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# TITOLO TESI

# VIRTUAL 3D RECONSTRUCTION OF ARCHAEOLOGICAL POTTERY USING COARSE REGISTRATION

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## ABSTRACT

The 3D reconstruction and modelling of objects has not only improved visualisation of digitised objects, it has also helped researchers to actively and easily carry out related studies. Such studies include the classification and reconstruction of archaeological pottery. Reconstructing, and documenting, pottery is significant in archaeological studies, analysis and research, but has been a challenging task among practitioners. For one, excavated potteries are hardly complete enough to provide exhaustive and useful information, hence archaeologists attempt to reconstruct them with available tools and methods. While this is the case, it is also challenging to apply existing reconstruction and modelling approaches, as is, in archaeological documentation. This limitation makes it difficult and time consuming to carry out studies within a reasonable space of time. Hence, interest has shifted to developing new ways of reconstructing archaeological artefacts with new techniques and algorithms.

This has led to refining existing processes to solve existing challenges. Therefore, this study focuses on providing interventions that will ease the challenges encountered in reconstructing archaeological pottery. It applies a data acquisition approach that uses a 3D laser scanner to acquire point cloud data that clearly show the geometric and radiometric properties of the object's surface. The acquired data is processed to remove noise and outliers before undergoing a coarse-to-fine registration strategy which involves detecting and extracting salient keypoints from the point clouds and estimating descriptions with them. In addition, correspondences and matches are estimated between point pairs of a pair of point cloud scan, leading to a pairwise and global registration of the acquired point clouds. While some tests and visualisations were carried out in CloudCompare and MATLAB, the registration process was implemented in C++.

The peculiarity of the approach of this thesis is in adapting and adjusting parameters as required due to the peculiar nature of the data acquired. This improves the efficiency, robustness and accuracy of the approach, evident in the final registration output. The approach and findings show that the use of real 3D dataset can attain good results when used with the right tools. High resolution lenses and accurate calibration help to give accurate results. While the registration accuracy attained in the study lies between 0.08 and 0.14 mean squared error for the data used, further studies will validate this result. The results obtained are nonetheless useful for further studies in 3D pottery reassembly.

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# CHAPTER 1: INTRODUCTION

## 1.1 Introduction

From time immemorial, people and their way of life have evolved in every way possible. This evolution can be seen in the craftsmanship of a people, leading to discoveries – some of which are lost and some discovered. In addition to the craftsmanship of a people, the making and remaking of objects or artefacts is an activity that is done by people in different communities and environment and passed from one generation to another. Because the objects are unique to a people or environment, they are usually referred to as cultural heritage.

Cultural heritage refers to a communal bond among a people or community that characterises their identity and history, inherited from past generations (Barrère, 2016; Vecco, 2010). It involves the culture, values and traditions of a people. Hence, cultural heritage is usually classified into intangible and tangible heritage (Kreps, 2015; Vecco, 2010).

According to UNESCO (2018), intangible heritage refers to those that are not physically perceived and so cannot be touched. They include language, values, traditions, folklore, music, dances, beliefs among others, and are perceived through cuisine, dressing, traditional craftsmanship, social practices, religious ceremonies, performing arts, storytelling and the likes (Barrère, 2016). On the other hand, tangible heritage refers to artefacts that can be seen and touched. They include architectures, monuments, landscapes, literary texts and documents, art, frescoes, sculptures and archaeological sites and remains, among others. Some of these artefacts tend to increase in value and appreciation over time and have been an important means of understanding past civilisation so that present society might learn from and improve current ways of living.

Understanding past civilisation is important to certain professions and studies, that Thurley (2005) proposed a model that could help with this process. The model is called the heritage cycle (Thurley, 2005), shown in Figure 1.1.

