted soil sample was prepared and its SS fingerprint generated five times. The five results were correlated mathematically to ascertain if the MVI produced consistent SS fingerprints.

Investigation 2: Validation of the sample preparation procedure	The aim of this investigation was to determine if soil sample preparation was consistent. To meet this aim, five pre-constituted soil samples of the same ratio of pure Bentonite clay to sand, were prepared. The MVI was then used to generate SS fingerprints of the pre-constituted soil samples. The SS fingerprints were correlated mathematically to determine consistency.
Investigation 3: Determination of the differentiation ability of the MVI	The aim of this investigation was to determine if the MVI could accurately distinguish between soil samples containing different percentages of clay. To meet this aim, five pre-constituted soil samples of 10%, 20%, 40%, 70% and 80% Bentonite to sand ratios, were prepared. The MVI was then used to generate SS fingerprints of all the soil samples. The SS fingerprints were correlated mathematically to ascertain if differences existed for different amounts of clay.
Investigation 4: Validation of the MVI by generating SS fingerprints for coded soil samples	The MVI was validated by comparing SS fingerprints generated for randomly labelled soil samples (coded soil samples) to SS fingerprints generated for pre-constituted soil samples.
Phase 4: Training of the ANN for automatic clay prediction	
Investigation	Description
Investigation 5: Evaluation of the accuracy of the ASCS	The aim of this investigation was to train an ANN with all the SS fingerprint data that were generated from the pre-constituted soil samples using the MVI. The trained ANN was then used to predict the percentage of clay in a pre-constituted soil sample and its accuracy was evaluated.
Phase 5: Evaluation of the ASCS compared to the Hydrometer	
Investigation	Description
Investigation 6: Comparison of both the accuracy, as well as the amount of time it took for the ASCS to generate results, compared to that of the Hydrometer method	The aim of this investigation was to test and evaluate the accuracy and duration of soil classifications by the ASCS and to compare the results with that of the Hydrometer method.

2.3 Chapter discussion and summary

The steps undertaken to construct the MVI (Phase 2) are presented in Chapter 4. The methods and results of the four investigations of Phase 3 are discussed in Chapter 5, while the methods and results of investigation 5 and 6 of Phase 4 and Phase 5 are discussed in Chapter 6. In Chapter 7 an overall discussion of all the results are presented and integrated with current knowledge of this topic.

Chapter 3

Literature Review

3.1 Introduction

Foundation selection in the construction industry is the foremost and arguably the most important part of any superstructure design (Department of the Army, 1983). The purpose of any foundation is to adequately support the superstructure that is built on top of it (Figure 3.1). Proper foundation design and selection ensures stability and longevity of the superstructure. The selection of the foundation type and design depends mainly on the type of soil that a structure will be built on. Many different methods exist to determine the type of soil, but the accuracy of these methods vary (Kaur and Fanourakis, 2016; Stott and Theron, 2016). If the soil is not classified accurately, the inappropriate foundation type might be selected that does not provide sufficient support to a structure. This can lead to the uneven settlement of the structure, causing damage to the structure (Kaur and Fanourakis, 2016; Monye, 2018).

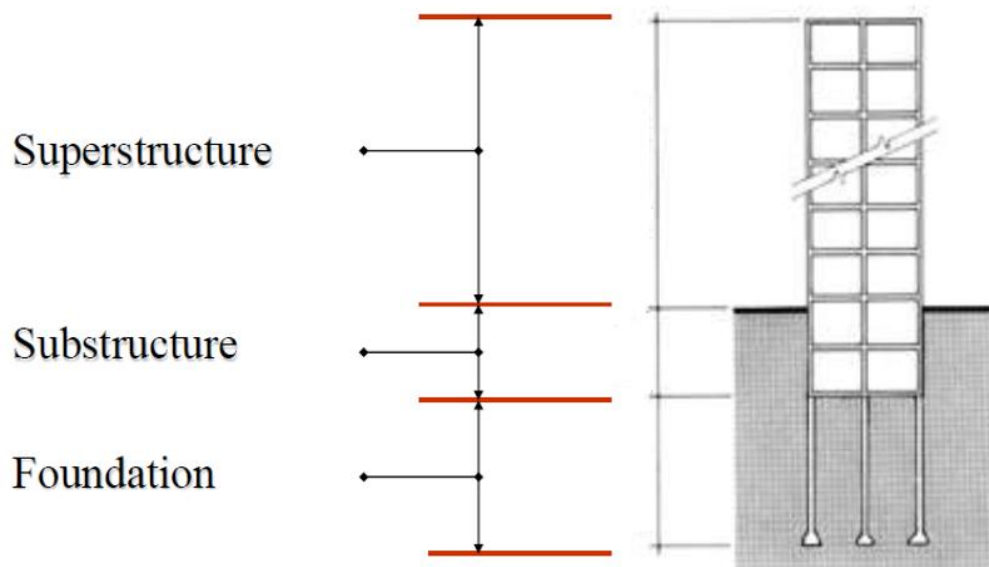


Figure 3.1 Superstructure, substructure and foundation.

3.2 Construction industry

To demonstrate the importance of soil classification in the construction industry, one firstly needs to consider the history of the construction industry itself. The construction industry, also known as the building environment, developed from the early human need to erect structures, primarily for providing shelter from their environment (Chang and Svenson, 2019). The evolution of this trade continued through the ages as structures became more and more advanced and the need for larger and higher buildings increased.

In modern times, many standards and guidelines have been developed to govern the construction of almost every structure (Chang and Svenson, 2019). These guidelines were developed over the last 300 years, and today, form the basis of building science. Factors considered in building science include the theories of the elasticity of structures, the illumination of structures, electricity planning, fluid flow layouts, as well as the types of materials required in construction. In addition, a construction team also needs to collect site-specific data from the site where the building will be constructed (Sudarsan *et al.*, 2018). Besides including topographic and boundary survey data, one of the most important site-specific factors to be considered is the composition of the subsoil on which the foundation will be constructed (Department of the Army, 1983; Reale *et al.*, 2018; Chang and Svenson, 2019).

3.2.1 History of foundations

The foundation of a building structure transfers the load of the structure built upon it into the earth, preventing it from settling or sinking. Historically, building structures did not require foundations. These structures were light in weight and were constructed using small stones, animal skins and wood. According to archaeological records, these early historical structures were built by nomadic hunter-gatherers of the late Stone Age. Even after the introduction of bricks as a construction

material during the Bronze Age, these bricks were made from mud and straw; and therefore, the structures constructed from these bricks did not require any foundations, as no sizeable load was transferred to the soil underneath (Chang and Svenson, 2019).

It was only after the first appearance of stone bricks, when buildings became larger and heavier, that the need for foundations became apparent. The first traces of foundations were found underneath stone buildings that were constructed at Saqqara in Egypt. As the size of stone bricks increased, the need for foundations became more prevalent. Surprisingly though, despite the heavy loads of the large stone structures, these foundations consisted of small blocks of poor quality stone. It was not until 750 to 656 BC that indications of better quality building foundations were found. Important buildings were placed on underground platforms that were constructed using better quality stone and were several metres thick (Chang and Svenson, 2019). The placement of important buildings on high quality foundations showed the realisation that the longevity and durability of superstructures relied on the quality of the foundation on which they were built.

3.2.2 Lessons from history

The stability of any superstructure is determined by its foundation. Therefore, selecting the appropriate foundation type and designing it properly are important prerequisites for any structural engineer to consider prior to constructing a superstructure (Department of the Army, 1983; Salam and El-kady, 2017). The leaning tower of Pisa is a good example of where proper foundations were not used to support a superstructure (Encyclopaedia Britannica, 2017). Construction of the tower started in 1173 using white marble blocks. Because of the extreme weight of the white marble blocks, the soft soil on which the tower was constructed, did not offer adequate support for the superstructure. This resulted in the uneven settling of the foundations, which caused the tower to lean to one side at more than five degrees (Encyclopaedia Britannica, 2017). It was only through extensive repair work and millions of dollars in repair costs, that the structure could be saved.

Even in modern times, these types of constructions have presented similar problems. The Millennium Tower is the tallest concrete structure in San Francisco (Bendix, 2018). In 2016 it was discovered that this 58 storey, 197 m high luxury apartment building, had started to sink. Since its completion in 2008, an independent consultant found that the tower had sunk by 400 mm and indications of tilting was identified. During the following two years, the tower continued to sink for a further 300 mm due to uneven settlement of the foundations. The cause of the uneven settlement of the foundations of the tower could be attributed to the removal of large quantities of water from soil by nearby construction work. This caused the sand on which the tower was constructed to compress, which resulted in the sinking of the tower. The sinking of the Millennium Tower resulted in cracked windows, malfunctioning elevators and large visible cracks in the basement of the tower (Bendix, 2018). The proposed solution of the tower's problem was to anchor it to the bedrock underneath the structure to circumvent further sinking. The anchorage of the tower is estimated to be a US\$500 (2018) million project.

These two examples show how important it is to obtain comprehensive knowledge of the properties of the soil on which a superstructure will be constructed. The selection of the appropriate foundation type, according to accurate soil classification results, could have prevented the uneven settlement of these structures.

3.3 Types of building foundations

Different types of foundations are used as support for superstructures constructed in the building industry. The type of foundation is determined by the type of soil that the superstructure will be constructed on (Department of the Army, 1983; Bowles, 1997). There are two main categories of foundation, namely shallow and deep foundations (Department of the Army, 1983). Shallow foundations are mostly used where a structure is built upon rocky soil types, when little or no expansion or compression of the soil is expected. Shallow foundations include termed bases,

footings, spread footings or mats and are usually around 1 m deep or less (Bowles, 1997). On the other hand, deep foundations are preferred where fine-grained soil deposits are found, containing peats and clays (Bowles, 1997; Peduto *et al.*, 2016). Deep foundations are usually more than 4 m in depth and include piles, drilled piers or drilled caissons (Bowles, 1997). To determine an appropriate foundation type in the building industry, detailed knowledge of the soil composition is a requirement (Ramesh, Kuklik and Válek, 2017).

3.4 Soil classification

Composition, or soil texture, is one of the most important properties of soil (Department of the Army, 1983; Department of Public Works, 2007). The composition of a soil sample determines the physical characteristics, the mechanical characteristics, as well as the hydrological, hydro-physical and chemical properties of the soil (Hillel, 1982; Marshall and Holmes, 1988).

Soil is mainly composed of clay, sand and silt (Das, 2018). The soil type is determined by the relative percentages of clay, sand and silt in a soil sample. When clay, sand and silt are present in equal parts in a soil sample, the soil type is referred to as loam (Rowell, 2014). If a soil sample contains a high percentage of clay in comparison to sand and silt, the soil type is clay loam. Figure 3.2 shows a soil classification diagram containing the different combinations of clay, sand and silt, creating various types of soils, as well as the pure types.

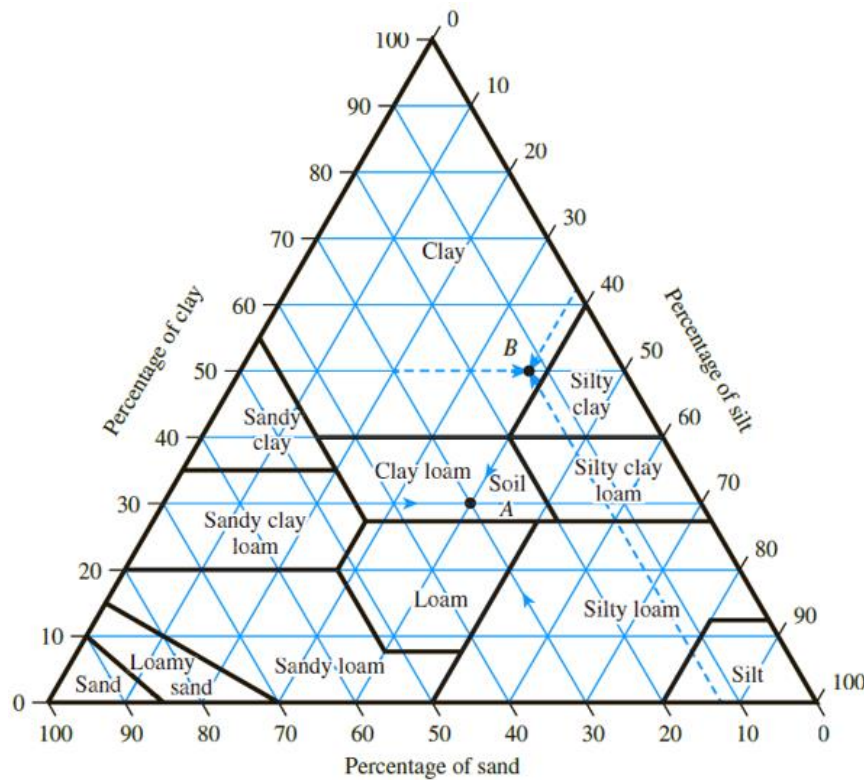


Figure 3.2 Soil classification diagram (Das, 2018).

The soil classification diagram was developed by the United States Standard Sieving Numbers. This diagram shows how soil samples are classified according to the relative percentages of clay, sand and silt present in the soil sample (Rowell, 2014).

3.5 Soil classification methods

Soil classification is the process of determining the composition of a soil sample (Fanning and Fanning, 1989). Soil composition is determined through various soil classification methods, which involves the process of particle-size analysis (PSA) to determine the particle size distribution (PSD) of a given soil sample (Rowell, 2014; Ghasemy, Rahimi and Malekzadeh, 2019). The PSD of a soil sample shows the relative proportions of soil particles of varied sizes in the soil sample. Therefore, the result of the PSA shows the relative percentages of clay, sand and silt present in a soil sample (Fanning and Fanning, 1989).

There are several traditional methods that are used for classifying soil samples. These include mechanical methods that are applied to coarse soil samples and sedimentation methods, which are applied to fine-grained soils (Sudarsan *et al.*, 2018). The sieving method is an example of a mechanical method, and the Hydrometer and Pipette methods are examples of sedimentation methods. Many more methods exist and more modern methods are constantly being developed.

3.5.1 Sieving method

The sieving method is a mechanical method that involves the separation and quantification of different-sized particles in a soil sample by means of sieving the soil sample with different grained sieves. The sieving method is usually applied to sandy soils or soils of a coarse nature (Figure 3.3). However, this method can only be used for the classification of sandy soils or soils of a coarse nature, because of the limitation of the grain-size of the sieves (Sudarsan *et al.*, 2018).

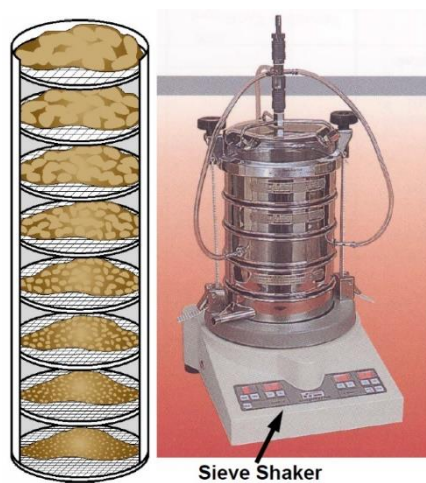


Figure 3.3 Sieving method apparatus (Or and Tuller, 2004).

3.5.2 Pipette method

For fine-grained soils, such as silt and clay, the pipette and Hydrometer methods are usually applied (Sudarsan *et al.*, 2018). Both the pipette and Hydrometer methods determine particle size through

the sedimentation rate of the soil sample's particles after the soil sample is mixed with water and dispersant in a sedimentation cylinder. The pipette method determines the weight of soil particles at a pre-determined sampling depth, while the Hydrometer method measures the concentration of particles in suspension. With the pipette method (Figure 3.4), liquid samples are extracted from the mixture in the sedimentation cylinder at a pre-determined sampling depth at different time intervals. These extracted samples are then dried and the weight of the soil for each sample is measured. Through this process, the PSD of the soil sample is determined.

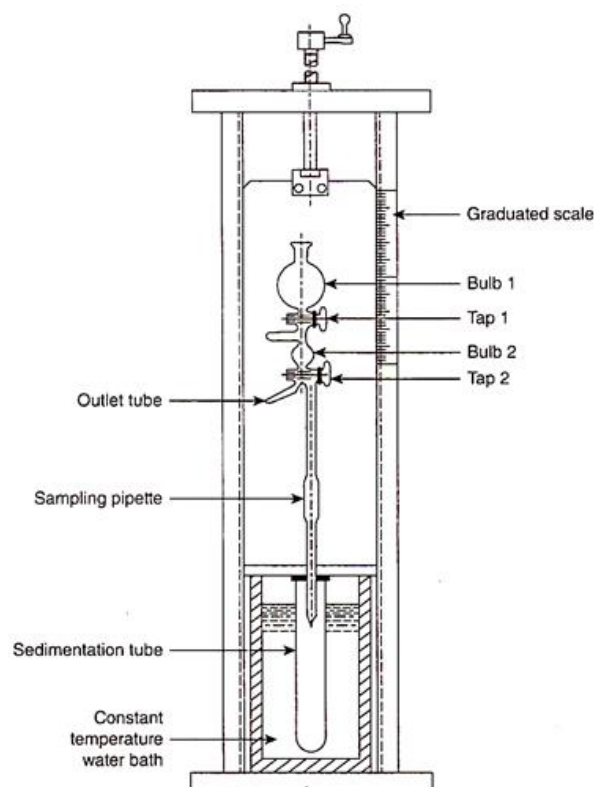


Figure 3.4 The Pipette method apparatus (Bedaiwy and Naguib, 2012).

3.5.3 Hydrometer method

The hydrometer was invented by William Nicholson in 1790 for the purpose of measuring certain characteristics of liquids (Encyclopaedia Britannica, 2013). The hydrometer can be used to determine the density of the liquid (weight per unit volume) or specific gravity (weight per unit volume compared to water)(Encyclopaedia Britannica, 2013). The hydrometer consists of a weighted,

sealed, long-necked glass bulb (hydrometer bulb) that is immersed in a liquid to measure the characteristics of the liquid. The depth at which the hydrometer bulb floats in the liquid is then used to determine the density or the specific gravity of the liquid (Ashworth *et al.*, 2001). Original uses for the hydrometer was to determine the amount of alcohol or sugar in a solution (Encyclopaedia Britannica, 2013).

In the construction industry, the hydrometer is used to classify soil samples by determining the PSD of a soil sample. Soil sample classification is achieved by measuring of the concentration of soil particles in suspension for a given mass of soil that was mixed with a known volume of water and dispersant in a sedimentation cylinder (Bedaiwy and Naguib, 2012). Similarly to the Pipette method, the Hydrometer method also relies on the sedimentation rate of the particles in a soil sample for soil classification (Ashworth *et al.*, 2001; Bedaiwy and Naguib, 2012). Soil classification methods based on the sedimentation rate of soil particles in a mixture, are all founded on Stokes' law (Bedaiwy and Naguib, 2012). Stokes' law states that when a soil sample is mixed with water and dispersant in a sedimentation cylinder, the different sized particles will sediment at different velocities depending on their size, weight and the viscosity of the water (Das, 2018). Stokes' law also assumes that all soil particles are spheres and therefore, the velocity at which the soil particles sediment in the sedimentation cylinder is relative to their diameter. Stokes' law can be expressed by the following equation (Das, 2018):

Equation 1 Stokes' Law.

$$v = \frac{P_s - P_w}{18\eta} D^2$$

Where:

η	= velocity
P_s	= density of soil particles
P_w	= density of water
v	= viscosity of water
D	= diameter of soil particles

During the sedimentation of the soil particles in suspension, the concentration of the particles in suspension changes over time. By introducing a hydrometer bulb to the mixture, the geometric centre of the hydrometer bulb changes in height, as the sedimentation process continues (Figure 3.5). The measurements taken of the position of the geometric centre of the bulb at certain times are then used to calculate the PSD of the soil sample (Ashworth *et al.*, 2001). The Hydrometer method is labour intensive and can take a long time to complete (Sudarsan *et al.*, 2018).

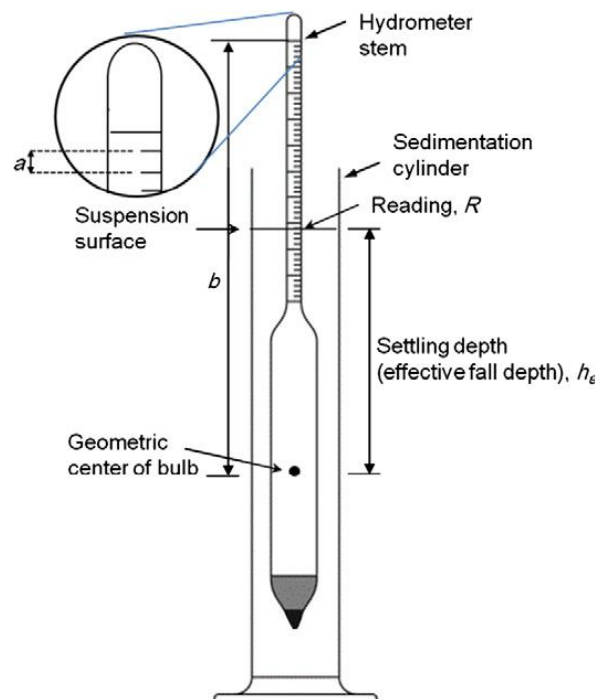


Figure 3.5 The Hydrometer method apparatus (Bedaiwy and Naguib, 2012).

The method for clay fraction estimation by the Hydrometer method in South Africa is similar to the Hydrometer methods used in Britain, America, Australia and many other countries (Stott and Theron, 2016). Although the Hydrometer method is relatively inexpensive and has a relatively simple testing method when compared to other soil classification methods, its accuracy is doubtful. (Stott and

Theron, 2016). Inaccuracies of the Hydrometer method can be attributed to mainly four factors (Savage, 2007):

- Stokes' law assumes that all particles are spherical, while clay particles are flaky;
- The sedimentation of clay particles may be accelerated by larger particles that drag down smaller particles or clay particles sticking to larger particles;
- A common relative density is assumed for all particles, which may not be true; and
- De-flocculation of many clays is seldom fully completed at the time of testing.