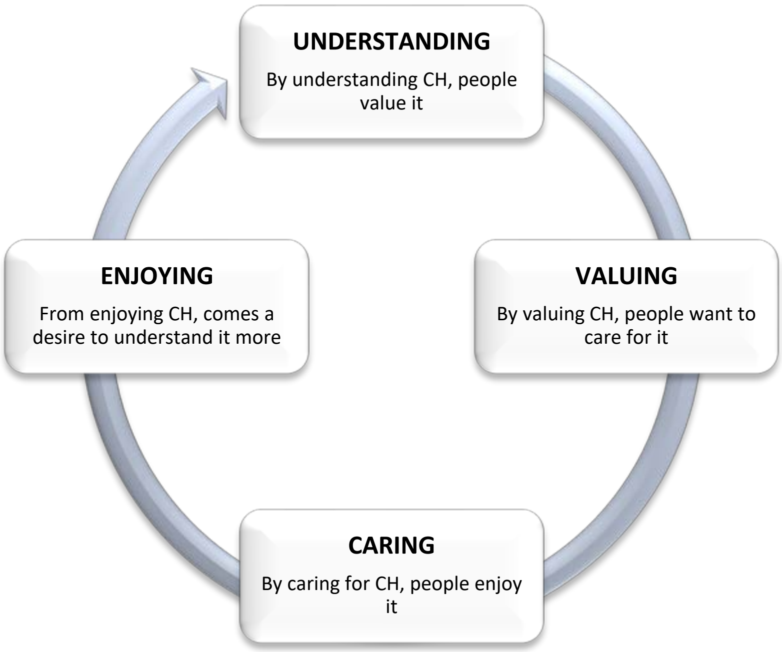


**Figure 1.1: The Heritage Cycle**

The heritage cycle consists of four stages namely understanding, valuing, caring and enjoying. The cycle focuses on making the past part of the future. It achieves this by increasing an understanding of the cultural heritage (first stage), leading to an increase in the way people value cultural heritage (second stage), and preserving and caring for it as a result (third stage). Thus, people enjoy and appreciate cultural heritage through their perception (fourth stage), and then a thirst to understand it more arises.

This postulation, though unconsciously practiced in general, could be a veritable tool in cultural heritage studies. In addition, one thing that stands out from the third stage of the heritage cycle is the fact that cultural heritage must be preserved. For there to be any value in cultural heritage artefacts, preservation is a key component. This has led to the concept of cultural heritage preservation or documentation. In this thesis, the terms ‘preservation’ and ‘documentation’ are used interchangeably to convey similar meaning.

## 1.2 Cultural Heritage Preservation

The preservation of artefacts of value help a people to connect with and understand their origin so that they do not lose the essence of their being, which is their identity. The preservation of these cultural heritage artefacts is an age-long problem. Cultural heritage preservation is the act of safeguarding cultural heritage artefacts of the past and present for future appreciation (Barrère, 2016; UNESCO, 2018). Because some people do not seem to appreciate cultural heritage as expected, professionals and researchers tend to educate and promote cultural heritage for a wider awareness and appreciation. In addition, cultural heritage artefacts tend to be threatened by armed conflicts and natural disasters. Hence, governments and nations are cooperating to preserve cultural heritage artefacts. Preserving these artefacts have thus led to identity cohesion, social cohesion, communal reconciliation and economic growth (Barrère, 2016; UNESCO, 2010).

Furthermore, these artefacts undergo certain methods and processes of craftsmanship to become what they are. The methods can include planning, material gathering and production. These processes have been streamlined from generation to generation. In addition, the methods of preservation also evolved with time. One of such methods of preservation is termed *digital* or *virtual heritage*.

### 1.2.1 Virtual Heritage

Virtual heritage refers to the use and application of digital and information technologies to visualise and perceive cultural heritage (Ch’ng, 2015; Stone & Ojika, 2000). It is supposedly an intersection between virtual reality and cultural heritage. The technological instruments applied in virtual heritage include websites, internet, camera, laser and lidar among others. These instruments are applied through computer visualisation of artefacts, digitisation of artefacts, 3D modelling, 3D animation, photogrammetry, virtual reality and augmented reality (Ch'ng, 2015; Maver, 2001). Thus, cultural heritage artefacts can be preserved for research purposes by researchers and appreciation purposes by audiences.

Preserving cultural heritage through technology offers new possibilities and convenient ways to learn, convey, interpret and experience cultural heritage artefacts in new and exciting avenues (Ch'ng, 2015). In addition, virtual heritage applications are gaining popularity with the technical ability to create boundless possibilities in the cultural heritage field. An application area of virtual heritage is virtual archaeology or simply archaeology, which this study is based on. This chapter introduces the thesis that focuses on the application of technological instruments in the archaeology domain.