When using the Hydrometer method, these four factors may lead to inaccurate clay fraction calculations. As clay fraction calculations are an important factor to consider when determining the type of foundation to be used for any superstructure, inaccuracies during the clay fraction calculation for a soil sample can lead to structural engineers selecting the wrong foundation type. For example, the Hydrometer method was used to classify soil samples obtained from a construction site for a government subsidy housing project in Kimberley, South Africa. The soil classification results showed that the soil had a clay content of 6% and the foundations were designed accordingly. These foundations demonstrated uneven settling, causing extensive cracking of the structures, which resulted in unstable housing structures being built. Many of these houses became completely uninhabitable shortly after construction was completed (Monye, 2018). The damage to these houses could be attributed to the selection of the wrong foundation type for the structures as a result of inaccurate readings obtained from the Hydrometer method (Monye, 2018). The selected foundation type could not offer sufficient support to the houses that were built on the clay-rich soil.

3.5.4 Modern methods

More recently, several modern methods have been developed to classify soil samples (Ghasemy, Rahimi and Malekzadeh, 2019). These methods, such as the Cone Penetration Test (CPT), X-ray absorption, electrical sensing, laser diffraction, single optical sizing and visible-near infrared

spectroscopy, apply sophisticated technology to classify soil samples according to their PSD (Viton and Sadler, 1997; Tillmann *et al.*, 2008; Dhawale, 2015; Fisher *et al.*, 2017; Sudarsan *et al.*, 2018). These modern PSA methods are expensive, because they require highly sophisticated machines, specialised maintenance and can only be operated by trained operators. In most cases, the machines are only suitable for laboratory conditions (Taubner, Roth and Tippkötter, 2009). Although these machines are sophisticated, they can still produce inconsistent soil classification results. These inconsistencies are attributed to homogeneous materials, such as quarts or glass beads being used to calibrate the machines. This is in contrast to the heterogeneous nature of the soil being analysed by the machines (Taubner, Roth and Tippkötter, 2009). Because of the constraints that these modern PSA methods pose, the Hydrometer method remains one of the most commonly used methods to classify soil samples.

3.6 Machine Vision Systems

Machine Vision systems extract information from images in an automated manner. This information is then analysed through various methods and techniques to provide a system with an automated output or answer (Luwes, 2010; Pinnamaneni, 2013). The purpose for each MV system is unique, and so is the design and techniques used to provide the required output for a MV system. A typical MV system combines three steps to achieve its goal, namely; an image acquisition step, an image processing step and a data analysis or image classification step (Frey, 2005; Radcliffe, Cox and Bulanon, 2018). These steps are presented in a logical diagram in Figure 3.6.

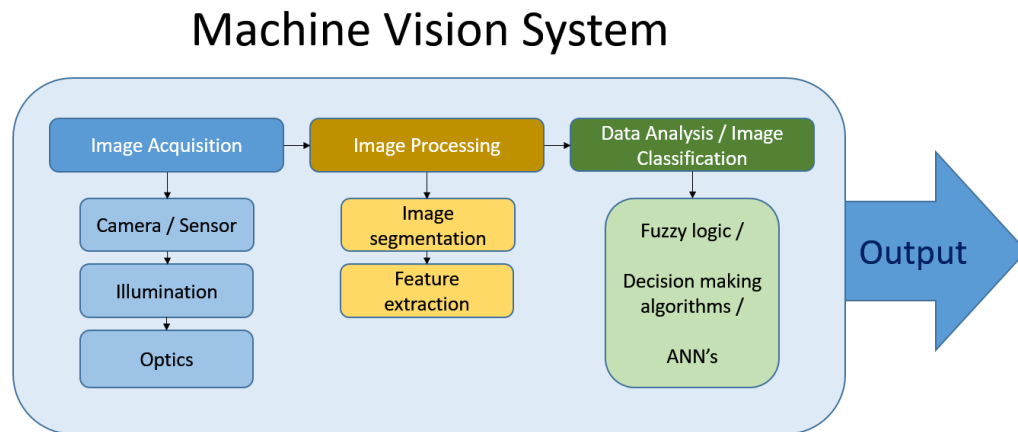


Figure 3.6 Logical diagram of a typical MV system.

3.6.1 Image acquisition step

The first step in any MV system is to acquire digital images of real-world objects. The acquisition of these images requires a hardware source to perform this digitisation, for instance a digital camera or digital sensor (Radcliffe, Cox and Bulanon, 2018). When an image acquisition system is created, a suitable camera and lens should be selected. Thereafter, a proper illumination solution should be devised so that optimal results can be achieved (Cowan, Modayur and DeCurtins, 1992; Frey, 2005; Kopparapu, 2006).

3.6.2 Camera selection for a Machine Vision system

The selection of an appropriate camera for image acquisition is a crucial step when developing an MV system (Kopparapu, 2006; Luwes, 2010). When selecting an appropriate camera for a MV system, the following factors need to be taken into consideration (Frey, 2005; Luwes, 2010; Fell, 2017):

- The type of object from which images would be captured;
- The speed at which images should be captured;
- The required quality and colour depth of images to be captured; and
- The cost of the camera.

Cameras that are used in the field of digital image acquisition are dominated by Complementary Metal Oxide Semiconductor (CMOS) cameras and Charge Coupled Device (CCD) cameras (Frey, 2005; Babcock, 2018). With CMOS cameras, the electronics that convert light into a digital signal are integrated into the surface of the sensor in the camera. This makes CMOS cameras ideal for high speed image capturing (Babcock, 2018). On the other hand, CCD cameras capture more light and are therefore better suited when high quality, low noise and high colour fidelity images are needed (Fell, 2017).

Colour is also a determining factor when selecting a suitable camera. When the application of a MV system does not require colour images, it is better to use a monochrome camera, because it is more sensitive than colour cameras and therefore captures more detailed images (Fell, 2017). By using a monochrome camera, resources are conserved as no processing is required to convert colour images into greyscale images. In contrast, colour digital cameras use a matrix to capture colour data as pixels. Each pixel has a colour filter to which an algorithm is applied to determine the actual colour of the pixel (Fell, 2017). The colour determination of each pixel slows down the image capturing process and needs to be considered when high speed image capturing is required. The cost of digital cameras varies substantially according to the quality, as well as the make and application, therefore the highest quality camera that the budget allows should be selected.

3.6.3 Lens selection for a Machine Vision system

The choice of an appropriate optical lens for specific applications in MV is of utmost importance (Pinnamaneni, 2013; Williamson, 2019). The two fundamental characteristics that influence the selection of an optical lens are the focal length and the maximum aperture (Pinnamaneni, 2013; Williamson, 2019). The focal length of a lens determines the magnification of the image projected on to the sensor of the camera, while the aperture determines the light intensity of the captured image.

Guidelines that facilitate the choice of an appropriate optical lens for a specific application, are set out in Table 3-1 (Frey, 2005).

Table 3-1 Guidelines for choosing a lens with the appropriate focal length.

Focal length (mm)	Lens type	Applications
8 – 24	Ultra wide angle (fisheye)	Wide panoramic images
24 – 35	Wide angle	Landscapes, architectural images
35 – 85	Standard	General purposes
85 – 135	Short telephoto	Portraits, candid images
153 – 300	Medium telephoto	Close up sport or action images
>300	Super telephoto	Wildlife and nature images, astronomy

3.6.4 Illumination techniques for a Machine Vision system

For MV systems, a highly controlled illumination environment is a requirement (John and N, 2019). Such an illumination environment requires an appropriate illumination technique, as well as an optimal light source to capture the highest quality images (Frey, 2005; John and N, 2019). Table 3-2 provides several illumination techniques that can be considered for MV systems (Frey, 2005).

Table 3-2 Selecting the appropriate illumination technique (Frey, 2005; Semeniuta *et al.*, 2018).

Illumination technique	Applications
Front illumination	This technique is the most basic illumination method where the camera and the light source are on the same side of the object. Problems can arise from this technique as shadows might be projected onto the object.
Back illumination	This technique can be used in instances where high contrast images with dark silhouettes are required against a bright background.

Illumination technique	Applications
Diffuse illumination	This technique ensures even, multi-directional light, minimising the effect of reflections on shiny objects.
Directional illumination	This technique is applied to enhance details on surface inspections.
Bright field illumination	This technique is used when there is a direct path from the light source to the camera. This technique works well when inspecting metallic surfaces.
Dark field illumination	This technique can be used to enhance small surface imperfections to inspect objects for scratches.

Light sources vary in shape, colour, size, light frequency and many other features (Katemake *et al.*, 2019). Therefore, experiments should be conducted to verify the appropriate illumination type for each application (Kopparapu, 2006). The power source should also be considered; All alternate Current (AC) powered lights flicker at 50 Hz, which is too fast for the naked eye to see, but if images are captured at high frequency, the flicker might impact the image acquisition process negatively (Frey, 2005). If the flickering of the light source impacts image acquisition process negatively, Direct Current (DC) powered light sources can be used to eliminate any flicker from the light source (Sieczka and Harding, 1992). For light sources, the following options should be taken into consideration (Sieczka and Harding, 1992; Frey, 2005):

- Conventional electric light bulbs,
- Fluorescent tubes,
- Infrared lights,
- Halogen or tungsten lamps with fiber optics and
- Light emitting diode (LED) light sources.

3.6.5 Image processing step

Image processing is the process of applying an algorithm to an image to produce a more enhanced image (Semeniuta *et al.*, 2018). Images acquired during the image acquisition step can be enhanced, segmented or manipulated to extract useful features from the images through image processing (Semeniuta *et al.*, 2018; Utai *et al.*, 2019). Image processing also includes the process of feature reduction in which the original amount of features in an image is reduced to application-specific features only (Frey, 2005; Semeniuta *et al.*, 2018; Utai *et al.*, 2019). A Region of Interest (ROI) can be defined to remove unnecessary parts of an image that does not need to be processed by the image processing software (Sun *et al.*, 2019). These extracted, application-specific features are then easier to manipulate and be analysed by the software to generate useful data. Thereafter, the useful data can be used by image processing techniques to manipulate or improve images.

An image histogram is an example of an applied image processing technique. To create a histogram for an image, all the pixels with the same value of the colour spectrum are summed together and the resulting values are plotted on a graph (Knuth, 2012; Kolakshyapati *et al.*, 2019). The data can then be parsed by decision-making algorithms to adjust the exposure or colour saturation settings of the image to produce an image of better quality (Agrawal *et al.*, 2019).

Many software environments exist that have been specifically designed for the development of MV systems. When deciding which software environment would be most suited for the development of a MV system, the following key features should be taken into consideration:

Table 3-3 *Features that should be considered when selecting the development software for a MV system (Dalsa Coreco, 2017).*

Feature	Selection consideration
Performance	Does the software fulfil all the requirements of the application in terms of speed and accuracy?
Learning	Are there software packages familiar to the engineers? How much time will it take engineers to learn to use unfamiliar software packages effectively to accomplish the required tasks?
Ease of use	Does the software package offer drag-and-drop functionality, comprehensive help files and a digital community to provide support (blogs, social media)?
Reliability	Is the software stable and does it function properly under all conditions?
Support	How much technical support is available and would the software package still be supported in the near future?
Availability	Which software packages are freely available?

3.6.6 Data analysis step

Data analysis in a MV system involves the processing of the captured digital data to extract useful information (Utai *et al.*, 2019; Zhang and Dahu, 2019). After capturing the digital data during the image acquisition step, the data are processed to produce a result as required by the particular MV system. Initially, hand-crafted software programs were developed to process the captured data to produce a desired result (Semeniuta *et al.*, 2018). However, subsequently, machine learning in the form of Artificial Neural Networks, has proven to be a promising alternative to these hand-crafted programs, because of their accuracy and ability to recognise complex patterns in the captured data (Semeniuta *et al.*, 2018; Zhang and Dahu, 2019). Although ANN's are still programmed manually, frequently software suits are used to facilitate the development of functional ANN's for data analysis.

3.6.7 Applications of Machine Vision systems

The purpose of this section is to discuss applications of machine vision systems that led to the hypothesis of using machine vision as a solution for soil classification. It is shown that there are many applications of MV systems and many more are added continuously as technology advances (Rukmani *et al.*, 2018). MV systems have been applied successfully in many fields, of which some examples are shown in Table 3-4.

Table 3-4 Examples of MV systems applications (Pinnamaneni, 2013).

Field	Example
Law enforcement	Automatic number plate recognition, traffic control, surveillance.
Medical and pharmaceutical	Sorting and counting tablets, blister pack inspection, blood cell counting.
Material science	Surface inspection, particle analysis and counting.
Robotics	Automatic part assembly, robot guidance, area mapping.

MV systems have also been applied successfully in a variety of applications in the building trade. Examples of MV applications in the construction industry include Structural Displacement Monitoring (SDM) and Structural Condition Assessment (SCA) (Ye, Dong and Liu, 2016). By applying image sequencing, pattern matching algorithms, edge detection and other MV techniques, the structural displacement of several key points on certain structures could be obtained accurately, automatically and in real time (Ye, Dong and Liu, 2016). By applying an MV system, the deformation and displacement of high-rise buildings could be monitored and used as an early warning system for structure failures.

3.7 Artificial Neural Networks

An ANN is a computational model that was inspired by the neuron, the most basic unit of the human nervous system (Jimenez-Martinez and Alfaro-Ponce, 2019; Taheri, Abbasi and Khaki Jamei, 2019).

ANN neurons work together in a designed network topology in an attempt to mimic the human brain in the way it processes information and makes informed decisions. An ANN becomes functional when the artificial neurons are linked together by adjustable weights and when an activation function is applied (Luwes, 2010; Nigrini, 2012).

3.7.1 ANN topologies

z. To help determine the type of topology that should be used when designing an ANN, the following questions should be asked (Nigrini, 2012):

- How efficient can the network topology and parameters be adapted?
- What is the level of accuracy needed?
- How many network layers are needed?
- How many artificial neurons should be in each layer?
- Is there enough historical data to train the ANN?

The topologies of ANNs differ because their intended applications are unique. The most common topologies are shown in Figure 3.7, where A shows a Feed Forward Single-Layer Perceptron (FF-SLP) topology, B a Feed Forward-Back Propagation (FF-BP) topology and C a Feed Forward Multi-Layer Perceptron (FF-MLP) network (Taheri, Abbasi and Khaki Jamei, 2019).

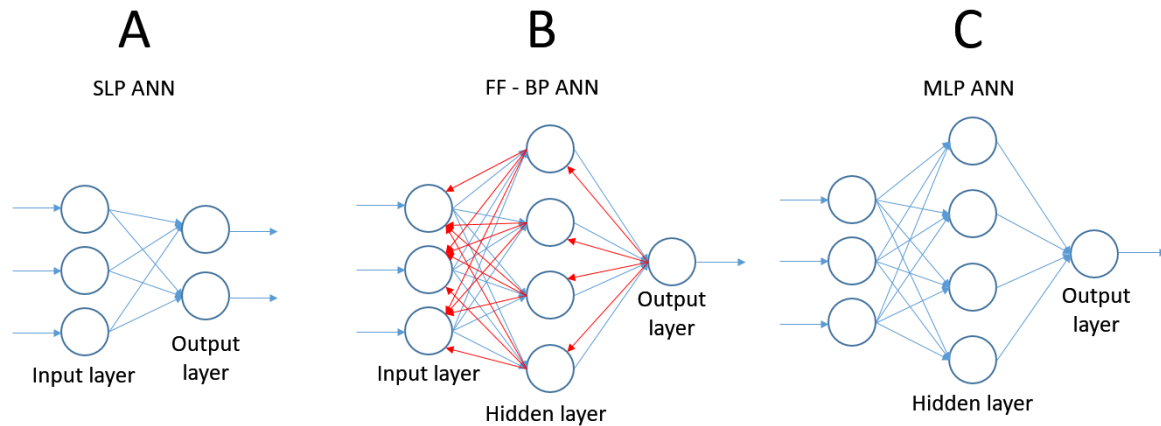


Figure 3.7 Examples of ANN topologies. A) MLP topology; B) SLP topology; C) FF-BP topology.

The efficiency of ANNs to process large amounts of data makes this technology an attractive solution in many industries (Rukmani *et al.*, 2018). This efficiency is due to the complexity of the ANN technology (Marr, 2017; Rukmani *et al.*, 2018). The many and varied industries can be seen from the aerospace industry where ANNs are used to improve the autopilot functionality of aircraft to where the insurance industry applies ANNs for policy application evaluation and product optimisation. Other examples include the telecommunications industry where ANNs are used for automated information services, real-time language translations and image recognition (Jimenez-Martinez and Alfaro-Ponce, 2019).

One of the most advanced developers of artificial intelligence systems, Google, have implemented ANNs across many of its products and services (Marr, 2017). The first practical solution, where Google applied ANNs, was to sort and classify the millions of images that are uploaded to the internet on a daily basis. This application of ANN technology provided more accurate search results to Google searchers (Marr, 2017). The multi-layered ANN designed by Google proved to be very efficient at processing and classifying these vast amounts of image data and was therefore implemented in a multitude of Google services.

3.7.2 ANN training

All ANNs need to be trained before they can be used to execute a function (Nigrini, 2012; Bahrami *et al.*, 2019). The main feature of ANNs are their ability to learn from sequential training procedures by self-adapting to input data. The self-adaptation process is achieved by a back-propagation algorithm that adjusts the values of the weights and biases that connect the artificial neurons together (Taheri, Abbasi and Khaki Jamei, 2019). The process of adjusting the weights of the artificial neurons until the target output is achieved, is referred to as training of the ANN (Jimenez-Martinez and Alfaro-Ponce, 2019).

Two types of training methods can be used to train an ANN. These training types comprises of unsupervised training and supervised training (Nigrini, 2012; Shahsavar *et al.*, 2019). Unsupervised training provides the network with inputs, but the desired output is not specified. The network then automatically selects the relevant data to generate the desired output. Unsupervised training, at present, is still not well understood but provides the promise of a continuous learning artificial intelligence system that can adapt to new situations and environments (Reingold and Nightingale, 1999; Heung *et al.*, 2016). Currently, most developers use supervised training to train an ANN. For supervised training, the inputs as well as the desired outputs are provided to the system. The network then compares the current output to the desired output and applies the back-propagation algorithm until the desired output is achieved (Reingold and Nightingale, 1999). The adjustments that are applied to each neuron's input weights and biases during training influences the neuron's behaviour in the network. How these adjustments are made, is decided by the learning algorithm chosen to train the network (Heung *et al.*, 2016; Taheri, Abbasi and Khaki Jamei, 2019). Although there are many training algorithms to choose from (Awolusi *et al.*, 2019; Shahsavar *et al.*, 2019), three commonly used algorithms are shown in Table 3-5.

Table 3-5 Common training algorithms used for the training of an ANN.

Algorithm	Description
Levenberg-Marquardt algorithm	This training algorithm is used when speed is a factor. This algorithm trains faster than other algorithms because the algorithm automatically stops training when generalisation stops improving as the mean squared error of the validation samples increases. The increase in speed requires more computer resources for training.
Bayesian regularisation algorithm	This training algorithm is a good candidate to use when datasets are small or noisy. It takes longer to train and determines when to stop according to adaptive weight minimisation.
Scale conjugate gradient algorithm	This training algorithm is used when computer resources are limited. Training is automatically stopped when training results stops improving as the mean squared error of the validation samples increases.

When selecting a training algorithm, various training algorithms should be evaluated to determine which produces the most accurate output (Plumb *et al.*, 2005; Nigrini, 2012; Shahsavar *et al.*, 2019). After the training of an ANN, its accuracy is evaluated by the Mean Squared Error (MSE) and Regression (R) values, which are produced by the training software (Nigrini, 2012; Mohi Alden *et al.*, 2019). The MSE value shows the average squared difference between the ANN's output and the target output. The MSE value is inversely proportional to the accuracy of the ANN. A MSE value of zero indicates that there is no difference between the output of the ANN and the target output. The R-value shows the correlation between the output value of the ANN and the target output. An R-value of "1" shows a close correlation, while an R value of "0" shows no correlation between the output and target output. When the desired MSE and R-values are achieved, the weights of each artificial neuron is "locked" and the ANN can be implemented.

3.8 Motivation for the use of Machine Vision and Artificial Neural Networks in soil classification

Machine Vision (MV) is the process of creating digital models of the real world from captured images (Pinnamaneni, 2013). These real-world digital models are then processed and analysed to achieve a certain goal. To achieve this goal, MV is combined with decision-making algorithms so that these digital models can be analysed and interpreted. Such a MV system achieves its purpose through image acquisition, image processing, and statistical data analysis of the digital model (Frey, 2005). MV applications, in combination with processing algorithms, have received much attention with new technological advancements in the fields of computational power and image acquisition systems. MV systems have been successfully applied in a multitude of fields, of which some examples are shown in Table 3-6.

Table 3-6 Applications for MV systems.

Field	Applications
Aerospace	High performance autopilots for aircraft.
Automotive	Automatic guidance systems for automobiles.
Electronics	Integrated circuit chip design and circuit board fault finding.
Entertainment	Animation and special effects.
Manufacturing	Process control and quality checks.
Medical	Electroencephalogram (EEG) and electrocardiogram (ECG) analysis.

Several attempts have been made to calculate the sizes of soil particles in soil samples. As early as 1997, Raschke and Hryciw, attempted to classify soil samples by means of MV, in combination with computational algorithms (Sudarsan *et al.*, 2018). In 1998, Tuceryan and Jain attempted to calculate the size of soil particles from an acquired image, after matching textural patterns in an image

acquired by a digital microscope. However, at that time, computational power was lacking and therefore the studies delivered unreliable results.

MV systems have also been used successfully in the mining industry. In the mining industry, the quality of a material is determined by the particle size of the material (Andersson, Thurley and Carlson, 2012). To determine the particle size of the material, manual sampling and sieving is done. These techniques are performed infrequently and can be inconsistent, because of mechanical faults or inconsistent application by different technicians (Andersson, Thurley and Carlson, 2012).

Andersson et al. (2012) developed a MV system in combination with an algorithm to automatically determine the size of limestone particles on a conveyor belt. The results of the MV system produced good estimates of the particle size distribution of the limestone particles.

Large amounts of data are collected during a MV process. These volumes of data need to be processed in real-time to obtain an output for a MV system. With the advances in computational power, ANNs have become a popular and effective solution to process large volumes of data. More recent studies have been undertaken to process large volumes of data. In a study conducted in Northern Croatia, Cone Penetration Test (CPT) data were collected from various locations across the country for soil classification (Reale *et al.*, 2018). In this study these large volumes of data were used to train, test and validate an ANN model as a means to automate soil classification. The ANN proved to be almost 90% accurate in predicting the soil classification of unknown soil samples (Reale *et al.*, 2018). These studies showed that an MV system, in combination with an ANN can produce accurate particle size estimations in soil classification (Minasny *et al.*, 2004; Nakhaei, 2005; Zhao *et al.*, 2009; Kumar, Venkatesh and Kumar, 2012; Mukhlisin, Sharina and Abd, 2017; Allievi *et al.*, 2018; Merouane and Mamoune, 2018; Parameswari and Manikantan, 2018). Therefore, for this study an Automated Soil Classification System (ASCS) was envisioned by combining a MV system

with an ANN for the capturing and processing of soil sample sedimentation data to classify a soil sample more accurately and reliably.

3.9 Chapter discussion and summary

In the construction industry, the selection of an appropriate foundation is of vital importance. To facilitate the selection of an appropriate foundation, an accurate soil classification system is required. The successful application of MV and ANNs in many fields, including the construction industry, shows that the application of these technologies have the potential to accurately and reliably classify soil samples. If MV technology can be successfully combined with an ANN to create an Automated Soil Classification System, it would have the potential to make a significant contribution to the construction industry by providing an accurate and reliable soil classification system.

Chapter 4

Development and construction of the Machine Vision Instrument

4.1 Introduction

Phase 2 of this study focused on the development of the Machine Vision Instrument (MVI) that was responsible for the generation of Soil Sample (SS) fingerprints. An SS fingerprint is a consolidated histogram of images captured during the sedimentation process of soil samples and was generated by means of a two-step process. In Step 1, images of the sedimentation process of a pre-constituted soil sample were acquired, while in Step 2 image processing techniques were applied to the acquired images to generate the SS fingerprint for a soil sample. To achieve these two steps an MVI had to be constructed. Figure 4.1 provides the overall study design, highlighting Phase 2, which involved the development and construction of the MVI, which is part of the Automated Soil Classification System (ASCS).

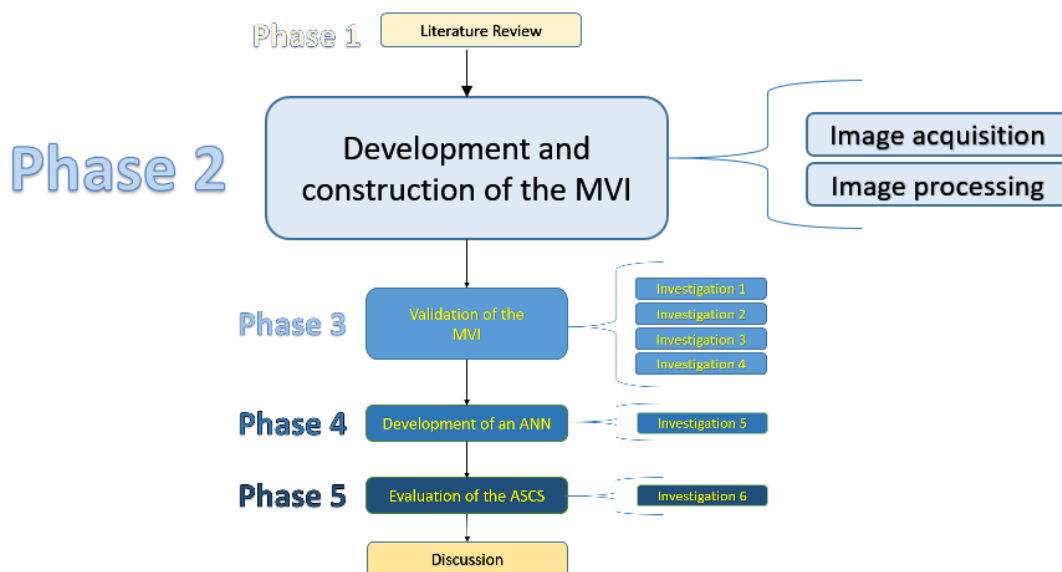


Figure 4.1 Overall study design.

To acquire digital images of the sedimentation cylinder during the sedimentation process of a soil sample, without environmental and other interferences, a light-proof box, containing the necessary image capturing components, was assembled. It is important to note that the box should be completely light proof and therefore be fully opaque. The light-proof box was constructed from light-proof Perspex panels and contained a digital camera to acquire the images, a suitable light source and the sedimentation cylinder containing the soil sample of interest.

Three software programs were developed for the functionality of the MVI. The first software program was developed to calibrate the image acquisition process. This was achieved by ensuring that the soil sample was positioned correctly, setting the focus of the camera as well as light-balancing techniques to ensure the proper exposure setting of the digital camera. The second software program was developed to process the acquired digital images and to generate the SS fingerprint for a soil sample. This was achieved through various image processing techniques, which included region of interest (ROI) definition, image extraction and histogram generation. The third software component was developed with correlation functions to correlate the generated SS fingerprints of the various soil samples. The layout for the logical design for the MVI shown in Figure 4.2

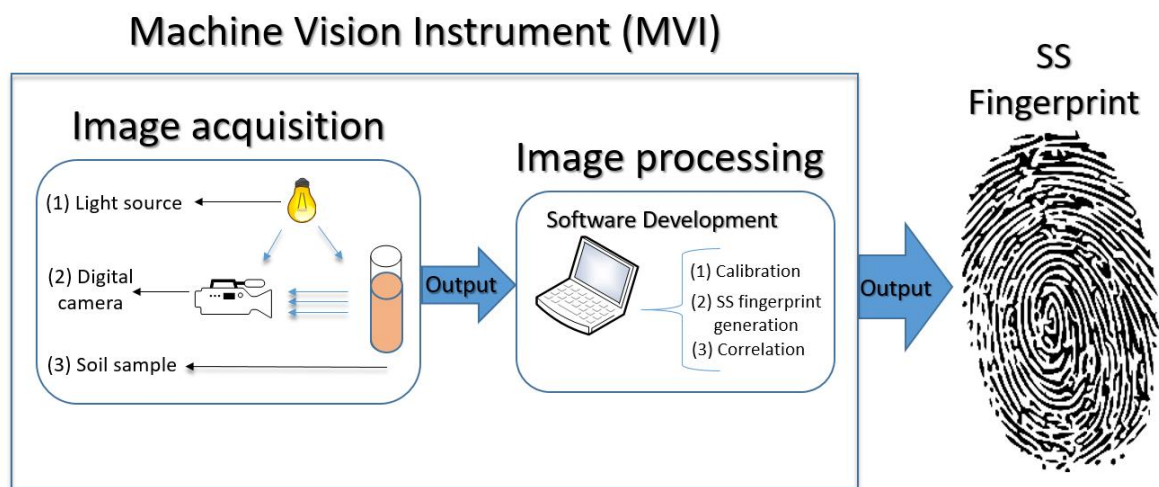


Figure 4.2 Logical design of the MVI.

Once the hardware and software components were completed, they could be combined to form the functional MVI. The functional MVI was then able to generate unique SS fingerprints for the respective soil samples comprising of different clay compositions.

4.2 Step1: Image acquisition

Three components were needed for the image acquisition step of the MVI. These components included a digital camera, a light source and a sedimentation cylinder containing a pre-constituted soil sample. The components were placed inside the lightproof box to acquire images during the sedimentation process of a soil sample. The functions of these components were as follows:

- Component 1: **Digital camera.** A digital camera was needed for image acquisition during the soil sample's sedimentation process.
- Component 2: **Light source.** Optimal illumination of the soil sample was needed to capture images in consistent lighting conditions during the soil sample's sedimentation process.
- Component 3: **Soil sample.** Pre-constituted soil samples were used for SS fingerprint generation so that the composition of the soil sample could be paired with its unique SS fingerprint.

4.2.1 Component 1: Digital camera selection

Image acquisition is a key component of any machine vision system (Frey, 2005). The quality of the acquired images could directly influence the result of the image processing step of the MVI. If the acquired images are pixelated because of a low quality image capturing device, data could be lost and the image processing result could be negatively influenced. Therefore, the highest possible image resolution, as permitted by the hardware, was used to acquire images. Only the opaqueness of the liquid during the sedimentation process was of interest in the study, therefore, a colour image was not required. For these reasons and taking budget constraints into account, a Basler digital black and white camera was selected for the acquisition of high resolution, greyscale images. The sample rate for image acquisition in this study was experimentally determined to be one image

captured every 5 s over a period of 10 min. during the sedimentation process of a pre-constituted soil sample.

Optimal camera settings and precise camera positioning were needed to capture images in a consistent manner during the sedimentation process of each prepared soil sample. These settings had to be standardised to ensure consistency across all MVI applications. The following settings were standardised:

- **Resolution setting of the camera:** The resolution setting of the camera had to be standardised across all MVI image acquisition steps to prevent variation in the quality of the captured images. Therefore, the resolution setting of the camera was set to the highest possible value of 5 megapixels.
- **Focus setting of the camera:** The focus setting was also standardised across all MVI image acquisition steps. Therefore, the autofocus setting was disabled and a fixed focus setting was used instead. To determine the focal point of the camera, the camera was placed as close as possible to the cylinder containing the soil sample, ensuring that the entire cylinder was in the camera's field of view. Thereafter, the focus setting on the camera was adjusted until the image was in focus.
- **Exposure setting of the camera:** The exposure setting of the camera was standardised to ensure that the same light intensity was measured consistently by the camera across all MVI image acquisition steps. To standardise the exposure setting of the camera, a piece of black insulation tape, taken from a single roll, was taped onto all the cylinders containing the prepared soil samples. Before the MVI could be used to capture the images during the sedimentation process, a test signal from the camera that focused on the black tape, was inspected on the computer. If necessary, the exposure setting was slowly adjusted from high to low until the greyscale measurement of the black tape just changed from 1 to 0 (completely black).
- **Camera lens type:** The same type of lens needed to be used across all MVI applications to ensure consistency in image acquisition. The most appropriate lens available was selected to fit the narrow ROI that needed to be captured, therefore, an industrial machine vision lens with $f = 16 \text{ mm}$ and F2.0 was selected. The aperture setting was set as low as possible to ensure the least amount of depth of field.

4.2.2 Component 2: Soil sample illumination

Lighting plays a vital role in the image capturing process (Frey, 2005; Kopparapu, 2006). When selecting an appropriate light source to illuminate the sedimentation cylinder, containing the soil sample, several factors had to be considered. Firstly, Alternating Current (AC) light sources were not considered for the construction of the MVI, because all AC light sources flicker at rate of 50 hertz. Because of this flicker they produce intermitted lighting which may result in inconsistent capturing of images during a soil sample's sedimentation process. This meant that various Direct Current (DC) light sources had to be tested for application as a light source for this project, as DC light sources do not flicker. Secondly, the selected light source had to illuminate the cylinder containing the soil sample consistently over its entire length.

To determine the optimal positioning for the light source in the MVI, a DC light source was positioned at several places (top, bottom, front and back) in relation to the cylinder containing the soil sample. Backlighting proved to be the most appropriate position for the illumination of the cylinder. Light Emitting Diode (LED) light sources are popular DC light sources and commonly used in machine vision applications. For this reason, an LED light sources were tested as backlighting light sources for the cylinder containing the prepared soil sample. However, LED light sources were unable to illuminate the entire length of the cylinder evenly. The uneven distribution of the lighting along the cylinder was caused by the gaps between the individual LED's on the LED lighting strip. The individual LED's caused a series of circular "hotspots" on the cylinder containing the soil sample (Figure 2.1 A) and was therefore deemed to be an inappropriate lighting source. Finally, when an elongated DC fluorescent light source was tested as backlighting. The elongated fluorescent light source was able to illuminate the entire length of the cylinder evenly and completely (Figure 4.3 B Left).

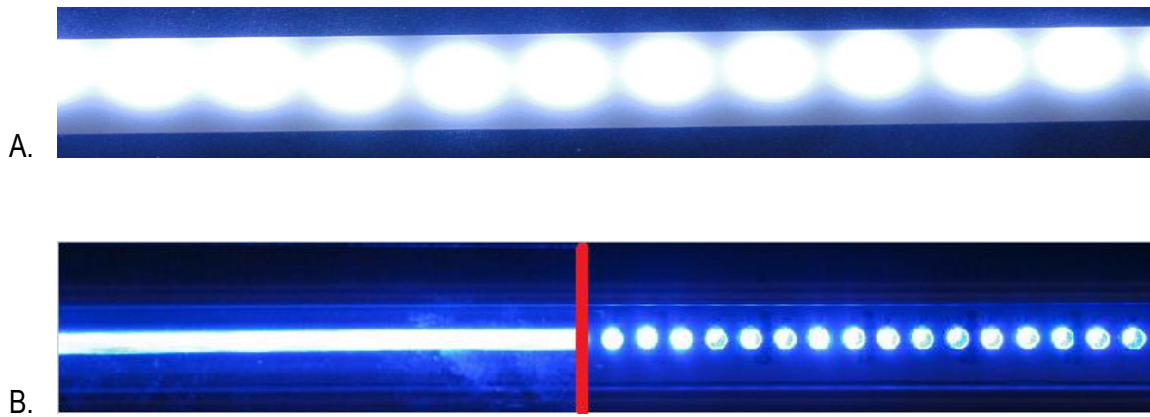


Figure 4.3 Light sources tested: A) Hotspots caused by using LED lighting strip. B) The difference between a DC fluorescent light source (left) and a LED light source (right).

To eliminate external light sources from causing anomalies during the image capturing process, the camera, light source and soil sample cylinder were enclosed in a lightproof box. For the construction of the lightproof box, a 1300mm × 750mm × 750mm aluminium frame was assembled and enclosed with painted Perspex panels on all sides. The Perspex panels were painted with an opaque, non-reflective, matt black paint to ensure consistent lighting conditions inside the lightproof box. The specifications of the components mounted inside the lightproof box of the MVI were as follows (Figure 4.4):

- $a = 315 \text{ mm}$ – The distance from the front of the camera lens to the front of the cylinder.
- $b = 420 \text{ mm}$ – The distance from the front of the camera lens to the front of the fluorescent light.
- $c = 300 \text{ mm}$ – The distance from the base of the booth to the center of the camera lens.
- $d = 60 \text{ mm}$ – The distance from the base of the booth to the bottom of the cylinder.
- $e = 35 \text{ mm}$ – The distance from the fluorescent light to the back of the cylinder.
- $f = 90^\circ$ – The fluorescent light and the cylinder needs to be measured at exactly 90° to the vertical and horizontal.
- $g = 90^\circ$ – The camera was mounted at exactly 90° to the horizontal.

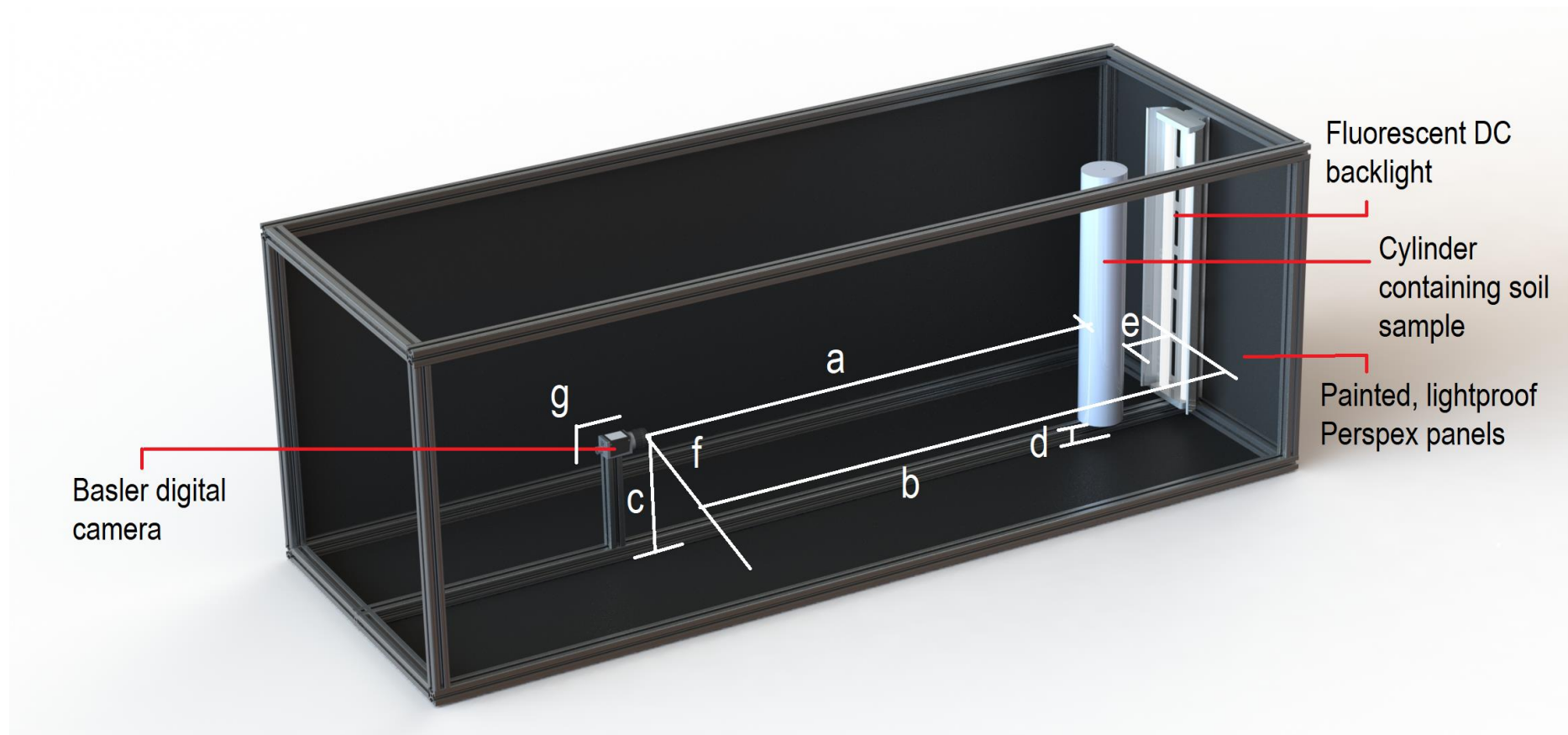


Figure 4.4 Light-proof box specifications.

The distance of the camera lens to the cylinder (measurement (a) in Figure 4.4) was determined by moving the camera as close as possible to the cylinder, whilst keeping the cylinder in focus. This ensured that the highest possible image resolution was obtained during the image acquisition step. Care had to be taken that the whole cylinder remained visible to the camera. Distance (b) was reliant on measurement (a) as this measurement needed to be determined prior to measurement (b). Measurement (c), the height of the camera, was determined by measuring the height of the cylinder, while ensuring that the middle of the camera lens was perpendicular to the exact middle of the cylinder. Distances (d) and (e) were determined by the thickness of the construction material and could not be adjusted. For the angles (f) and (g), it was decided to use 90 degree angles to simplify setup of the MVI.

4.2.3 Component 3: Soil sample preparation

The preparation of the soil samples for analysis by the MVI had to be consistent to ensure that the generation of SS fingerprints were repeatable and comparable. To prepare soil samples, samples of pure, washed sand and pure Bentonite clay, that contained a negligible amount of contaminants, were used. The sand and Bentonite clay were then mixed together to create pre-constituted soil samples containing different percentages of clay mixed with sand.

Prior to the preparation of the pre-constituted soil samples for the project, a suitable weight of dry materials (sand and Bentonite clay mixture) in a volume of 1,030 ml of water had to be determined. This was achieved in the following manner:

- Three dry material samples weighing 10 g, 20 g and 30 g (1:1 ratio of sand and Bentonite clay) were prepared.
- Each of the dry material samples were mixed with 1,030 ml of filtered tap water in a 1,030 ml cylinder and left to stand for 24 hours while observing the sedimentation process of the samples. It

should be noted that because pure samples of clay and sand were used, no dispersant was added as is the norm with the Hydrometer method.

- The sedimentation process of the 10 g dry material sample completed substantially faster than the other two dry material samples, therefore it was decided that for this study all pre-constituted soil samples would be prepared using 10 g of dry material as this would speed up the overall process.

After the dry weight of the material that had to be mixed with 1,030 ml was determined, a procedure needed to be established to mix the dry material with water in a consistent manner. When the same soil sample (dry material mixed with water) was mixed in different sedimentation cylinders, it should be in similar states of sedimentation when the MVI was applied. This would guarantee that consistent SS fingerprints were generated from all soil samples. To achieve a consistent way of mixing, the following steps were followed:

- A mixing apparatus was constructed to automatically mix the soil samples with the water in the cylinder.
- As with the Hydrometer method, the soil samples were left to settle for 24 hours before mixing. This allowed the dry material to disperse properly in the water leaving as little as possible conglomerations before automatic mixing could commence.
- The cylinder containing the dry material and water mixture was placed inside the mixing apparatus and the mixture was rotated vertically in a clock-like manner for 10 minutes. Various mixing durations were tested and the least amount of time that still properly mixed the sample was selected. 10 minutes was therefore deemed sufficient time to properly disperse the dry material within the 1,030 ml of water.

After the mixing was completed and the soil sample was properly prepared in the sedimentation cylinder, the cylinder was placed inside the MVI. The soil sample cylinder had to be placed inside the lightproof box as quickly as possible so that the start button in the SS fingerprint generation software could be pressed 30 seconds after automatic mixing was completed. Once the cylinder containing the soil sample was properly placed inside the lightproof box, image processing could be applied to generate the SS fingerprint for a particular soil sample.

4.3 Step 2: Image processing

Three software components were developed for the image processing step of the MVI. Before the SS fingerprint generation software could be applied, calibration software had to be developed to ensure that the setup specifications of the MVI remained consistent. Secondly, the SS fingerprint generation software had to generate unique SS fingerprints for each pre-constituted soil sample from the images that were captured during the image acquisition step of the MVI. Finally, correlation software was developed to correlate the SS fingerprints that were generated by the SS fingerprint generation software. Details for the three programs are as follows:

- **Calibration software:** The calibration software was developed to ensure that the sedimentation cylinder was positioned correctly, lighting was setup appropriately and that the camera's focus and exposure settings were properly set before the MVI could be used. The calibration software used image processing techniques in combination with human interaction to calibrate the MVI.
- **SS fingerprint generation software:** The SS fingerprint generation software was developed to capture images during the sedimentation process of a soil sample, process these images and create a unique dataset for each pre-constituted soil sample. This dataset was known as the soil sample fingerprint and was saved as a Comma Separated Values (CSV) file in a suitably named folder on the computer. Each SS fingerprint that was generated, uniquely identified the corresponding pre-constituted soil sample that was analysed by the MVI.
- **Correlation software:** The correlation software was developed to determine how accurately the MVI generated SS fingerprints. SS fingerprints generated for the same sample or soil samples containing the same amount of clay, should correlate closely, while soil samples with different constitutions should have low correlation results. The correlation software retrieved two SS fingerprint files that were saved on the computer, correlated the two SS fingerprints mathematically and displayed the correlation information to the user.