## 1.3 Archaeological Documentation

Archaeology is a discipline that recovers, studies and analyses ancient and modern artefacts and material remains from past societies of humans and closely related species, recording its primary data for the purpose of reusing them for historical understanding of human culture (Marchetti *et al.*, 2017). The discipline involves surveying, excavating, observing and interpreting the fieldwork data to learn more about the past. In learning about the past, the archaeologist searches for patterns that can be observed in the evolution of significant cultural practices that identify a community, such as farming, communal practices, conflict handling – among others, for clues of how and why these events happened. This helps the archaeologist to contribute to the present, based on the findings of the past, by better predicting how cultures will change and how to plan better for the future. Thus, an archaeologist's work can be seen as humanistic as they focus on studying the past for the present and future.

Being a cultural heritage discipline, archaeology also focuses on documentation or preservation of archaeological artefacts. Archaeological preservation is the act of safeguarding archaeological artefacts and findings of the past and present for future appreciation. This helps the archaeologist to have easier access to these artefacts for study purposes, as well as making it available for people to appreciate in general. Some professionals believe that studying the past, coupled with collecting and preserving surviving artefacts, is a good way of strengthening the consciousness and identity of people (Barrère, 2016). Thus, preserving archaeological artefacts has an influence on the perception, quality and way of life of a people.

Moreover, to be able to preserve these artefacts as intended, it is necessary to follow processes that will make the preservation satisfactory. Usually, the primary challenge in archaeological work is to acquire data in a whole and complete condition (Addison, 2000). Ergo, archaeologists have employed different time-consuming means of attaining that goal of studying and preserving artefacts (Marchetti *et al.*, 2017). Such methods may include physical examination, classification, illustration and reassembly of fractured artefacts physically and through drawing. These methods which are carried out manually have made the archaeologist's work meaningful. Thus, artefacts are preserved in whatever state they are acquired because they are considered to inherently have a specific cultural, economic or social value that is capable of benefits for the present and the future (Barrère, 2016). However, these methods have also made the archaeologist expend time and effort to observe and possibly extrapolate from the observations of these artefacts (Marchetti *et al.*, 2017). One of such artefacts that this study is focused on is pottery.

### 1.3.1 Pottery Preservation

Of all the artefacts recovered from archaeological excavations, pottery is one of the most significant because of its ability not to decay when compared with other archaeological artefacts of other materials (Barclay *et al.*, 2016). When archaeologists recover pottery from a site, they are hardly recovered close to their original state. They could be degraded due to “wear and tear” and/or broken to various fragmental pieces. In addition, depending on how the recovered pottery is preserved, it could be recovered as a complete pot on site or as fragments known as pottery. Most pottery, especially the ones of the pottery rim, usually carry information – such as the shape of the pottery, decoration on the pottery and colour of the pottery among others – on the inner and/or outer surfaces (Di Angelo, Di Stefano, & Pane, 2017). This information helps the archaeologist to carry out studies such as dating, and to understand the culture of the potter.

However, some of the pottery may not exhibit enough information for the archaeologist to carry out meaningful scientific or archaeological studies. Hence, the archaeologist attempts to manually reassemble the available pottery to have a clearer picture of the excavated pottery (Oxholm & Nishino, 2013). Going a step further, the reassembly can also be done by drawing the pottery form by extrapolation from the arranged pottery (Collett, 2012), a process that will be referred to as reconstruction in this thesis.

While this approach of reassembly, and reconstruction, is quite effective for the archaeologist, a more efficient approach that will improve the effectiveness of the work of the archaeologist is desired. This is because when certain basic tasks are not taken into consideration in the reconstruction process, there is the tendency to spend a long time trying to solve the puzzle of reconstruction and not achieving it, leading to a lack of understanding and missing valuable information (Barclay *et al.*, 2016). For this reason, technology approaches have been widely adopted in this field. These technologies include computer visualisation, computer graphics, 3D digitisation, 3D modelling, 3D animation, photogrammetry, virtual reality and augmented reality, among others (Ch’ng, 2015; Maver, 2001).

### 1.3.2 Technology in Pottery Preservation

While the progress in pottery preservation has been due to improved methods of inquiry than the tools and instruments used, new and improved methods depend on these instruments for effective use and validation. For example, analysing ten pieces of data may be done with calculations and drawing without using a computer. However, analysing hundreds and thousands of data may require enhanced computational methods and instruments. This has led to the adoption of technology in archaeological studies, and pottery in particular. A practice usually referred to as virtual archaeology.