4.3.1 Software development environment

The three programs were developed and programmed in the National Instruments LabVIEW 2015 (LabVIEW) software suite (National Instruments ref 2015). The LabVIEW software suite is a block-

orientated drag-and-drop, visual programming environment. The LabVIEW development environment consists of two windows, namely, the Block Diagram (BD) window (Figure 4.5 A) and the User-Interface (UI) window (Figure 4.5 B). The logical programming development of the three software programs was executed in the BD window. On the other hand, user-interaction controls, logical indicators and relevant information were created in the UI window.

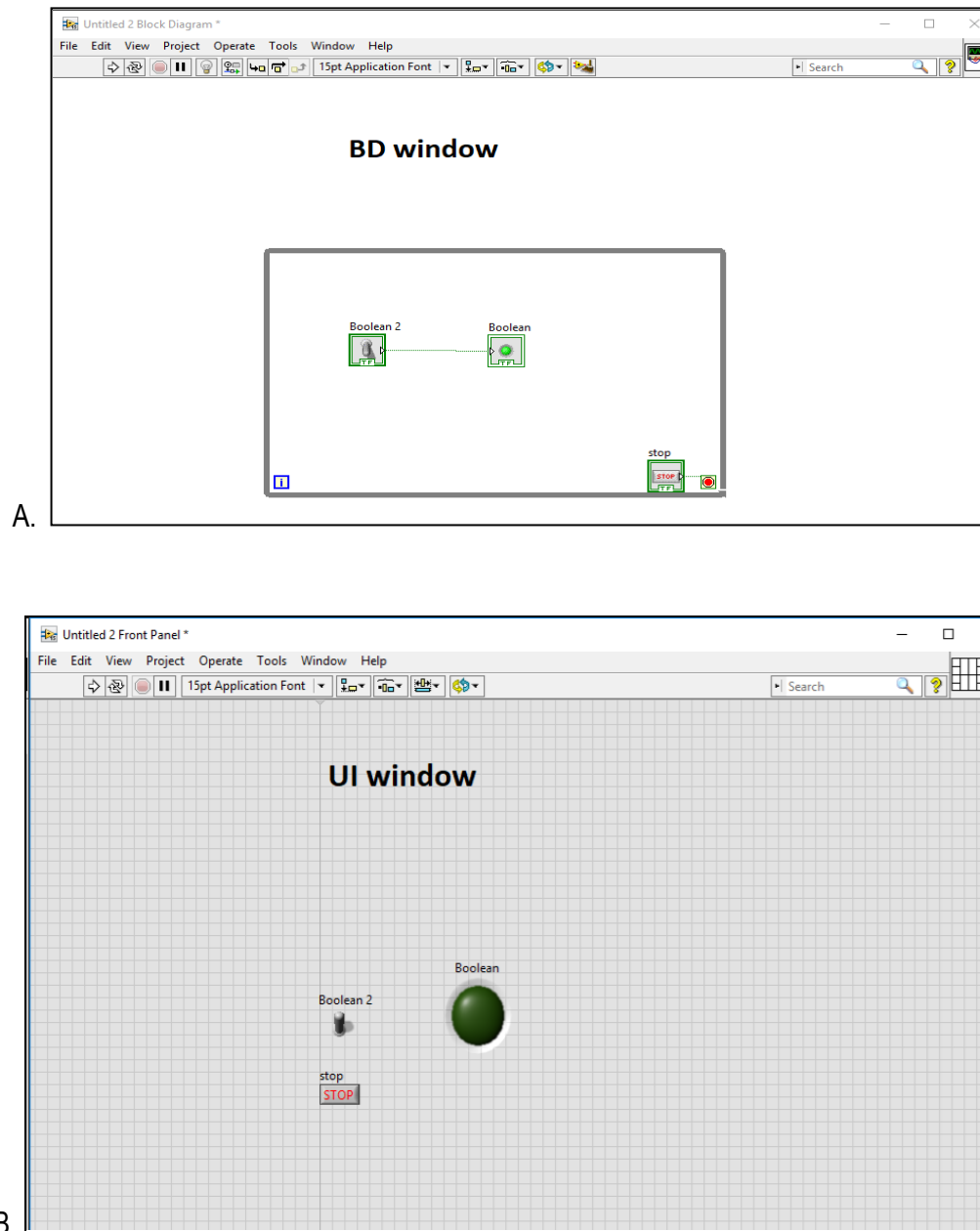
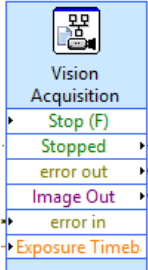
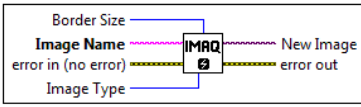
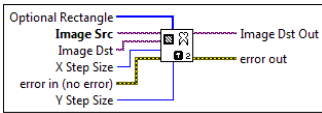
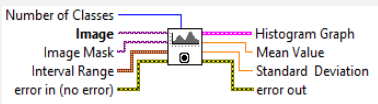
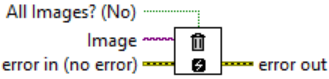


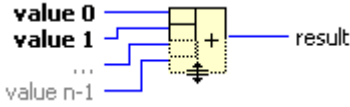
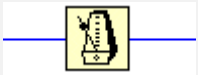
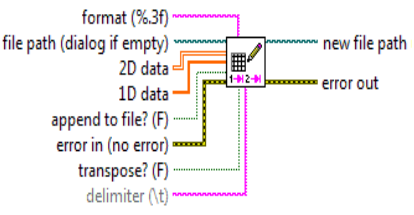
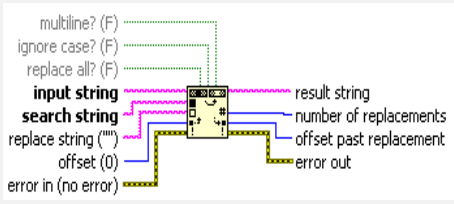
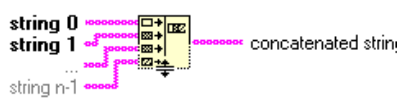
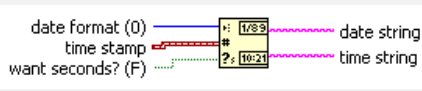
Figure 4.5 Windows of the LabVIEW development environment. A) BD window and B) UI window.

The LabVIEW software suite contains a collection of pre-programmed blocks of code known as Virtual Instruments or VIs. VIs are dragged and dropped into the BD window from the VI library and connected to one another other by means of “wires” that transfers data between the VIs. Each VI has a specific function that is executed when it receives data via the connected wires. The data, which flows between the VIs, can either be used as input data for the next VI, or it can be displayed as output data to the user by means of a display VI or an indicator (for example and a light indicator) in the UI. Table 4-1 provides a list of the VIs used in the development of the three software programs, as well as a description of the function of each of the VIs.

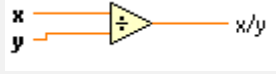
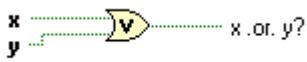
Table 4-1 List and description of VIs used in software development (National Instruments, 2009).

Identifier	Name of VI	Block image	Description
A	While loop		The while-loop repeats the code within its sub diagram until a specific condition occurs. A while-loop always executes at least one time.
B	Vison Acquisition VI		The Vison Acquisition VI initialises the digital Basler camera and readies it for image capturing, captures a single image from the camera and stores it in the memory space allocated by the IMAQ Create VI. The stored image can then be accessed by other VIs for manipulation end examination.

Identifier	Name of VI	Block image	Description
C	IMAQ Create VI		The IMAQ Create VI reserves computer memory space to store the image that is about to be captured by the Vision Acquisition VI.
D	IMAQ Extract 2 VI		The IMAQ Extract 2 VI is used to cut out a piece of an image to create a new smaller image.
E	IMAQ Display Image VI		The IMAQ Display Image VI is used to display an image to the user on the U.I. for example.
F	Display Waveform VI		The Display Waveform VI is used to display waveform data to the user on the U.I. that was created by the IMAQ HistoGraph VI.
G	IMAQ HistoGraph VI		The IMAQ HistoGraph VI is used to create a waveform from a dataset.
H	IMAQ Dispose VI		The IMAQ Dispose VI clears the memory space reserved by the IMAQ Create VI for the image that was captured by the Vision Acquisition VI.
I	Stop Button		The Stop Button halts the program.

Identifier	Name of VI	Block image	Description
J	Compound Arithmetic Function		The Compound Arithmetic Function performs arithmetic on one or more numeric, array, cluster, or Boolean inputs.
K	Timed Delay VI		The Timed Delay VI waits until the value of the millisecond timer.
L	Write Delimited Spreadsheet VI		The Write Delimited Spreadsheet VI write input values to specified file and file type.
M	Search and Replace String Function		The Search and Replace String Function replaces one or all instances of a substring with another substring.
N	Concatenate Strings Function		The Concatenate Strings Function concatenates input strings and 1D arrays of strings into a single output string.
O	Get Date/Time String Function		The Get Date/Time String Function retrieves current date and time from system and places the result into a string variable.

Identifier	Name of VI	Block image	Description
P	Elapsed Time Express VI		The Elapsed Time Express VI indicates the amount of time that has elapsed since the specified start time.
Q	String to path function		The String to path function converts a string variable to a path.
R	Light indicator		Boolean light indicator.
S	Value indicator		The Value indicator displays a variable on the UI.
T	File path indicator		The File path indicator displays a file path on the UI.
U	Read Delimited Spreadsheet VI		The Read Delimited Spreadsheet VI reads a specified number of lines or rows from a numeric text file.
V	Array Subset Function		The Array Subset Function returns a portion of array starting.
W	Index Array Function		The Index Array Function returns the element or subarray of an n-dimension array at index.

Identifier	Name of VI	Block image	Description
X	Array Size Function		The Array Size Function returns the number of elements in each dimension of array.
Y	Division function		The Division function divides two input variables.
Z	Add Array Elements Function		The Add Array Elements Function returns the sum of all the elements in numeric array.
AA	Multiplication function		The Multiplication function multiplies two input variables.
AB	OR gate		The OR gate computes the logical OR of the inputs.
AC	Array size indicator		The Array size indicator displays the array size on the UI.

4.3.2 Software development 1: Development of the Calibration software

The logical design of the calibration program was developed in the BD window of the LabVIEW software suite and consisted of four logical steps. These steps involved the initialisation of the camera, the definition of the region of interest, the generation of a histogram using the HistoGraph VI and a clean-up step in which computer resources were cleared. The logical layout and the VIs used to create these steps in the BD window of the LabVIEW software suite, are shown in Figure 4.6.

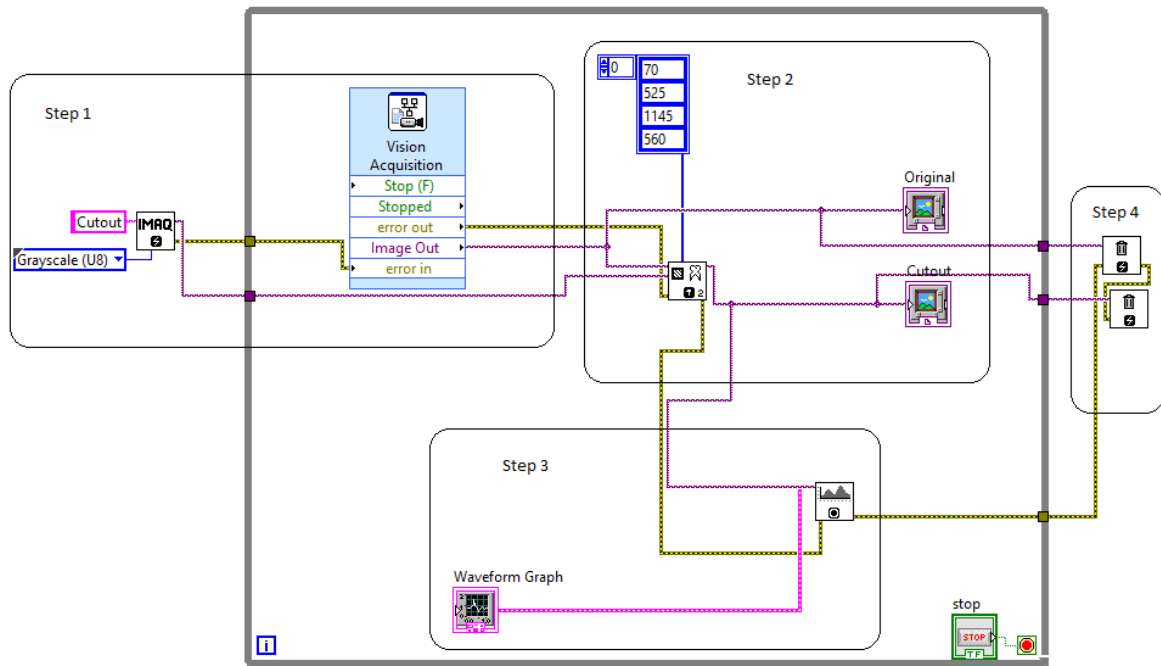


Figure 4.6 Block diagram of calibration program.

The details of the four logical step are as follows:

- Step 1: Initialisation of camera.** The first step in the calibration software was to reserve a space in the computer memory, named 'Cut-out', for image capturing using the IMAQ Create VI. The image type of the image to be captured was specified as "Greyscale U8". Thereafter, the Image Acquisition VI was used to initialise the BASLER digital camera, capture an image and store it in the reserved memory space.
- Step 2: Definition of the region of Interest.** The region of interest (ROI) was defined to save time and processing power by only processing a part of the original captured image. In this study, the ROI was a rectangular cut-out of the original image captured of the cylinder containing the dissolved soil sample. This cut-out image was therefore a smaller image that required less time and computer resources to be processed by the software. To determine the coordinates for the ROI, the x-coordinates were measured from the exact centre of the cylinder sideways, and only wide enough to limit distortion from the curvature of the cylinder. The y-coordinates were measured by filling the cylinder with water and taking the y-coordinate values of the pixels at the top of the water level and the bottom of the cylinder. These x- and y-coordinates were then supplied as input variables to the IMAQ extract 2 VI to cut out the rectangular ROI from the original image.

- **Step 3: Histogram generation.** A pixel intensity histogram of the ROI was generated by applying the Histogram VI to the cut-out image. This histogram showed the amount of pixels at each pixel intensity level (0 to 255) for the ROI and was displayed in the UI window using the Display Graph VI.
- **Step 4: Clean-up of computer resources.** After the completion of steps 1 to 3, the IMAQ Dispose VI was applied to clear the computer resources. This ensured that no computer resources were wasted and prevented memory leaks from occurring that could potentially cause the software program to become unstable.

After the completion of the logical steps performed in the BD window, the outputs of the logical steps were displayed in the UI window. The UI for the calibration process contained three displays, which are shown in Figure 4.7. Display A (Figure 4.7 A) contained the entire image of the cylinder containing the prepared soil sample. In display A, the cylinder had to be correctly positioned by adjusting the position of the cylinder to fit the green rectangle in the display. Display A was also used to ensure that the complete image was in focus. Once adjustments in Display A were completed, the ROI would be in focus and horizontally aligned in Display B (Figure 4.7 B). Display C (Figure 4.7 C) showed the histogram that was generated from the ROI. This histogram was used to determine the appropriate exposure setting for the camera. After the completion of the calibration process, the MVI was properly calibrated and generation of SS fingerprints could commence.

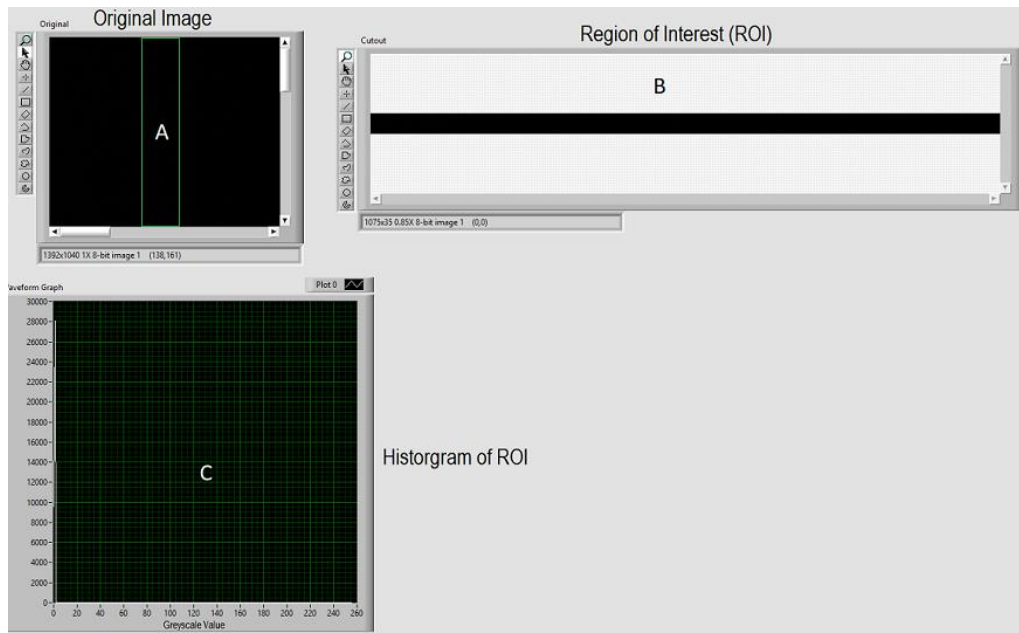


Figure 4.7 Calibration program User Interface window. A) Original image display, B) ROI copied from original image (A), and C) Histogram display of the ROI.

4.3.3 Software development 2: Development of the soil sample fingerprint generation software

The SS fingerprint generation software was developed in the BD window of the LabVIEW software suite and consisted of five logical steps. Step 1, the image acquisition step, was duplicated from the calibration program and included camera initialisation, definition of the ROI and generation of a histogram from the ROI. The remaining four logical steps were:

- Smoothing of the histogram,
- data transfer,
- write data to file and
- a timing loop.

The logical layout and the VIs that were used to create these steps in the BD window of the LabVIEW software suite, are shown in Figure 4.8.

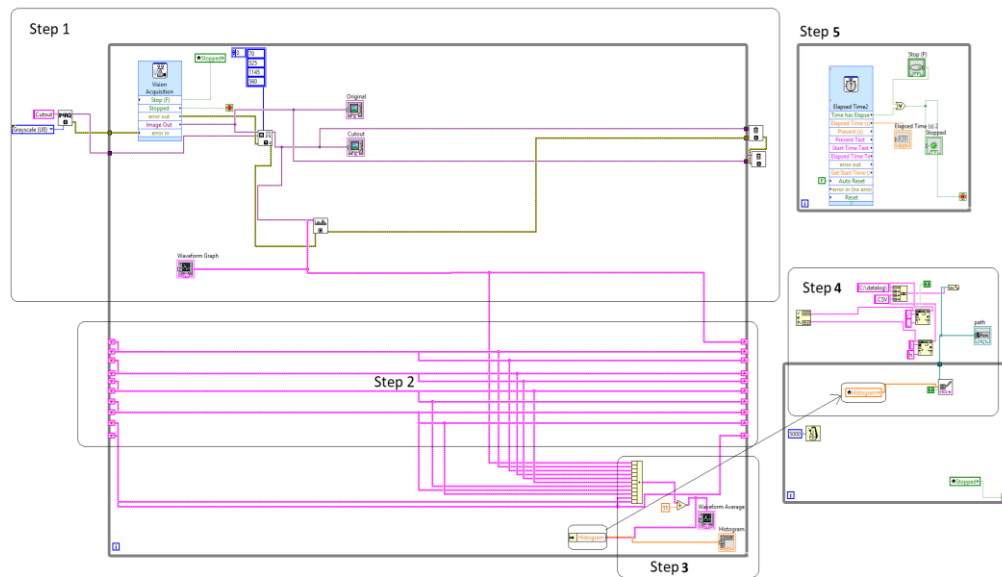


Figure 4.8 The BD window for the SS Fingerprint generation program.

The details of the five logical steps were as follows:

- Step 1: Image acquisition.** Step 1 of the SS fingerprint generation software was duplicated from Step 1 in the calibration software as it requires the same initial steps. Step 1 initialises the camera and starts capturing images.
- Step 2: Smoothing of the histogram.** Step 2 of the SS fingerprint generation software buffered the data that was generated by the histogram VI with a buffer size of 11. The buffered data was added together and divided by 11 again to generate an averaged, smoothed version of the histogram as displayed in Figure 4.9 C.
- Step 3: Data transfer.** The smoothed data that was generated in Step 2 was converted to a two dimensional, comma delimited array and stored in a variable called Histogram. The Histogram variable was transferred to Step 4 so that the data could be saved to disk.
- Step 4: Write data to file.** After the Histogram variable data were transferred to Step 4 from Step 3, the data needed to be appended to a comma-separated values (CSV) file and saved to the computer's hard drive. If it was the first time the process was run, a new file was initialised and a filename created that uniquely identified the particular fingerprint that was being generated for a specific soil sample. The software did this by generating a name that contained the exact time and date that the SS fingerprint generation procedure was started.
- Step 5: The timing loop.** To make sure that the MVI process was not dependent on human interaction and ran for precisely 10 min every time, a timer was needed to automatically terminate

the SS fingerprint generation program. Step 5 achieved this by using a timer VI that started counting when the start button was pressed and terminated the program 10 min later (10 min was previously determined to be the optimal run-time for the software). The elapsed time was displayed to the user on the UI.

When the SS fingerprint generation program was run, the UI window for the program was displayed. The UI window consisted of the live image being captured (Figure 4.9 A), an unsmoothed histogram (Figure 4.9 B), a smoothed histogram (Figure 4.9 C) and the ROI, rotated 90 degrees for display purposes (Figure 4.9 D).