Furthermore, it is worth noting that archaeologists have used technology as a means of making, keeping and preserving records and information to make it available for further research and future use (Eiteljorg, 2004; Marchetti *et al.*, 2017; Smith, 2004). This is to considerably reduce the likelihood of information degradation and loss (Smith, 2004). Hence, modern technological methods have been considered at various stages of archaeological works. For example, digital preservation of archaeological data and virtual reconstruction of archaeological artefacts. This is to avoid degradation of artefacts through wear and tear during studies. This way the artefacts can be preserved, and studies can be carried out with the digital copy of the artefact without incessantly resorting to the physical artefact. Also, because complete fragments of artefacts are mostly not recovered, researchers began to look at alternative ways of reconstructing these artefacts using technological means to aid their studies. Thus, the virtual reconstruction of artefacts became a desired area.

The virtual reconstruction of artefacts needs to be done accurately for the reconstruction to be good enough for study and research purposes. Hence, various works have been done to reconstruct artefacts in two-dimensional (2D) and three-dimensional (3D) views. While some of the studies performed well for their chosen scenarios, no study has been a “one-size-fits-all” solution. As a result, reconstructing whole and fragmented pottery accurately is still an open issue. How image analysis techniques could be useful in the archaeological context and how these techniques could be put to good use with pottery reconstruction is a focus in this study.

This thesis approaches this challenge by presenting a path towards reconstructing archaeological pottery acquired in 3D point cloud data. Multiple views of the pottery were acquired as point clouds and aligned to form a whole through the registration process. To achieve this, feature detection, feature selection and feature extraction techniques have been utilised. Since the path to an optimal registration process begins with the quality of data and how it is collected, it was ensured that the point clouds were captured with the utmost accuracy. Two objects (see Figure 1.2) were virtualised and studied preliminarily. However, one does not have enough features on the surface while the other has features but require a more complex data acquisition and registration procedure to align the inner and outer surfaces of the point clouds.

**(a)** **(b)**

**Figure 1.2: (a) Flower Vase (b) Flower Vase with Design**

Due to the peculiarity of the two vases and the intended goal of this study, the focus of this study rested on the virtualisation of a third object with archaeological significance – an oil lamp fractured pottery and its sherd (see Figure 1.3). This is because the pottery has rich intrinsic geometric information on its surface for the feature extraction approach. The pottery was excavated at the Claterna archaeological site of the metropolitan city of Bologna.

(a) (b)

**Figure 1.3: (a) Oil lamp fractured pottery (b) Oil lamp sherd**

## 1.4 Statement of the Research Problem

The preservation and documentation of archaeological pottery have been quite challenging a task (Makridis & Daras, 2012; Marchetti *et al.*, 2017). Such challenge was observed in the process of classification and study of pottery, with respect to reconstruction of pottery by physical assembly and by drawing (Di Angelo et al., 2017). In addition, recovered pottery from archaeological sites are rarely complete enough to provide an exhaustive and useful information, hence archaeologists fall back on the time-consuming method of reconstructive drawing by extrapolation (Drucker, 2012:89). Reconstructing pottery is significant in the field of archaeological studies, analysis and research. Barclay *et al.* (2016) note that the excavated potteries are used as a reliable tool for dating, and as evidence for ancient tradition, culture, civilisation and technology. In fact, the use of technology and computer aided techniques have impacted positively on the studies on pottery and archaeology in general

(Collett, 2012; Pintus *et al.*, 2016). However, pottery reconstruction coupled with the time, effort and cost expended make an optimal and accurate means of reconstruction vital. According to Barclay *et al.*, "If the study of pottery is to reach its full potential, it is vital that it is recovered and analysed to a high standard." This refers to recovery with high accuracy. Hence, being able to assemble and reconstruct pottery accurately and with ease will greatly impact pottery and archaeological studies. Unfortunately, there is little evidence that various research works have addressed this persisting issue satisfactorily (Oxholm & Nishino, 2013; Pintus *et al.*, 2016; Rice, 1987:286).

## 1.5 Research Aim

While attempts have been made to virtually reconstruct archaeological pottery, an automatic, low-cost and high accuracy reconstruction method is still desired. Hence, the aim of this research is to investigate a means of reconstruction of archaeological pottery to and with a high accuracy. This would be achieved using a coarse-to-fine registration strategy. The coarse registration will involve extracting salient keypoints from the point clouds and estimating descriptions with them.