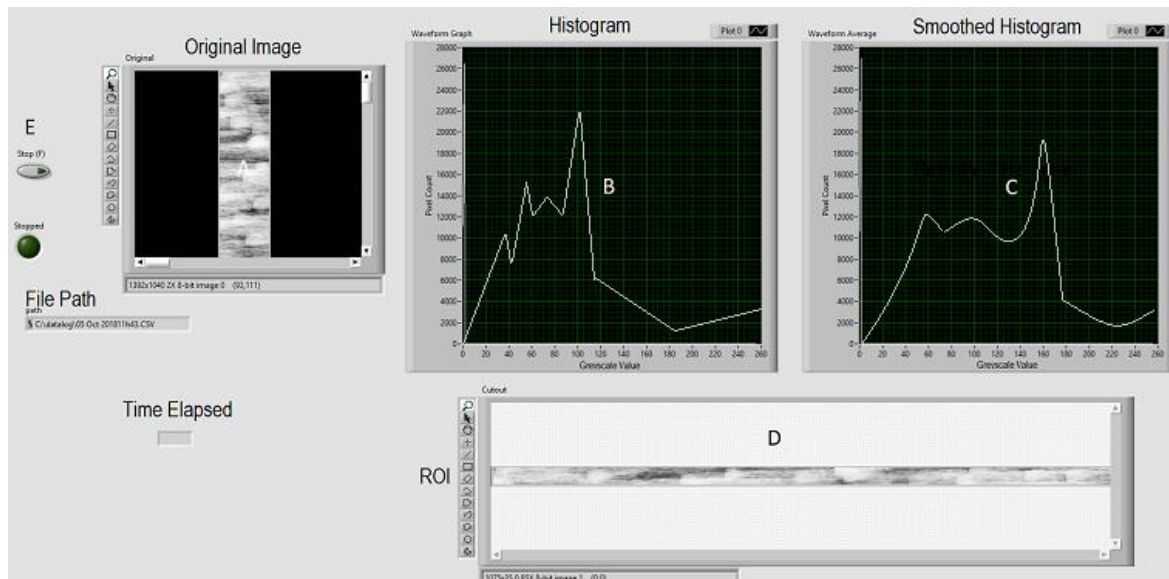


Figure 4.9. UI for the SS fingerprint generation program. A) Original image, B) Unsmoothed histogram, C) Smoothed histogram, D) Cut-out image of the ROI.

The final file that was saved to the computer comprised of the consolidated histogram data that was generated for each image, captured every 5 s for the duration of 10 min. This consolidated dataset was called the Soil Sample fingerprint and uniquely identified each prepared soil sample that was analysed by the MVI.

4.3.4 Software development 3: Development of the correlation software

The logical design of the correlation program was developed in the BD window of the LabVIEW software suite and consisted of two logical steps. In the first step, two SS fingerprint files (File A and File B in Figure 4.10) were opened and the data inside the files were read and stored in two separate arrays. The second step was to correlate the data of the two SS fingerprints by averaging the sum of products for SS fingerprint A and SS fingerprint B. The mathematical formula used by the correlation program is shown in Equation 2.

Equation 2 Correlation equation.

$$r_{12} = \frac{1}{N} \sum_{n=0}^{N-1} x_1(n) \cdot x_2(n)$$

Where: N = Maximum sample range
 n = Sample number
 x_1 = Dataset 1
 x_2 = Dataset 2

The equation was logically reconstructed in step 2 of the software by using the appropriate mathematical VIs. The numerator and denominator were also swopped around and only the result out of 100% was selected and displayed in the UI window of the correlation software.

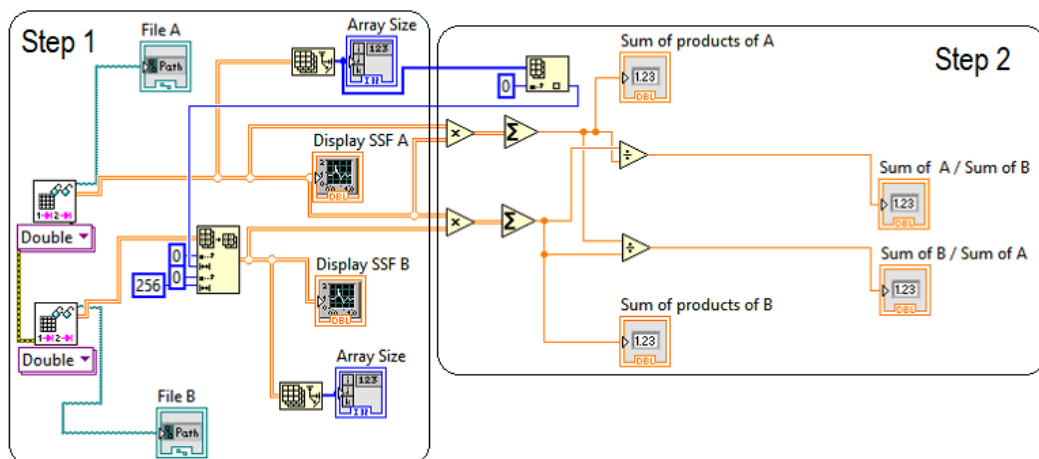


Figure 4.10 BD window for the correlation program.

When the correlation program was started, the user was presented with a list of SS fingerprint files of which any two could be selected and correlated. The consolidated histogram (SS fingerprint) was displayed to the user for each file opened, the correlation formula was applied and the result was displayed in the Correlation Result box.



Figure 4.11 The UI for the correlation program.

4.4 Chapter discussion and summary

After all the components of the MVI were development and construction it could be implemented as part of the Automated Soil Classification System (ASCS). The purpose of the MVI was to acquire a sequence of high fidelity images during the sedimentation process of a pre-constituted soil sample and generate a SS fingerprint for the specific soil sample. This was achieved through two steps namely the image acquisition step and the image processing step. In the image acquisition step, a proper digital camera was selected, a light source was selected and lightproof box was constructed for optimal illumination of the soil sample. Lastly, a soil sample preparation method was established to prepare pre-constituted soil samples in a consistent manner. In the image acquisition step, three software programs were developed to firstly; calibrate the MIV, secondly; capture images and

generate a SS fingerprint of a soil sample and lastly; correlate SS fingerprints that were generated by the software. After the MVI was constructed and functional, it could be applied as part of the ASCS to undertake investigations 1 to 5 as laid out in chapter 3.

Chapter 5

Validation of the Machine Vision Instrument

5.1 Introduction

Phase 3 of this study focused on the validation of the Machine Vision Instrument (MVI). Phase 3 consisted of two steps. In the first step, two protocols were developed, one for preparing a soil sample and the other for generating SS fingerprints with the MVI. In the second step, the ability of the MVI to generate SS fingerprints reliably and accurately was validated by undertaking four investigations. Figure 5.1 provides a flow diagram of the overall study design, highlighting Phase 3, which involved the validation of the Machine Vision Instrument.

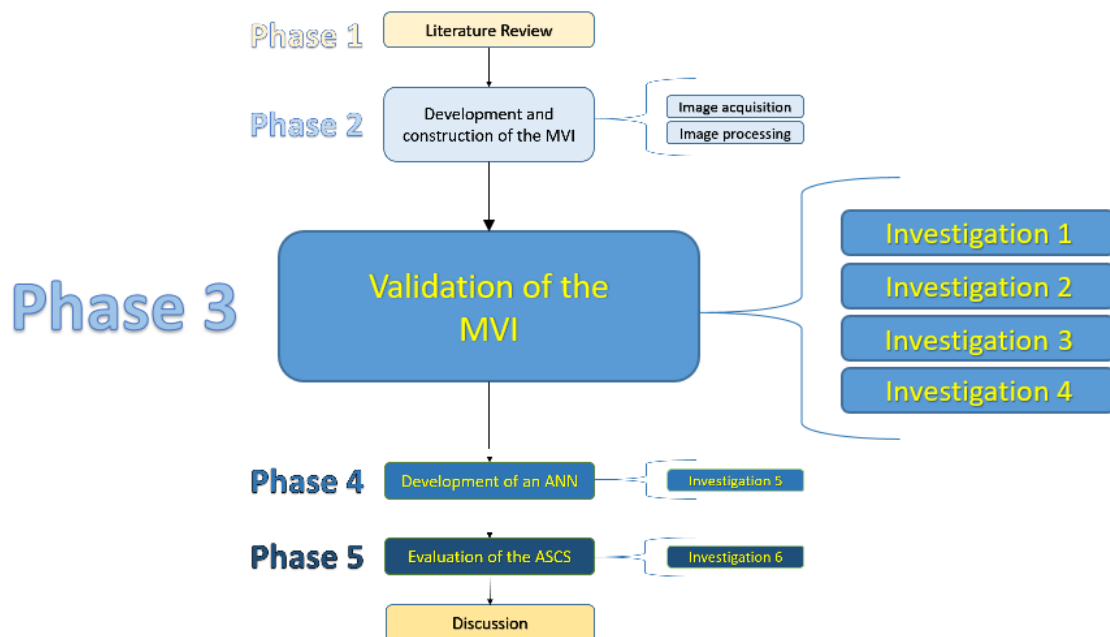


Figure 5.1 Positioning Phase 3 in the overall study design.

For the application of the MVI, a protocol had to be established to guarantee that the MVI was applied consistently when generating SS fingerprints for soil samples. Before the protocol could be established, two factors needed to be considered. Firstly, a timing window needed to be established

for the placement of soil samples in the lightproof box after the mixing of the soil samples were completed until the SS fingerprint software was started. Secondly, the length of time allocated to the run time of the SS fingerprint generation software to generate a SS fingerprint for a particular soil sample, had to be established. Figure 5.2 provides the logical design for the establishment of a functional MVI.

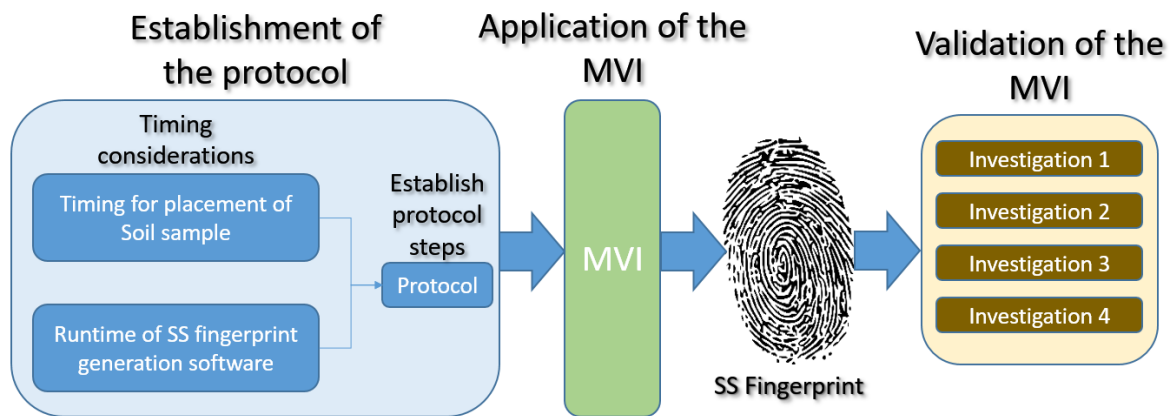


Figure 5.2 Logical design for the establishment of a functional MVI.

After a functional MVI was established, the four investigations were undertaken to validate the functionality of the MVI. These investigations evaluated the ability of the MVI to generate consistent SS fingerprints and also investigated if the MVI was able to distinguish between soil samples of different constitutions.

5.2 Materials and methods in preparation for investigations

Before Investigations 1 through 4 could be performed, two protocols needed to be developed. Firstly, a soil sample preparation protocol was developed to ensure that all soil samples for the investigations were prepared in a consistent manner. Secondly, an SS fingerprint generation protocol was needed to guarantee that all SS fingerprints were generated in a consistent manner during the investigations.

5.2.1 Development of the soil sample preparation protocol

The preparation of soil samples for SS fingerprint generation by the MVI had to be consistent to ensure that the generation of SS fingerprints were repeatable and comparable. To prepare soil samples, pure samples of sand and Bentonite clay containing negligible amounts of contaminants, were used. The sand and Bentonite clay were mixed together to create pre-constituted soil samples containing different percentages of clay mixed with sand.

Prior to the preparation of the pre-constituted soil samples for the project, suitable weights of dry sand and Bentonite clay had to be determined. The dry weights of the sand and Bentonite clay were determined for a volume of 1,030 ml (standard soil sample cylinder volume) in the following manner:

- Three dry material samples, weighing 5 g, 10 g and 20 g, were prepared in ratio of 1 sand : 1 Bentonite.
- Each of the dry material samples was mixed with filtered tap water in a 1,030 ml cylinder. No dispersant was added to the mixture.
- The mixture was left to settle for 24 hours to allow for the clay particles to properly disperse in the water mixture.
- After the 24 hour settling time, each cylinder was placed inside the automatic mixer and thoroughly mixed for 10 min, after which the sedimentation process of each sample was visually observed.

From the visual observation of the sedimentation process, it was found that the 5 g dry material sample sedimented substantially faster than the other two dry material samples, but too quickly to allow for the capturing of accurate digital image data during the sedimentation process. Although both the 10 g and 20 g samples allowed for enough sedimentation time to capture accurate digital image data, it was concluded that the 10 g soil sample was best suited for the study because it sedimented faster than the 20 g soil sample. Therefore, using the 10 g soil sample would speed up the SS fingerprint generation process.

All soil samples had to be mixed in a consistent manner to produce comparable SS fingerprints. To ensure that prepared soil samples, of the same constitution, were in similar states of sedimentation before SS fingerprint generation took place, a mixing procedure had to be established. To achieve a consistent way of mixing the dry material with water in the sedimentation cylinder, the following steps were followed:

- An automated mixing apparatus was built to mix the prepared soil sample dry materials with the water in the cylinder (Figure 5.3).
- The prepared soil samples were left to settle for 24 hours before mixing, to properly disperse the dry materials throughout the water.
- The cylinder containing the dry materials and water mixture was then placed in the mixing apparatus and mixed for 10 minutes, which was deemed long enough to disperse the dry materials in the water.
- Once the soil sample was mixed, it was placed in the lightproof box to generate an SS fingerprint for the soil sample.

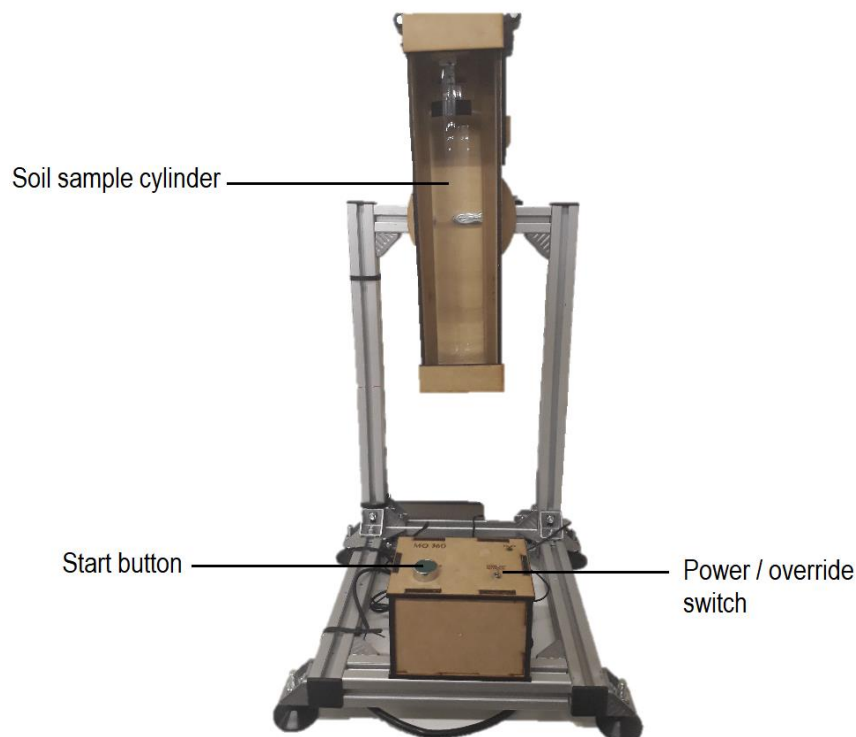


Figure 5.3 *Mixing apparatus built to mix soil samples consistently.*

After a soil sample was mixed in the automated mixer, it was placed in the lightproof box for SS fingerprint generation. Because sedimentation commenced immediately after the mixing process had stopped, a timing window had to be defined from the time when the mixer stopped, the soil sample cylinder was placed in the lightproof box and the start button of the SS fingerprint generation software was pressed. This timing window had to be standardised to maintain consistency when generating SS fingerprints. The timing window was determined in the following manner:

- The time it took to remove a mixed soil sample cylinder from the automated mixer, the placement of the soil sample in the lightproof box and the starting of the SS fingerprint generation software, was recorded multiple times.
- The longest time of 25 seconds was selected and another 5 s was added to this time to make sure there was enough time for the user to complete the process comfortably and within the specified limit of 30 s.

The decision of selecting 30 seconds as the appropriate timing window meant that the start button in the user interface (UI) of the SS fingerprint generation software had to be pressed 30 s after the mixer had stopped. This time included the removal of the soil sample cylinder from the mixer and placing it in the lightproof box. If the timing window was missed by more than 5 s, the mixing process had to be repeated.

Consistent SS fingerprints could only be generated if soil samples were at the same level of sedimentation when the SS fingerprint generation software was started. By following the soil sample preparation steps it was insured that all soil samples were prepared in a consistent manner. This guaranteed that all soil samples were at the same level of sedimentation when they were placed inside the lightproof box for SS fingerprint generation.

5.2.2 Development of SS fingerprint generation protocol

An SS fingerprint generation protocol needed to be established to ensure that SS fingerprints were generated in a consistent manner. The first step in developing the SS fingerprint generation protocol was to determine a fixed runtime for the SS fingerprint generation software. A suitable runtime for the SS fingerprint generation software had to be established that was as short as possible, but still long enough to produce an SS fingerprint that uniquely identified a particular soil sample. The runtime of the SS fingerprint generation software was determined in the following manner:

- Three soil samples of the same constitution were prepared for SS fingerprint generation.
- An SS fingerprint was generated for each soil sample by applying the SS fingerprint generation software. Different run times of 5, 10 and 20 min were applied for each soil sample.

The 5 min runtime did not allow enough time for sedimentation take place and produce distinguishable SS fingerprints. The 10 and 20 minute runtimes produced acceptable SS fingerprints, thus the 10-minute runtime was selected for this project to minimize testing times.

After the runtime for the software was established, the SS fingerprint generation protocol could be finalised. The final SS fingerprint generation protocol is a culmination of software development, timing considerations and the soil sample preparation method. These processes needed to be applied in a step-by-step manner to generate consistent SS fingerprints for the respective soil samples. The SS fingerprint generation protocol consisted of the following six steps:

- The MVI was calibrated using the previously developed calibration software.
- A pre-constituted soil sample was prepared using the established soil sample preparation method.
- Before the soil sample was placed in the, the SS fingerprint generation software was opened on the computer in preparation for SS fingerprint generation.
- The soil sample was then placed in the mixing apparatus and mixed for 10 min.

- Once the soil sample mixing process completed, the soil sample cylinder was removed from the mixing apparatus and placed in the lightproof box.
- The SS fingerprint generation process was then started by clicking on the start button in the UI of the SS fingerprint generation software 30 s after the mixing of the soil sample was completed. The SS fingerprint generation software then ran for 10 min and generated an SS fingerprint for the current soil sample.

5.2.3 Visual interpretation of an SS fingerprint

In a greyscale image, the difference in opacity is represented by the greyscale values of the pixels in the image. A value of 0 represents complete opaqueness while a value of 255 represents complete transparency. The complete spectrum of greyscale values for the BASLER digital black and white camera is shown in Figure 5.4. Once the soil sample cylinder is placed inside the lightproof box after mixing, the soil particles start to sediment. While the sedimentation of the soil sample continues, the opacity of the soil sample diminishes. This was caused by an increased amount light that penetrated the liquid from the backlight source as particles in the soil sample cylinder sediments. As the sedimentation process continues and more light is able to penetrate the soil sample cylinder, the greyscale values of the pixels in the camera image changes from a value of 0 (completely opaque) to 255 (completely transparent).

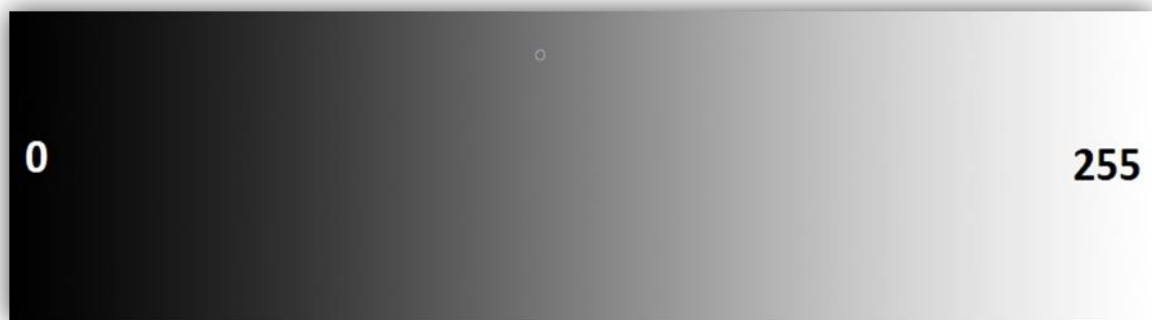


Figure 5.4 Greyscale spectrum representing opaqueness in a grayscale image.

A visual representation of an SS fingerprint consists of the superimposition of all the histograms that were generated for the snapshots captured every 5 s for a duration of 10 min during the sedimentation process of a soil sample. To visually portray the SS fingerprint generation process, a sample run was executed containing only three snapshot histograms as shown in Figure 5.1 A, B and C. These snapshots were taken at 25, 250 and 600 s during a single 10 min run of the SS fingerprint generation software. The histograms generated for each snapshot shows the pixel intensity count for each snapshot at that specific time. As the sedimentation process continued over time, the pixel intensity count changed for each snapshot taken. The final SS fingerprint histogram (Figure 5.5 D) is a result of the superimposition of these snapshots.

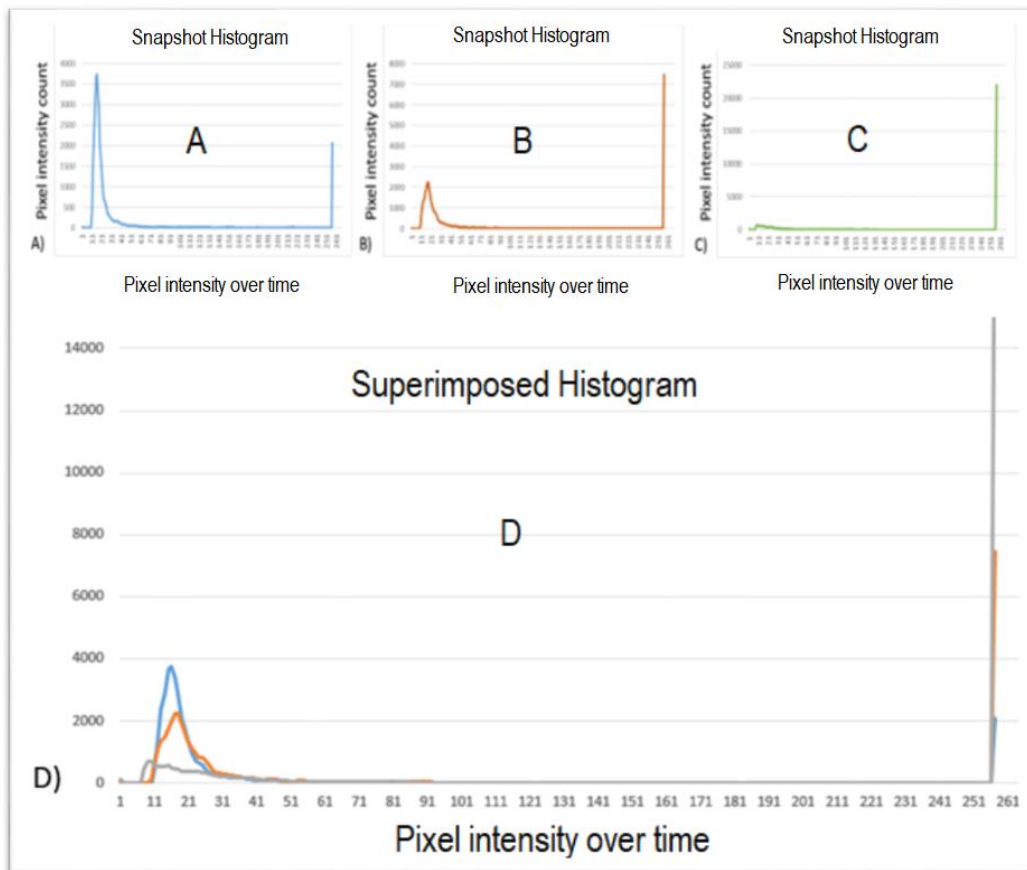


Figure 5.5 Histogram snapshots at specified time intervals and histogram superimposition. Histogram snapshots at specified time intervals A) 25 s, B) 250 s, C) 600 s, and D) Superimposition of histogram snapshots A, B and C.

For an actual SS fingerprint in this study, 113 histograms were superimposed to generate a visual representation of an SS fingerprint for a particular soil sample. In Figure 5.6, all 113 snapshots that were taken of the soil sample, every 5 s over a period of 10 minutes, were superimposed and displayed on a single histogram. This superimposed histogram is thus a visual representation of an actual SS fingerprint.

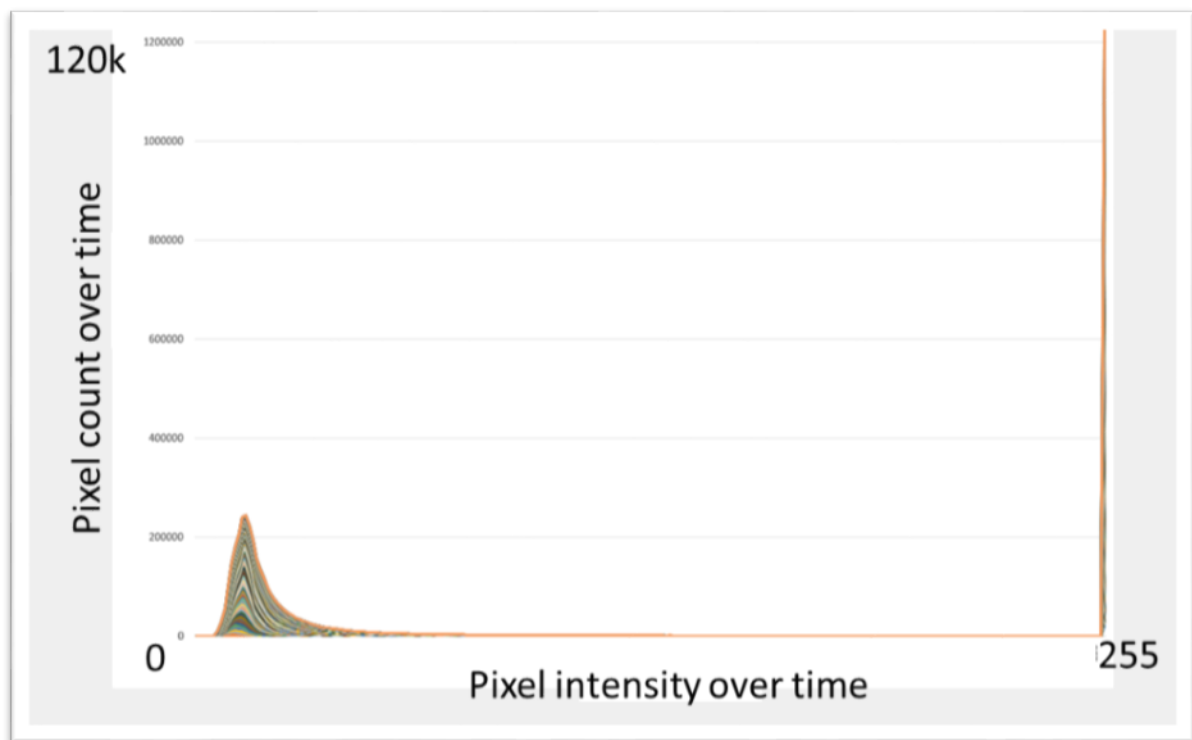


Figure 5.6 SS fingerprint consisting of superimposed snapshot histograms generated over a 10 min sedimentation period.

Various visual representations of an SS fingerprint are possible. The three dimensional (3D) surface plot provides a clear visual representation of the distribution of the pixel intensity of the superimposed snapshot histograms. To produce the 3D surface plot, the snapshot histogram data were exported to Microsoft Excel, where a 3D surface plot was generated of the SS fingerprint (Figure 5.7).

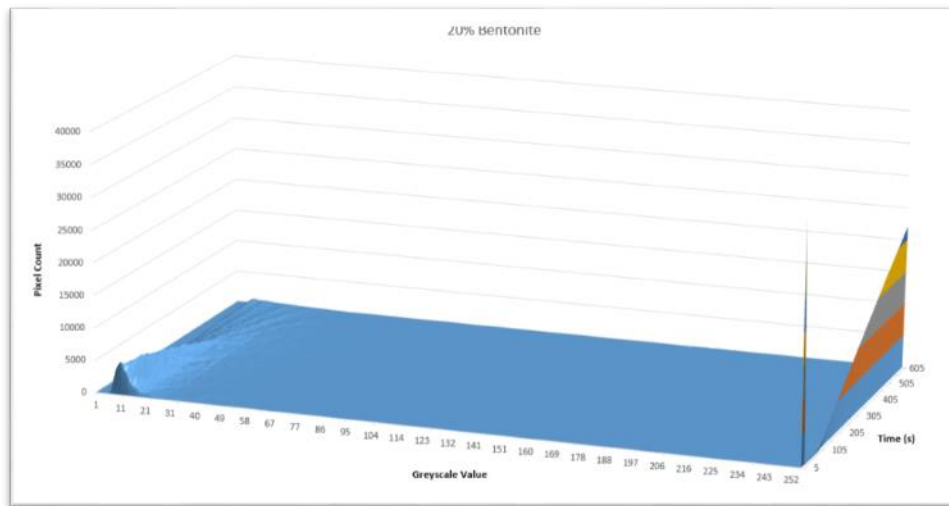


Figure 5.7 Three dimensional surface plot of an SS fingerprint.

The visual representations of the SS fingerprints could be used to manually observe the similarities, as well as the differences in the SS fingerprints generated for the various soil samples. However, to obtain exact correlations, the developed correlation software was applied in four investigations.

5.3 Materials and methods: Investigations 1 to 4

Four investigations were undertaken to validate the ability of the MVI to generate consistent SS fingerprints for the soil samples. The materials and methods for these investigations are set out in Table 5-1.

Table 5-1 Materials and methods for investigations 1 to 4.

Investigation	Materials and methods
Investigation 1: Validation of SS fingerprint generation	The validation of the generation of SS fingerprints for this study was as follows: - A pre-constituted soil sample, consisting of 2 g Bentonite to 8 g sand (20% clay), was prepared using the soil sample preparation method. - Five SS fingerprints were generated for the soil sample with the MVI.

Investigation	Materials and methods
	The five SS fingerprints were correlated using the correlation software, with the expectation of a correlation $\geq 0,90$, which allows for a 10% error.
Investigation 2: Validation of the soil sample preparation method	The validation of the soil sample preparation method was as follows: - Five separate soil samples, consisting of 4 g Bentonite to 6 g sand (40% Clay), were prepared in separate soil sample cylinders using the soil sample preparation method. - An SS fingerprint was generated with the MVI for each of the prepared soil samples. - The generated SS fingerprints were then correlated using the correlation software, with expectation of a correlation $\geq 0,90$, which allows for a 10% error.
Investigation 3: Determination of the differentiation ability of the MVI	The differentiation ability of the MVI was determined as follows: - Six pre-constituted soil samples were prepared using the soil sample preparation method. These pre-constituted soil samples were constituted as follows: 1 g Bentonite clay and 9 g pure sand (10% clay) 2 g Bentonite clay and 8 g pure sand (20% clay) 3 g Bentonite clay and 7 g pure sand (30% clay) 4 g Bentonite clay and 6 g pure sand (40% clay) 7 g Bentonite clay and 3 g pure sand (70% clay) 8 g Bentonite clay and 2 g pure sand (80% clay) - An SS fingerprint was generated with the MVI for each of the prepared soil samples. - The six SS fingerprints were pairwise correlated by applying the correlation software, with the expectation of correlation values of less than 0,90.

Investigation	Materials and methods
Investigation 4: Validation of the MVI by generating SS fingerprints for coded soil samples	- The MVI was validated by comparing SS fingerprints generated for randomly labelled soil samples (coded soil samples) to SS fingerprints generated for pre-constituted soil samples. - Four soil samples were prepared containing 10, 20, 40 and 80% of Bentonite clay using the soil sample preparation method. - To facilitate a blind soil classification process, each soil sample was allocated a code (for example, MM04) by a third party, who kept a record of the corresponding constitutions of the soil samples. The coded soil samples were labelled as follows: - MM06 (Containing 10% Bentonite) - MM04 (Containing 20% Bentonite) - MM11 (Containing 40% Bentonite) - MM07 (Containing 80% Bentonite) - The SS fingerprint was generated for each coded soil sample by applying the MVI. - The MVI generated SS fingerprints for the coded soil samples were compared to the SS fingerprints generated for known, pre-constituted soil samples.

The results from the four investigations should indicate if the construction and development of the MVI was successful so that it could be applied as part of the ASCS to generate unique SS fingerprints for soil samples in a consistent manner.

5.4 Results of the four investigations

Four investigations were undertaken to validate the SS Fingerprint generation process of the MVI. The result of the four investigations would be an indication of how consistently the MVI was able to generate SS Fingerprints.

5.4.1 Results of Investigation 1: Validation of SS fingerprint generation

Investigation 1 was undertaken to determine if the MVI could generate consistent SS fingerprints for soil samples. The calculated pairwise correlation values of the five SS fingerprints generated for the soil sample containing 20% Bentonite clay, showed correlation values of greater than 97,0% (Table 5-2). These correlation values were greater than the expected value of 0,90, thus the accuracy of the SS fingerprint generation ability of the MVI was deemed acceptable for this study.

Table 5-2 Correlation values of different SS fingerprint generated for the same soil sample.

SS fingerprint	A	B	C	D	E
A	-	-	-	-	-
B	0,981	-	-	-	-
C	0,984	0,974	-	-	-
D	0,992	0,996	0,972	-	-
E	0,992	0,981	0,988	0,984	-

To obtain a visual perspective of the similarity amongst the five SS fingerprints, the histograms of the fingerprints were generated and displayed in Figure 5.8 A to E. A cropped version of the five SS fingerprints showed that all the histograms were visually similar, supporting the high correlation values obtained for the pairwise correlation calculations.

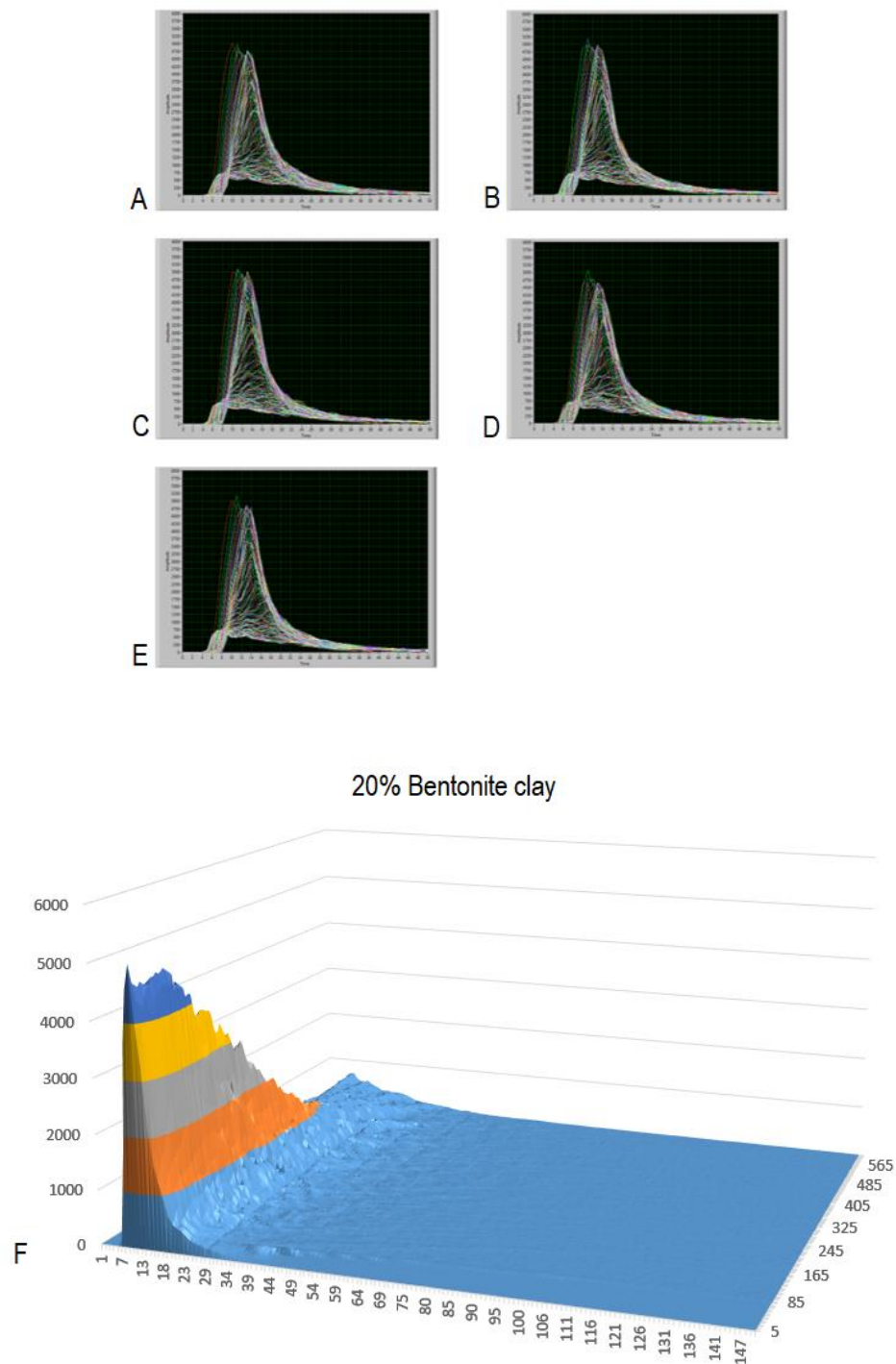


Figure 5.8 Visual representation of the five SS fingerprints generated for the same pre-constituted soil sample. A) B) C) D) E) and F) a representative 3D surface plot.

5.4.2 Results of Investigation 2: Validation of the soil sample preparation method

Investigation 2 was undertaken to ascertain if the soil sample preparation method was consistent. The calculated pairwise correlation values of the five SS fingerprints generated for the separately prepared soil samples containing 40% Bentonite clay, showed correlation values of 94,0% and greater (Table 5-3). Similarly, as shown in Investigation 1, these correlation values were greater than the expected value of 0,90, thus the consistency of the soil sample preparation method was deemed acceptable for this study.

Table 5-3 Correlation values of the SS fingerprints generated for the same soil sample prepared multiple times.

SS fingerprint	A	B	C	D	E
A	-	-	-	-	-
B	0,969	-	-	-	-
C	0,965	0,995	-	-	-
D	0,959	0,985	0,990	-	-
E	0,940	0,971	0,978	0,981	-

To obtain a visual perspective of the similarity amongs the five SS fingerprints, the individual histograms of the five soil sample fingerprints were generated. A cropped version of the five SS fingerprints (Figure 5.9 A to E) showed that all the histograms were visually similar, supporting the high correlation values obtained with the pairwise correlation calculations.

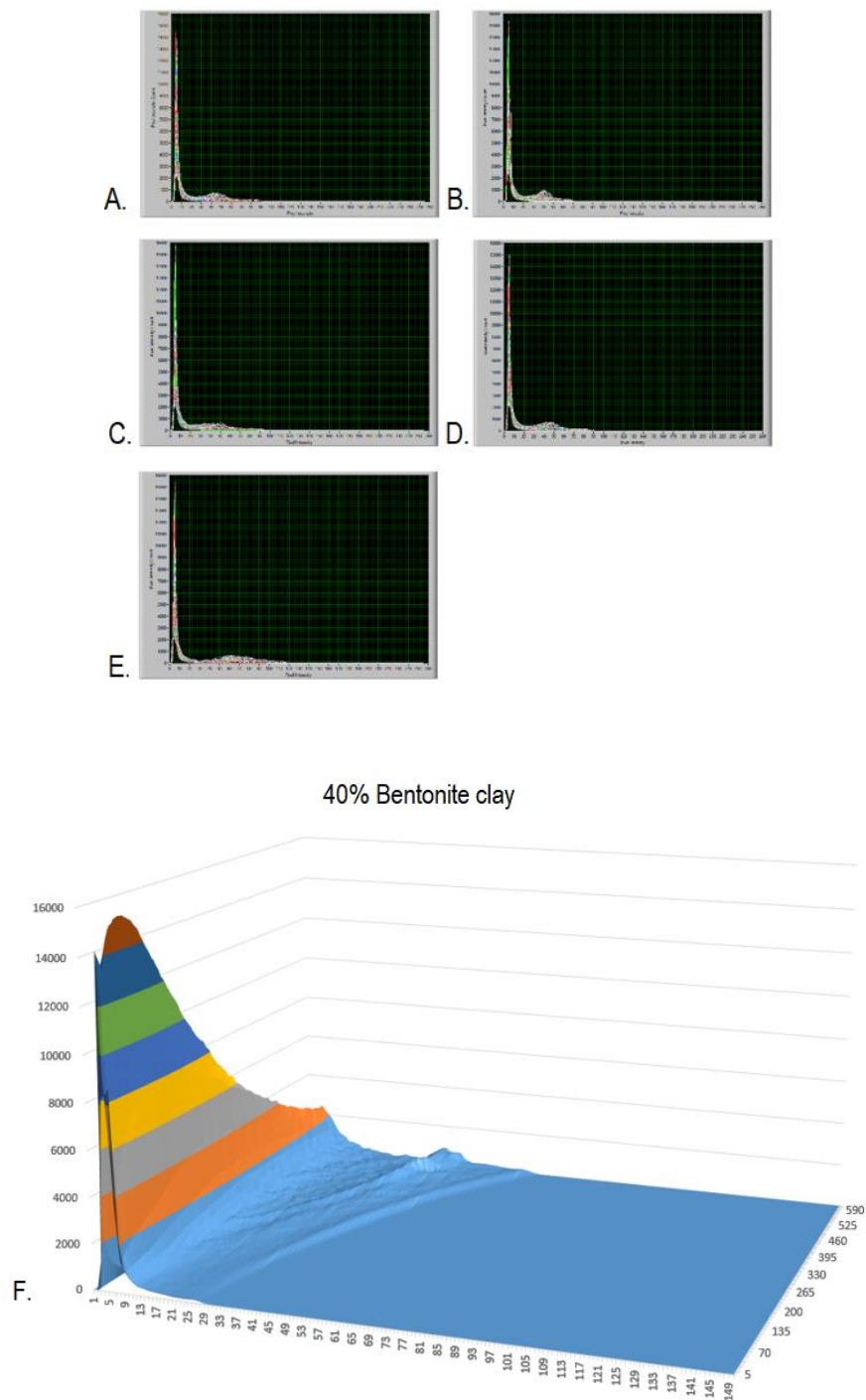


Figure 5.9 Visual representation of the five SS fingerprints generated for the five separately prepared soil samples. A) B) C) D) E) and F) a representative 3D surface plot.

5.4.3 Results of Investigation 3: Application of the MVI to soil samples containing different amounts of clay

Investigation 3 was undertaken to ascertain if the MVI was able to accurately distinguish between six soil samples of different constitutions. The calculated pairwise correlations of the six separately soil samples containing different percentages of Bentonite clay, showed correlation values less than 90%, ranging from approximately less than 87% to less than 0.01% (Table 5-4). This indicated that the MVI was able to distinguish between soil samples containing different clay constitutions.

Table 5-4 Correlation values of the SS fingerprints generated for the soil samples with different constitutions.

Clay percentage	A (10%)	B (20%)	C (30%)	D (40%)	E (70%)	F (80%)
A (10%)	-	-	-	-	-	-
B (20%)	0,526	-	-	-	-	-
C (30%)	0,537	0,862	-	-	-	-
D (40%)	0,001	0,059	0,200	-	-	-
E (70%)	0,006	0,026	0,070	0,214	-	-
F (80%)	0,000	0,008	0,034	0,086	0,636	-

To obtain a visual perspective of the difference amongst the six SS fingerprints, the histograms of the fingerprints were generated and displayed. The SS fingerprint histograms (Figure 5.10 A1 to F1), as well as the 3D surface plots for each of the six SS fingerprints (Figure 5.10 A2 to F2) showed that all the histogram were visually different, supporting the low correlation values obtained for the pairwise correlation calculations.