The study focuses on reconstructing an archaeological pottery clearly showing the geometric and radiometric properties of the surfaces and fractured faces required for easy further analysis.

## 1.6 Research Rationale

Many fields of study have applied the use of 2D and 3D reconstruction. Such fields include architecture, medical imaging, engineering, digital humanities, computer vision and cultural heritage, among others. Since the goal and application of these studies may differ, the approach applied in the studies may also differ. Thus, a breakthrough in one field may not be a breakthrough in another. As a result, the focus in this study is on the 3D reconstruction of archaeological pottery, which will be beneficial in the field of archaeology. Although the focus is on archaeology, the approach applies computer vision techniques in the investigation. Despite the unique application area, the underlying ideas and methods can be applied to a broad range of reconstruction problems.

## 1.7 Research Delineation

Virtual reconstruction of archaeological pottery is quite broad. It can refer to accurately virtualising and reconstructing whole or fragmented archaeological pottery. It can also refer to the virtual reassembly and reconstruction of fragmented archaeological pottery or potsherds. While this study started out to solve the virtual reassembly of potsherds problem, it has been restricted to the virtual reconstruction of archaeological pottery in general. This is because of specific challenges encountered with respect to 3D data acquisition and 3D registration of point clouds that are unique to this study. It will bode well if these challenges are solved first while other problems can be done in future studies. Thus, this study focuses on the 3D virtual reconstruction of archaeological pottery, aiming to improve the reconstruction process.

## 1.8 Clarification of Terms

While all terms are defined as they are used in the thesis, this section highlights the most prevalent terms and explains their meaning as used in this thesis. The most predominant terms in this study include digital heritage, virtual heritage, digitisation, point cloud registration, potsherd, pottery, pottery documentation, pottery reassembly, pottery reconstruction and virtualisation.

### 1.8.1 Digital/Virtual Heritage

Digital heritage refers to the use and application of digital and information technologies to visualise, perceive and preserve cultural heritage of lasting value and significance (Ch’ng, 2015). According to the UNESCO’s charter for the preservation of digital heritage (UNESCO, 2004: 81), digital heritage “embraces cultural, educational, scientific and administrative resources, as well as technical, legal, medical and other kinds of information created digitally, or converted into digital form". The usage scenario in this thesis focuses on cultural and technical resources. That is, applying technology processes in cultural heritage for visualisation and preservation. Additionally, in this thesis, the terms ‘digital heritage’ and ‘virtual heritage’ are used synonymously.

### 1.8.2 Digitisation

Digitisation is the process of converting and representing objects or information in a digital form (Brennen & Kreiss, 2016; Conway, 2010; Roosevelt, Cobb, Moss, Olson, & Ünlüsoy, 2015). It can be done with objects (for example, a physical object to a digital image) or signals (for example, analogue signal to digital signal) using a capturing device, so that the rendered result reliably represents the original one. This allows for easy computer processing of the digital information.

Another term that is sometimes erroneously used synonymously with digitisation is digitalisation. The meaning of both words has evolved over time to mean different things in separate scenarios. Digitalisation is the process of leveraging digitisation to improve work processes that will impact people and provide value (Bloomberg, 2018; Gobble, 2018; Orellana, 2017). For example, displaying artefacts for general viewing in a digital museum either online or at a physical location; meetings held remotely by video conference, thus bypassing the logistics of getting everyone together in a meeting room. In essence, digitisation is a part of digitalisation. Furthermore, in some instances relating to business and industry processes, digitalisation is used synonymously with automation (Bloomberg, 2018). When processes are digitalised in this instance, they are simply automated. In this thesis, digitisation is the process used.

### 1.8.3 Point Cloud Registration

Registration is the process by which two or more datasets are brought into alignment. It is an important step in combining multiple datasets, which is used for further studies. The dataset used is mainly images, acquired with image sensors. Point cloud registration is the process of finding the correspondence, spatial transformation and best alignment between two or more point cloud data. The point cloud data are usually acquired with 3D scanning sensors.

### 1.8.4 Potsherd

A potsherd is a fragmented piece of pottery, or earthenware generally, with archaeological value. It is an invaluable part of archaeological documentation because it can withstand heavy weather conditions without being significantly degraded. Thus, archaeologists find it most useful in carrying out studies.

### 1.8.5 Pottery

Pottery is generally referred to as vessels made from clay and hardened by heat into desired shapes. The vessels can be hollow as in a water pot or flat as in a plate. Since potsherds are fragmented pottery, they are referred to as pottery in this thesis except where specifically stated.

### 1.8.6 Pottery Documentation

Documentation is the act of capturing, classifying and recording information for archiving and safe keeping (Bentkowska-Kafel, 2017; Marchetti et al., 2017). This act, which can also be referred to as preservation, could involve procedures such as acquisition, processing and analysis. Preservation is simply the act of keeping a valued object free from damage. In the context of this study, the virtual documentation of pottery is the focus. Pottery documentation is the process of acquiring, classifying, processing, analysing and archiving the digitised pottery. While ‘pottery documentation’ and ‘pottery preservation’ might be argued by some to portray different meanings, they are both used synonymously in this thesis.

### 1.8.7 Pottery Reassembly

The term reassembly as used in this thesis refers to the act of joining fragmented items together to form a whole, as in a puzzle. The points at which the items join can still be visibly seen. Reassembly was used with respect to potsherds. Pottery reassembly is the act of joining potsherds to form a whole pottery, physically or digitally, so that it looks as its original condition as much as possible.

### 1.8.8 Pottery Reconstruction

The term reconstruction as used in this thesis refers to the process of joining and remaking fragmented items back to the original specification to form a whole. The points at which the items join are covered and sealed such that the lines are not visible. Similarly, pottery reconstruction is the process of joining and remaking potsherds to form a whole pottery, physically or digitally, so that it looks as its original condition as much as possible without the point of joining being visible.

### 1.8.9 Virtualisation

The term virtual can be referred to as something not physically existing but made by software to appear to be so. It is usually a representation of the original. Thus, virtualisation as used in this thesis is the process of creating a virtual model of a physical object. It is used synonymously with digitisation.

## 1.9 Structure of the Thesis

This section contains the organisation of the thesis, which is divided into five chapters and followed by the references. The thesis is organised as follows:

Chapter one begins with an introduction that informs the reader about cultural heritage in general, archaeological documentation and their preservation. It contains the statement of the research problem, research aim, research rationale and research delineation. The chapter rounds off with the clarification of terms, thesis structure and conclusion.

Chapter two reviews the existing literature on archaeological pottery reconstruction. It discusses the processes and procedures that have been adopted in pottery reconstruction. It further analyses the data collection methods, the type of data used, as well as the data analysis methods. In addition, the techniques, technologies and algorithms applied were discussed, stating their strengths and limitations in their unique scenario when implemented, and evolving gradually through the state-of-the-art.

Chapter three discusses the data acquisition approach of the pottery. It reviews related studies and the techniques applied in the acquisition of data. This leads to an explanation of the acquisition approach which involved the calibration of the acquisition system and the data acquisition.

Chapter four presents the registration approach of the acquired pottery data from the previous chapter. It reviews related studies and discusses the registration approach in general. This is followed by the specific registration approach and experiment applied in this study.

Finally, chapter five concludes the study and presents a summary of the chapters, together with recommendations for future work.

## 1.10 Chapter Conclusion

The discussion in this chapter presents a general overview of the study, namely the need for a simple, accurate and cost-effective solution for reconstructing archaeological pottery. While most studies and approaches work well for their specific scenario, there is no “one-size-fits-all” approach, prompting a necessary investigation into an appropriate approach that will be adequate for archaeological pottery reconstruction. Addressing errors due to data acquisition and accurate reconstruction of multiple data to form a whole is still an open issue with respect to pottery. Hence, this research focuses on improving accuracy and optimising the alignment process such that the registration error is significantly reduced. The research problem, aim, rationale, and delineation were highlighted. Furthermore, important terms and concepts used in the thesis were clarified and explained. The outline of the thesis was also explicitly stated. A comprehensive discussion of the research outline is presented in the succeeding chapters, with the background that provides a detailed analysis for the study presented in the following chapter, chapter two.