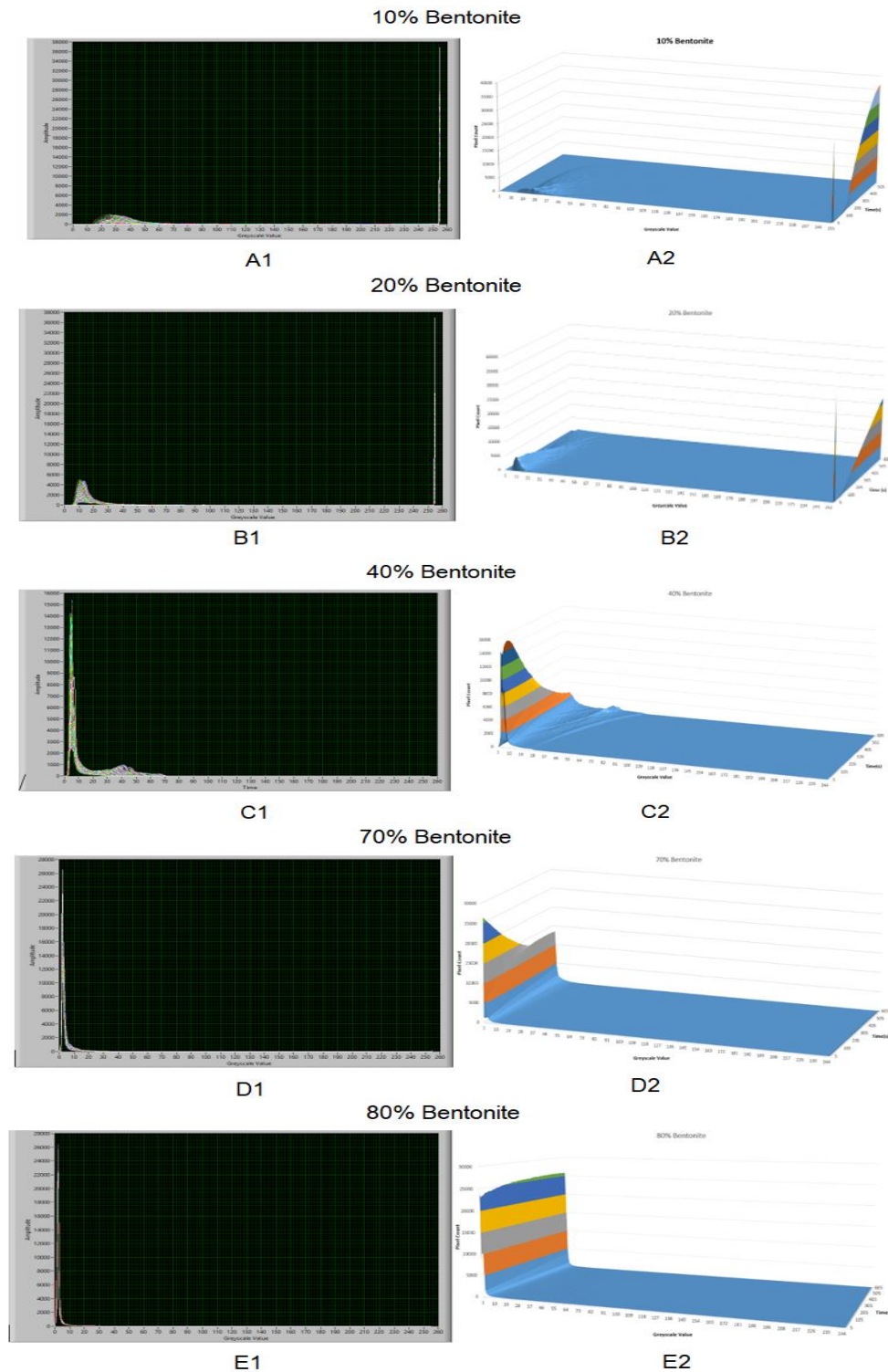


Figure 5.10 SS fingerprints (1) and their corresponding 3D surface plots (2) generated for differently constituted soil samples. A) 10% Bentonite clay, B) 20% Bentonite clay, C) 40% Bentonite clay, D) 70% Bentonite clay, E) 80% Bentonite clay.

5.4.4 Results of Investigation 4: Correlation between coded Soil Sample fingerprints and pre-constituted Soil Sample fingerprints

Investigation 4 was undertaken to validate the MVI by generating SS fingerprints from coded soil samples. These SS fingerprints were then correlated to the SS fingerprints generated for known, pre-constituted soil samples. The correlations between the coded soil samples and the pre-constituted soil samples revealed high correlation values between soil samples of the same constitution, but relatively low correlation values between samples of different constitutions. The highest correlation for each coded soil sample, highlighted in green, corresponded to the correct pre-constituted soil sample percentage indicating that the MVI was able to produce accurate SS fingerprints (Table 5-5). These high correlations support the notion that the MVI was able to produce SS fingerprints with an accuracy greater than 88%.

Table 5-5 Correlations percentages between the SS fingerprints generated for the coded soil samples and the fingerprints generated for the pre-constituted soil samples.

Soil sample	Correlation (%)					
	10%	20%	30%	40%	70%	80%
MM06 (10% Bentonite clay)	97,00	87,00	75,00	0,70	0,60	0,01
MM04 (20% Bentonite clay)	74,00	91,00	63,00	2,00	0,20	0,01
MM11 (40% Bentonite clay)	0,10	6,50	20,00	92,00	13,00	2,00
MM07 (80% Bentonite clay)	0,01	0,20	11,50	24,20	78,01	89,00

5.5 Chapter discussion and summary

In Phase 3 of this study, the SS fingerprint generation process of the MVI, which is part of the Automated Soil Classification System (ASCS), was validated. The four investigations that were undertaken to validate the SS fingerprint generation process of the MVI showed that the MVI had the potential to produce accurate soil sample fingerprints for any given soil sample. The MVI was therefore deemed reliable and accurate enough to be applied as part of the ASCS to undertake Investigation 5 as reported on in Chapter 6.

Chapter 6

Development of the Automated Soil Classification System

6.1 Introduction

Phase 4 and Phase 5 of this study involved the development of the Automated Soil Classification System (ASCS). The purpose of the ASCS is to predict the amount of Bentonite clay in a soil sample by applying an Artificial Neural Network (ANN) to a Soil Sample (SS) fingerprint generated by the Machine Vision Instrument (MVI). Phase 4 involved the development of an ANN to automatically predict the amount of Bentonite clay in a soil sample, while Phase 5 of this study involved the implementation of the developed ANN and the evaluation of the ASCS. Figure 6.1 provides a flow diagram of the overall study design, highlighting Phase 4, which involved development of the ANN, and Phase 5, which evaluated the performance of ASCS.

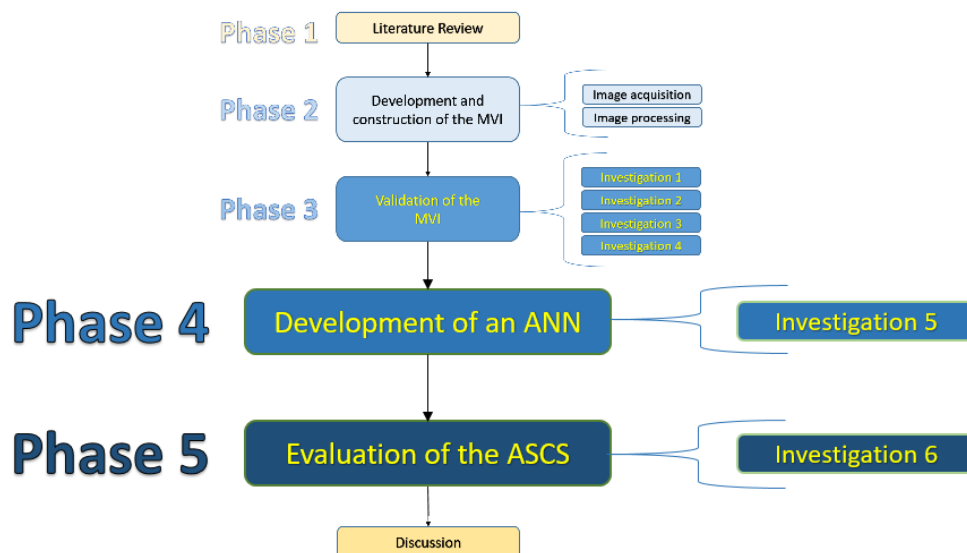


Figure 6.1 Positioning Phase 4 and Phase 5 in the overall study design.

6.2 Materials and methods in preparation for Investigations

Before Investigations 5 and 6 could be undertaken, several preparatory steps needed to be performed. These steps included the importation of the SS fingerprint data into the MATLAB environment, the preparation of the imported data in the MATLAB environment for the development and training of the ANN and lastly, the implementation and evaluation of the ANN in the Simulink environment.

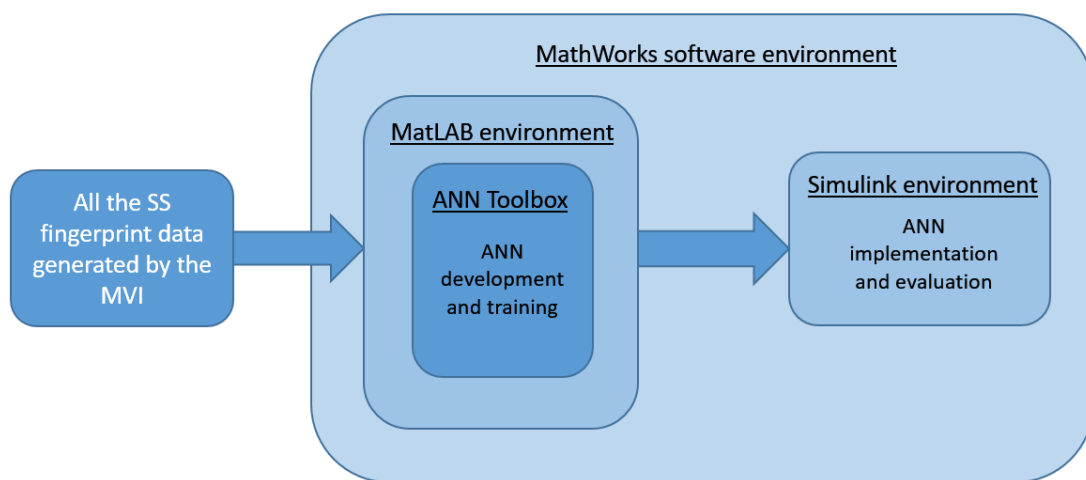


Figure 6.2 Logical layout for the preparations for Investigations 5 and 6.

6.2.1 Software environment selection for the development of the ANN

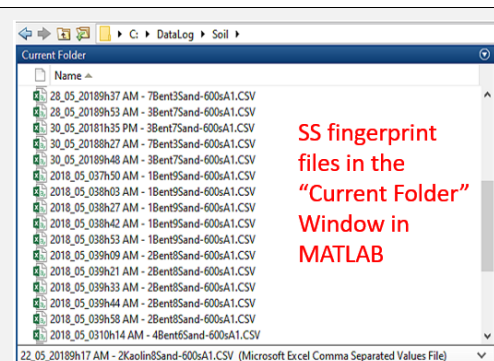
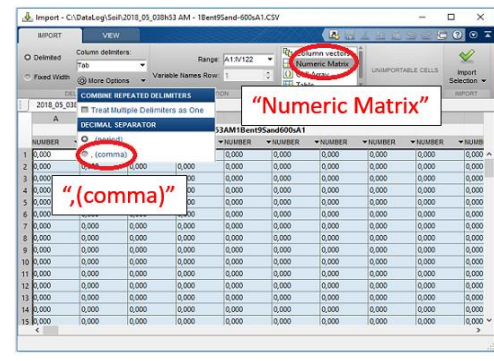
The software selected for the development and implementation of the ANN were MATLAB and Simulink. These software packages support data analysis, manipulation and simulation. The MATLAB and Simulink software packages were developed by MathWorks®, a privately held American corporation. MATLAB is a multi-paradigm numerical computing environment, which allows data matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages. MATLAB contains a Neural Network Toolbox that was used to develop and train the ANN for the ASCS. The Simulink

software package was used for the implementation and evaluation of the ANN that was developed in the MATLAB Neural Network Toolbox.

6.2.2 Importation of the SS fingerprint data into the MATLAB workspace

For the development and training of the ANN, the SS fingerprint data generated by the MVI had to be imported into the MATLAB workspace. This involved a two-step process as described in Table 6-1. After importation of the SS fingerprint data, the data could then be manipulated in the MATLAB environment to provide compatible data for the ANN Toolbox.

Table 6-1 Steps to import and consolidate SS fingerprint data into the MATLAB environment.

Description of step	Software window
The folder containing all the SS fingerprint data that were generated with the MVI, was selected in the <i>Current Folder</i> window of MATLAB. Each SS fingerprint file was then dragged into the MATLAB workspace.	
For each SS fingerprint that was dragged into the MATLAB workspace, an Import Data window was provided. In the Import Data window, the data type was set to “Numeric Matrix” and “,(comma)” was selected as the decimal separator (marked in red).	

6.2.3 Preparation of the SS fingerprint data for training of the ANN

For the development and training of the ANN, the imported SS fingerprint data had to be converted into appropriate data format for the training of the ANN. The data format was determined by the type of

training that was selected to train the ANN. In this study, the supervised training method was followed that requires both the input and output data to be provided as training data to the ANN Toolbox. The SS fingerprint data that were generated from the pre-constituted soil samples were provided as the input data, while the percentage of clay the soil samples contained was provided as the output data. The ANN was then trained whereby it “learned” the outputs (answers) from the input data (SS fingerprints) provided. Therefore, the format the data needed to be in for the supervised training method with the ANN Toolbox is shown in Table 6-2.

Table 6-2 Example of ANN data format

Data matrix				Answer matrix
Value A1	Value A2	Value A3	=	Element A
Value B1	Value B2	Value B3	=	Element B
Value C1	Value C2	Value C3	=	Element C

The SS fingerprint data that were generated by the MVI needed to be described mathematically in order for the data to be converted to the desired format that was required by the ANN Toolbox. The following five equations show how the captured SS fingerprint data were converted into the desired format for the ANN Toolbox:

Equation 3 SS Fingerprint data equation.

$$H_K = \sum_{x=70}^{1145} \sum_{y=525}^{560} P(x,y) \text{ of } K$$

Where: K = the greyscale values between 0 and 255.

P = the sum of all pixels at each greyscale value of K at the x and y coordinates of the ROI.

The SS fingerprint data, described by Equation 3 SS Fingerprint data, were then used to generate a snapshot histogram showing the pixel intensity count for each greyscale value in the snapshot. Every snapshot histogram consisted of 256 pixel-intensity count values. A snapshot histogram is mathematically described as follows:

Equation 4 Snapshot histogram equation.

$$H = [PI(0), PI(1), PI(2) \dots PI(255)]$$

Where: H = Histogram data and

PI = Pixel Intensity count for each value of the greyscale. The time between each generation of each H , was 5 s.

Each SS fingerprint consisted of the consolidated data for a 113 snapshot histograms. Each snapshot histogram contains 256 values, therefore each SS fingerprint consisted of 28,928 values. An SS fingerprint is mathematically described as follows:

Equation 5 Consolidated Soil Sample fingerprint equation.

$$SSF = [H1; H2; H3 \dots H113]$$

Where: SSF = Soil Sample Fingerprint

H = histogram data

SS fingerprints were generated with the MVI for five distinct pre-constituted soil samples containing 10, 20, 40, 70 and 80% of Bentonite clay. Five SS fingerprints were generated for each pre-constituted soil sample, resulting in a total of 25 SS fingerprints. The total of 25 SS fingerprints was consolidated into one $28\,928 \times 25$ matrix where each row contained the data of a complete SS fingerprint. The matrix was named the Original Data Matrix, and is mathematically described as follows:

Equation 6 *Original Data Matrix equation.*

$$\text{Original Data Matrix} = [SSF1; SSF2; SSF3 \dots SSF25]$$

Where: *SSF* = Soil sample fingerprint

Lastly, a separate Answer matrix was created to provide the ANN toolbox with answers (outputs) to the training data. The answer matrix was a 1×25 (one answer for each of the 25 generated SS fingerprints) matrix containing the clay percentages for each SS fingerprint:

Equation 7 *Answer Matrix equation.*

$$\text{Answer matrix} = [A1; A2; A3; \dots A25]$$

Where: *A* = Clay percentage for the corresponding SS fingerprint

The more data that could be provided as training data to the ANN Toolbox for the training of the ANN, the more accurate the training would be. Therefore, to improve the training accuracy of the ANN, more data was generated. To generate more data, the Original Dataset was used and a variance value of between -3% and 3% was added to each value of the Original Dataset, creating a new data matrix with a ± 0 to 3% variance in each value. A maximum variance of 3% was selected for accuracy purposes. This process was repeated 20 times and each new data matrix was appended to the Original Data Matrix. This resulted in a Final Data Matrix containing 525 (including the Original Data matrix) SS fingerprints. A script was used in MATLAB to generate the extra training data, append the data to the Original Data matrix and create the Final Data matrix. The script commands are shown in Table 6-3.

Table 6-3 Script to generate extra data.

Command	Command description
Open['ORIGINALDataset']	Load the original dataset
RandomPercentage = randi([0,30],[504,28928])/1000	Generate Random Percentage values between 0 and 3%
TempData = ORIGINALDataset.*RandomPercentage	Multiply the original dataset with randomly generated percentages of between 0 and 3%
PlusMinus = randi([-1;1],[504,28928])	Add or subtract the randomly generated percentage?
PlusMinus(PlusMinus==0) = 1	Remove all 0's from the randomly generated values (do not want to multiply with 0)
TempData = TempData.*PlusMinus	Add or subtract the generated random values from the original dataset
FinalData = ORIGINALDataset+TempData	Append the newly generated dataset to final dataset

After the Final Data Matrix was created, a corresponding 1×525 Final Answer matrix was created containing the percentage of Bentonite clay for each corresponding SS fingerprint (row) in the Final Data Matrix. The resulting matrices are shown in Figure 6.3.

Final Data matrix						Answer matrix
SS FINGERPRINT	VALUE1	VALUE2	VALUE3	VALUE4	...VALUE 28 928	ANSWER
#1	PiC1	PiC2	PiC3	PiC4	PiC28 928	%CLAY#1
#2	PiC1	PiC2	PiC3	PiC4	PiC28 928	%CLAY#2
#3	PiC1	PiC2	PiC3	PiC4	PiC28 928	%CLAY#3
...#225	PiC1	PiC2	PiC3	PiC4	PiC28 928	...%CLAY#225

Figure 6.3 Training matrices for the ANN Toolbox.

6.2.4 Development and training of the ANN

The ANN was development and compiled in the MATLAB software environment. The development of the ANN consisted of preparation steps to design the layout of the ANN and training steps to train and then evaluate the ANN design. During the preparation steps of the ANN development, the desired settings were selected in the ANN Toolbox provided by the MATLAB software environment. These settings included the input and an output dataset as well as selecting the type of training algorithm that was used to train the ANN. The ANN Toolbox had three training algorithms to choose from, these algorithms were:

a. ***The Levenberg-Marquart algorithm:***

This algorithm requires less time for training the ANN, but requires more computer resources for the training process.

b. ***The Scaled Conjugate Gradient algorithm:***

This algorithm is preferable when using large datasets as it requires less computer resources for the training process.

c. ***The Bayesian Regularization algorithm:***

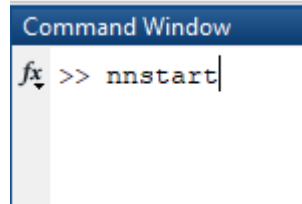
This algorithm requires more time for training, but is more accurate when datasets are complicated or noisy.

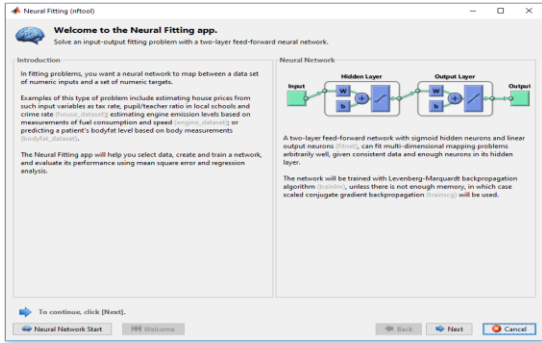
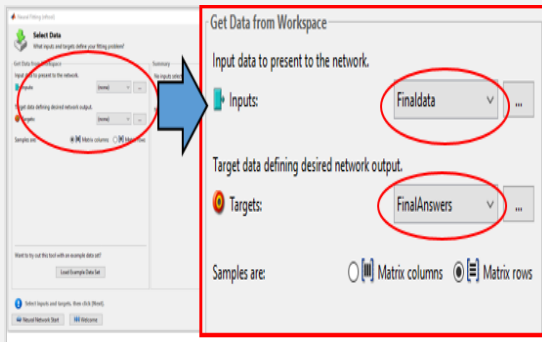
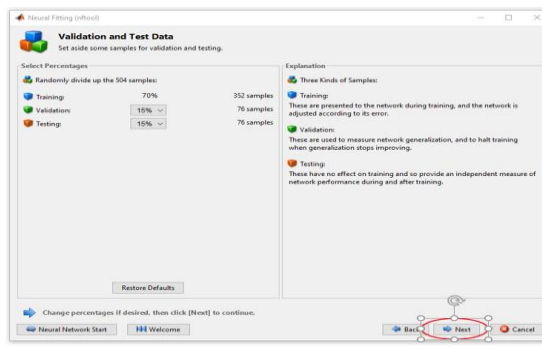
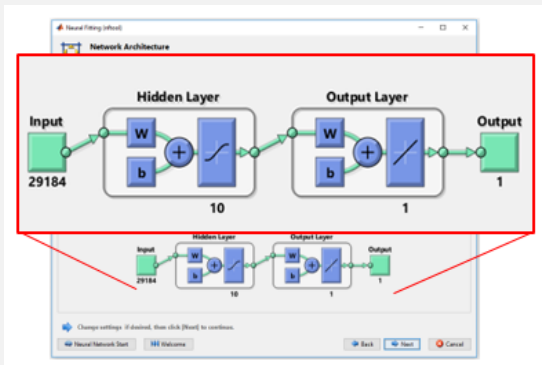
For this study, accuracy was more important than the time or resources required for the training of the ANN. Therefore, the Bayesian Regularization algorithm was selected to train the ANN.

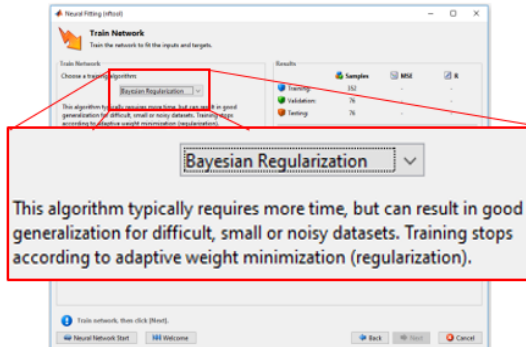
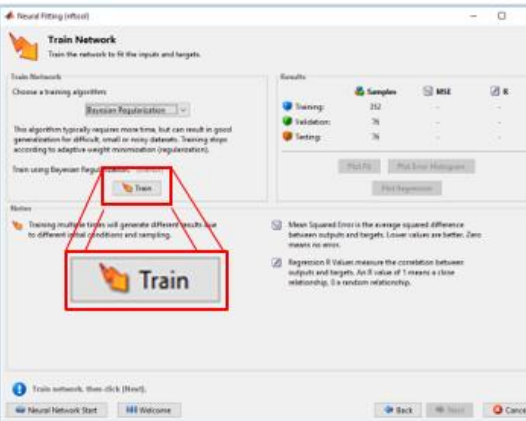
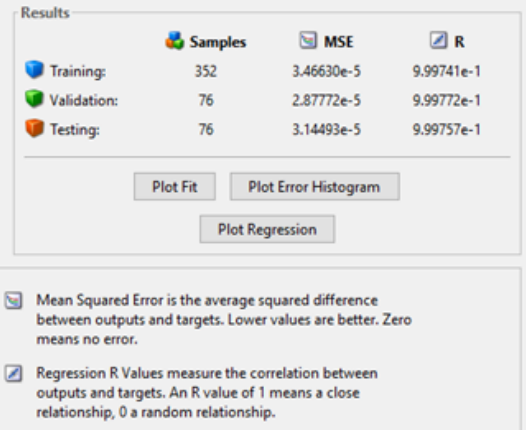
After the preparation steps of the ANN Toolbox were completed, the ANN was trained and then evaluated using the ANN Toolbox. Training of the ANN by the ANN Toolbox involved applying the Bayesian Regularization algorithm to the prepared Input and Output datasets. The results of the training process then needed to be evaluated to confirm the successful training of the ANN.

To evaluate the training of the ANN, the Mean Squared Error (MSE) and the Regression (R) values were inspected in the Results window. MSE values of close to 0 were expected, which would indicate accurate training of the ANN. The Regression (R) value, measured the correlation between the output and the target (actual) value. The closer the R value was to 1, the closer the relationship between the output and target values were while an R value of 0 meant there was no relation between the output and the target values. Therefore, R values of close to 1 were expected. The preparation steps of the ANN development are shown in steps 1 to 7 of Table 6-4 while the training and evaluation steps are shown in step 8 and 9.

Table 6-4 Development steps of the ANN.

Step #	Description of steps	Software window
Preparation steps		
1	The Neural Network Toolbox was started by typing “nnstart” in the Command Window of the MATLAB environment. This command will bring up the Neural Network Start window.	
2	In the Neural Network Start window, the “Fitting app” button was pressed to start the Neural Fitting app. This application was selected as the description provided for the application closely resembled the type of ANN that needed to be developed.	

3	The Welcome to the Neural Fitting application window was displayed and contained a block diagram of a typical Fitting ANN, a brief description of what a Fitting ANN is and examples of Fitting ANN applications. NEXT was clicked to display the Select Data window.	
4	In the Select Data window, the “Final Data” dataset was selected as the inputs and the Final Answer dataset was selected as the targets (answers).	
5	In the Validation and Test Data window, the default settings were used. NEXT was clicked to bring up the Network Architecture window.	
6	The ANN Toolbox then automatically generated an ANN from the input and output matrices provided and the result was shown in the Network Architecture window. The number of input nodes were shown as well as the number of hidden layers, output layers and outputs. The software designed the ANN to have 29 184 inputs, 10 hidden layers, 1 output layer and 1 output. NEXT was clicked to bring up the Train Network window.	

7	The Bayesian Regularization algorithm was selected as the training algorithm for the ANN.																	
Training step																		
8	After the preferred training algorithm was selected, training of the ANN could commence by clicking the TRAIN button in the Train Network window.																	
Evaluation of training step																		
9	The successful training of the ANN was evaluated by inspecting the MSE and R values in the Results window of the ANN Toolbox.	 <table><thead><tr><th></th><th>Samples</th><th>MSE</th><th>R</th></tr></thead><tbody><tr><td>Training:</td><td>352</td><td>3.46630e-5</td><td>9.99741e-1</td></tr><tr><td>Validation:</td><td>76</td><td>2.87772e-5</td><td>9.99772e-1</td></tr><tr><td>Testing:</td><td>76</td><td>3.14493e-5</td><td>9.99757e-1</td></tr></tbody></table>		Samples	MSE	R	Training:	352	3.46630e-5	9.99741e-1	Validation:	76	2.87772e-5	9.99772e-1	Testing:	76	3.14493e-5	9.99757e-1
	Samples	MSE	R															
Training:	352	3.46630e-5	9.99741e-1															
Validation:	76	2.87772e-5	9.99772e-1															
Testing:	76	3.14493e-5	9.99757e-1															

The Results window of the software contained the results of the training procedure. The window showed the Mean Squared Error (MSE) values from 2,877e-5 to 3,466e-5, which indicated a high accuracy in training as MSE values of close to 0 were expected. The R values varied from 0,9974 to 0,9977, which further indicated a more than 99% correlation between output and target values. To

further validate the training of the ANN, linear plots for the training, validation, test as well as the overall (average) outputs were generated. The linear line in Figure 6.4 A, B, C and D indicates the targets for each output, whereas the black dots indicates the actual output for each test. The closer the proximity of each output was to the linear line, the more accurate the outputs were. From Figure 6.4 it was clear that the training of the ANN was successful as all results were in close proximity to the linear target values. After the successful training of the ANN, the ANN was exported to the Simulink environment of MATLAB to be implemented as part of the ASCS.

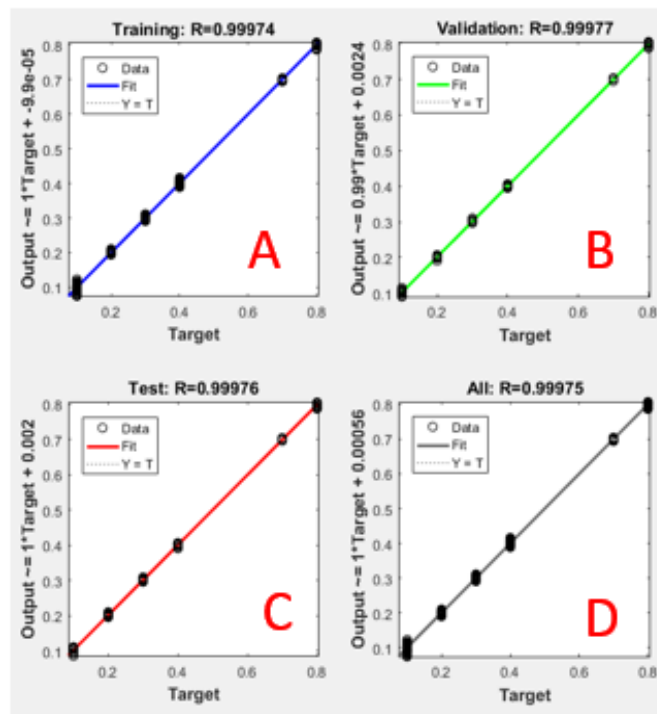


Figure 6.4 Linear plot of the ANN training results of: A) Training data, B) Validation data, C) Test data and D) Overall (average of A, B and C) data.

6.2.5 Integration of the ANN into the ASCS

To implement the ANN as part of the ASCS, the developed and trained ANN was exported to the Simulink environment of the MATLAB R2016a software. To export the ANN to the Simulink environment, the Deploy Solution window (Figure 6.5) of the ANN Toolbox software was used and the Simulink Diagram option was selected.

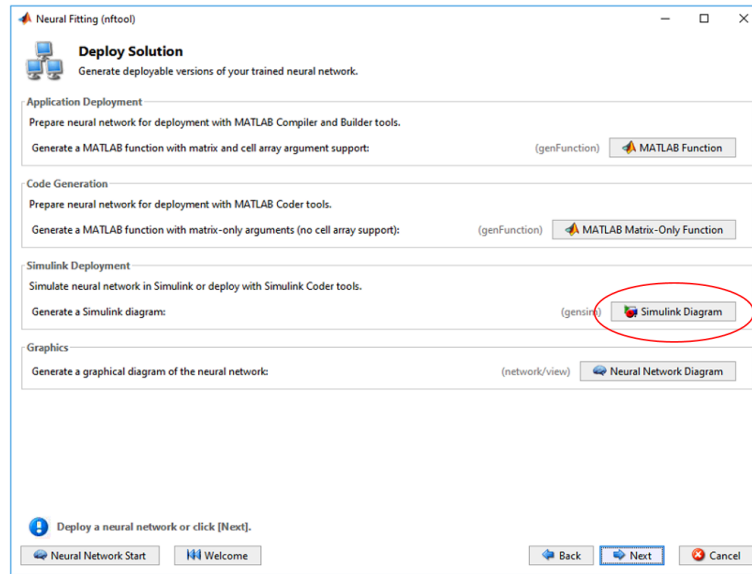


Figure 6.5 Deploy Solution window of the ANN Toolbox.

Three function blocks were automatically generated by the software and displayed in the Simulink environment. These function blocks operated together as a program to calculate results from any given input. The input for the x1 Constant block consisted of an SS fingerprint that needed to be processed by the ANN. The x1 Constant (input) block then provided the input data (SS fingerprint data) to the NNET block which represents the trained ANN. The NNET block then applied the trained ANN to the input data and the result was displayed in the y1 (output) block.

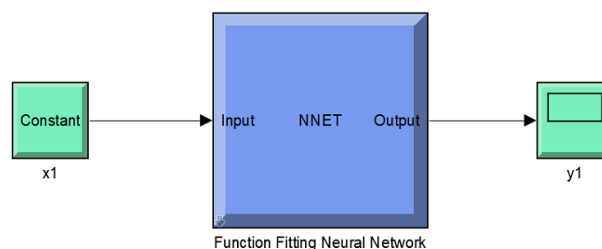


Figure 6.6 Automatically generated program displayed as a Simulink diagram.

The automatically generated Simulink program was then manually modified to improve functionality and to make the program more user-friendly. A “From Workspace” function block was added so that the SS fingerprint data (input data) that needed to be processed by the ANN could be selected directly from the MATLAB workspace environment. As the output of the NNET function block was displayed as a value between 0 and 1, a Constant function block was added to multiply the output with the Constant block value of 100, using the Product function block. The result was then shown as a percentage value in the Display function block. The modified Simulink program is shown in Figure 6.7.

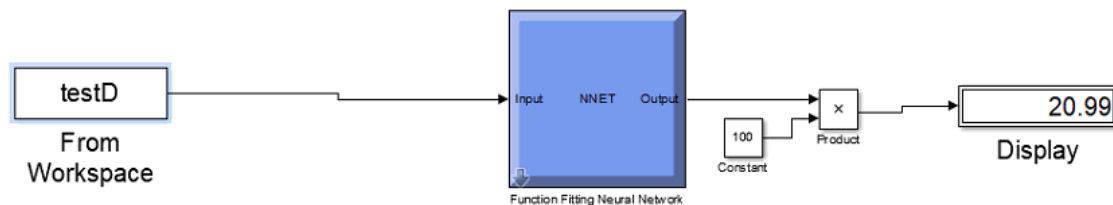


Figure 6.7 Modified Simulink program.

The user interface could be used to provide input data to the trained ANN in the form of an SS fingerprint. The SS fingerprint was then processed by the trained ANN which identified the percentage of Bentonite clay in the soil sample. Once all modifications were applied, the ANN was implemented as part of the ASCS to calculate the percentage of clay from SS fingerprints generated for soil samples by the MVI. Two investigations were undertaken to evaluate the functionality of the ANN as well as a comparison of its accuracy compared to that of the Hydrometer method.

6.3 Materials and methods for investigations 5 and 6

Two investigations were undertaken in this section. Investigation 5 was undertaken to evaluate how accurately the ASCS could determine the percentage of clay in a soil sample. Investigation 6 was undertaken to compare the results of the ASCS to that of the Hydrometer method. The details of the investigations are shown in Table 6-5.

Table 6-5 Layout of steps for Investigations 5 and 6

Investigation	Materials and methods
Investigation 5: Evaluation of the accuracy of the ASCS	To evaluate the accuracy of the ASCS, the following steps were followed: • Four soil samples were prepared containing 10, 20, 40 and 80% of Bentonite clay using the soil sample preparation method. • To facilitate a blind soil classification process, each soil sample was allocated a code (for example, MM04) by a third party, who kept a record of the corresponding constitutions of the soil samples. The coded soil samples were labelled as follows: • MM06 (Containing 10% Bentonite) • MM04 (Containing 20% Bentonite) • MM11 (Containing 40% Bentonite) • MM07 (Containing 80% Bentonite) • An SS fingerprint was generated for each coded soil samples using the MVI. • In the Simulink environment, the ANN program was provided with inputs of the SS fingerprints generated from each of the coded soil samples by the MVI. • The ANN outputs were compared to the actual amount of Bentonite clay in the coded soil samples. • The approximate amount of time it took to complete all tests were noted.
Investigation 6: Comparison of both the accuracy as well as the amount of time it took for the ASCS to generate results compared to that of the Hydrometer method	The ASCS was compared to the Hydrometer method in the following manner: • The same coded soil samples that were used in Investigation 5 were used to perform investigation 6 as the ASCS classification results were already known from Investigation 5. • Each coded soil sample was then also classified by means of the Hydrometer method by the soil classification laboratory of the Central University of Technology. • The output of the ASCS for each coded soil sample was then compared to the soil classification results of the Hydrometer method. • The total time it took to classify all the coded soil samples for each method was also noted for comparison.

6.4 Results of investigations

Investigation 5 were undertaken to evaluate how accurately the ASCS could determine the clay content of a soil sample. The accuracy and speed of the ASCS were then compared to that of the Hydrometer method in Investigation 6.

6.4.1 Results of Investigation 5: Evaluation of the accuracy of the ASCS

Investigation 5 was undertaken to determine how accurately the complete ASCS could determine the amount of Bentonite clay in a given soil sample. The soil classification results by the ASCS showed values with an accuracy from 95,75% to 98,50% (Table 6-6). These results showed that the ASCS was able to determine the amount of Bentonite clay in a soil sample with an accuracy of more than 95%. It took approximately 28 hours to complete all tests and included the compulsory 24 hour waiting period as specified by the Soil Sample Preparation method.

Table 6-6 Soil classification results by the ASCS.

Original sample label	New label given by third party	Actual clay content (%)	Clay content as calculated by ASCS (%)	Accuracy (%)
MM06	A	10	9,65	96,50
MM04	D	20	20,81	96,11
MM11	B	40	39,40	98,50
MM07	C	80	76,60	95,75

6.4.2 Results of Investigation 6: Comparison of the accuracy as well as the test duration of the ASCS compared to that of the Hydrometer method.

Investigation 6 was undertaken to compare the accuracy of the ASCS to that of the Hydrometer method. The duration of the classification process for each of the two procedures were also evaluated. The soil classification results by the Hydrometer method showed values with accuracy ranging between 49,26% to 88,63% (Table 6-7). These results indicated that the Hydrometer

method had a high inconsistency in its ability to classify soil samples, whereas the ASCS's accuracy was high when compared to that of the Hydrometer method. It took approximately 7 days for the soil classification laboratory at the Central University of Technology to classify all soil samples by means of the Hydrometer method. This was substantially slower than the ~28 hours taken by the ASCS.

Table 6-7 Comparison of the soil classification results by the Hydrometer method and the ASCS.

		Hydrometer method test results	ASCS test results	Hydrometer method	ASCS
Sample code	Actual % Bentonite clay	% Clay	% Bentonite clay	Accuracy (%)	Accuracy (%)
MM06	10,00	20,30	9,65	49,26	96,50
MM04	20,00	29,46	20,81	67,89	96,11
MM11	40,00	49,43	39,40	80,92	98,50
MM07	80,00	70,90	76,60	88,63	95,75
Approximate time taken to obtain results			7 days	28 hours	

6.5 Chapter discussion and summary

In Phase 5 of this study, an ANN was developed and implemented as part of the ASCS. The function of the ANN was to calculate the percentage of Bentonite clay in soil samples from the SS fingerprints that were generated for the soil samples by the MVI. Investigation 5 showed that the completed ASCS was able to determine the amount of Bentonite clay in any given soil sample with high accuracy. Phase 6 of this study compared the accuracy and duration of the soil classification processes of the ASCS and the Hydrometer method through Investigation 6. The results of Investigation 6 showed that the ASCS was more accurate and substantially quicker in classifying soil samples than the Hydrometer method.

Chapter 7

Discussion and Conclusion

7.1 Introduction

In the construction industry, one of the major considerations when designing a superstructure is which foundation should be selected for the superstructure. Foundations support superstructures by transferring the load of the structure evenly into the earth (Chang and Svenson, 2019). The selection of an appropriate foundation ensures the stability and longevity of the superstructure, whereas an inappropriate foundation type could result in damage to the superstructure, or even the collapse of such a structure (Salam and El-kady, 2017).

When selecting an appropriate foundation for a superstructure, detailed knowledge of the soil composition upon which the superstructure will be built, is critical (Bowles, 1997; Ramesh, Kuklik and Válek, 2017). In particular, the amount of clay the soil contains is a major determining factor in the selection of an appropriate foundation type (Chang and Svenson, 2019). Although there are a number of soil classification methods to determine the amount of clay in soils, a commonly used method in South Africa is the Hydrometer method that was invented by William Nicholson in 1790 (Encyclopaedia Britannica, 2013). This method is based on the sedimentation rate of the soil particles in a viscous fluid, whereby the particle size distribution is determined according to Stokes' law, which states that different sized particles will sediment at different velocities depending on their size (Das, 2018).

Two major limitations of the Hydrometer method were the inspiration to this study. Firstly, its soil classification accuracy is doubtful; and secondly, the Hydrometer method is a manual, time intensive

soil classification method (Stott and Theron, 2016). Therefore, this study was undertaken to circumvent these limitations by developing an Automated Soil Classification System (ASCS). The successfully, newly developed ASCS automatically classifies soil samples more accurately and more expeditiously by combining Machine Vision (MV) and Artificial Neural Network (ANN) technologies. In the ASCS, MV generates a digital soil sample (SS) fingerprint by taking snapshots of a soil sample's sedimentation process over time. The ANN then classifies the soil sample by identifying the digital SS fingerprint.

7.2 The Automated Soil Classification System

A primary challenge of this study was to acquire a sequence of high fidelity, greyscale images of the sedimentation process of a soil sample over time. These images were then used to create unique SS fingerprints for different compositions of soil samples. A Machine Vision Instrument (MVI) was constructed for the capturing of the high quality images in a consistent manner. The MVI acquired these images using a good quality greyscale camera in a controlled lighting environment.

A secondary challenge was to create a fingerprint-type representation of the sedimentation process that could uniquely identify soil compositions. This required a consistent soil sample preparation method, as well as a consistent SS fingerprint generation process. This was achieved by applying a soil sample preparation protocol and generating a pixel count histogram for each of the 113 snapshots taken by the MVI during the sedimentation process. These histograms were then consolidated into a single histogram by the MVI, which was referred to as the SS fingerprint. SS fingerprint consistency was evaluated by correlating several SS fingerprints; firstly, amongst SS fingerprints generated of the same soil sample; and secondly, of SS fingerprints generated from multiple soils samples with the same soil constitution prepared with the soil sample preparation protocol. Correlation amongst SS fingerprints, generated from the same soil sample, was in the order of 97%, while the correlation amongst SS fingerprints, generated from multiple soils samples

of the same constitution, was in the order of 95%. These correlations confirmed that the soil sample preparation protocol together with the MVI was able to generate SS fingerprints with high consistency.

The final challenge in this study was to automatically classify a soil sample by processing its SS fingerprint. To achieve this goal, an ANN was trained to identify soil compositions represented by their respective SS fingerprints. To accurately identify soil compositions, large volumes of data were necessary to train the ANN. To ensure the accurate classification of soil sample compositions, a large dataset was created to train the ANN. This was achieved by enlarging the original dataset of 25 SS fingerprints by adding a 3% variance to all values multiple times. This enlarged dataset that was used for training, comprised of 525 SS fingerprints, of which each SS fingerprint consisted of 29,070 values and produced training R values greater than 0,99. In the past, several attempts were made to classify soil samples using similar technologies, however because of large amounts of data that needed to be processes with limited computational power, these attempts delivered unreliable results (Tuceryan and Jain, 1998; Sudarsan *et al.*, 2018). Computational power was not a limiting factor in this study, therefore the ANN was successfully trained to classify soil samples by identifying their SS fingerprints.

Finally, the overall soil classification ability of the ASCS was compared to that of the Hydrometer method. By using blind, pre-constituted soil samples, the accuracy of the Hydrometer method proved to be relatively low, ranging from approximately 49% to 89%. In contrast, the accuracy of all the soil classifications performed by the ASCS, using the same soil samples as for the Hydrometer method, were greater than 95%. Furthermore, the ASCS produced soil classification results within 28 hours, whereas the Hydrometer method took about seven days.

7.3 Concluding remarks and future prospects

As was shown in this study, the Hydrometer Method has many challenges in terms of accuracy and speed. Experts in the field of soil classification stated that the Hydrometer method can be a lengthy process and results are sometimes inaccurate at best (Stott and Theron, 2016; Monye, 2018). Depending on the percentage of clay in a soil sample, a single soil classification by means of the Hydrometer method can take two weeks. The lengthy process combined by continuous human interaction can result in the Hydrometer method grossly underestimating the clay content of a soil sample.

By designing and developing an ASCS, the challenges posed by the Hydrometer method were circumvented. The ASCS system is shown to be more than 95% accurate in classifying soil samples and the process has been sped up from a potential two weeks to approximately twenty-eight hours. The successfully developed ASCS could be of great value to the building industry by speeding up the soil classification process immensely and ensuring the selection of appropriate foundation types for superstructures. The selection of appropriate foundation types will contribute to the stability and longevity of superstructures.

Further studies are necessary to determine how the ASCS will perform with real world soil samples as the development of the ASCS in this study was achieved by using pre-constituted soil samples.

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