# CHAPTER 2: ARCHAEOLOGICAL POTTERY RECONSTRUCTION

## 2.1 Introduction

This study aims to investigate a means of accurately reconstructing archaeological pottery in 3D by using a 3D laser scanner and RGB camera for data acquisition as point clouds, and accurately aligning the point clouds. The virtual reconstruction is meant to be such that broken edges of artefacts are reconstructed with the ridges and valleys of the broken surface visible as much as possible for further studies. In line with this, this chapter surveys literature of related studies in data acquisition methods and techniques, as well as pottery reconstruction. In fact, the studies on 3D reconstruction have gained significant interest over the years. Thus, there has been a steady rise in the research of virtual reconstruction of archaeological artefacts. Based on this success, the virtual reconstruction of archaeological pottery in 3D has garnered significant interest. Hence, a review of studies in this domain is presented.

To this end, the archaeological pottery reconstruction pipeline that is prominent in most studies today is presented in this chapter. Section 2.2 begins with the prominent data acquisition methods for 3D reconstruction and their use in various scenarios. Section 2.3 delves into the various acquisition techniques, which include structured light, time-of-flight (ToF) and 3D laser scanner. Each of these techniques are reviewed and discussed, with a detailed information on their performances and challenges. The unique challenges of the various techniques provide the inspiration for the study presented in this thesis. Section 2.4 presents the two major data forms or formats that pottery reconstructions are done. Section 2.5 discusses the various methods applied in archaeological pottery reconstruction. They include symmetry-based, template-based and feature-based reconstructions. Finally, Section 2.6 summarises the chapter and provides concluding remarks.

## 2.2 Data Acquisition Methods

One of the goals of acquiring 3D data is to obtain information from digital images or complex image data (Shapiro & Stockman, 2001). The data can be expressed in photometric values or others such as 2D or 3D geometric data. A 2D geometry is a projection of the physical universe as flat planes which have two values (length and width) but no depth. For example, a shadow is an example of a 2D appearance. On the other hand, a 3D geometry adds the dimension of depth or height so that they describe real-world objects with volume. While 3D objects can be acquired by converting 2D images to 3D, they can also be directly and more accurately acquired in 3D. Acquiring objects in 3D has many advantages over acquisition in 2D. For example, 2D images give limited information of the physical shape and size of an object with loose accuracy when reconstructed in 3D, while 3D objects express the geometry in terms of three-dimensional coordinates more accurately.

Furthermore, a 3D geometry can be captured using image sensing devices or sensors (also known as range sensors). Range sensors are devices that capture the 3D structure of the real world, measuring the depth to the nearest surfaces. The measurements could be at a single point across a scanning plane, or a full image with depth measurements at every point. Thus, range sensors may be categorised into passive or active. Passive 3D sensor systems only rely on reflected light, such as shape from silhouette and the stereoscopy system, made of a couple of sensors at a fixed known base distance (the baseline). Contrarily, an active sensor system is one emitting energy into the environment and measuring properties of the environment based on the response. Meaningful examples are laser-based and structured light sensor systems. While active sensors are more complex, from a constructive point of view, they are generally more robust than passive sensors since they exert some control over the measured signal (Christensen & Hager, 2016).

Having said that, only a few methods and approaches have the reliability needed for most 3D applications despite that 3D data can be captured in several ways. While these methods are good for visualisation purposes, acquiring images directly in 3D is preferable for studies and analysis of this nature. Some of the known methods of acquisition include stereoscopy (with and without structured light), Time-of-Flight (ToF), multiple views and laser, among others.

### 2.2.1 Stereoscopy Method

Stereoscopy is a technique for creating or enhancing the illusion of depth in an image by triangulation to estimate the distance to points in a scene imaged by two cameras. It can be implemented in two ways: with or without structured light (Christensen & Hager, 2016). The implementation with structured light is also referred to as active while that without structured light is referred to as passive. While active systems project a pattern onto the scene and are thus less sensitive to scene characteristics, passive systems rely on the appearance of viewed surfaces when performing dense or sparse feature matching, thus making the active system much more accurate than the passive one, whose degradation in accuracy is noticeable in the 3D reconstruction image (Konolige & Nüchter, 2016). While the challenge of the passive system is in finding reliable matches for image elements in the two images that correspond to the same point in the scene, the active system can only be applied in controlled environments and industrial applications. In general, some issues with cameras used in stereoscopy are that there is often too little texture, especially indoors, to make reliable matches; and the matching uses small patches, which blurs out the spatial resolution. Thus, better sensors are desired since most studies with the sensors are done indoors.

### 2.2.2 Time-of-Fight (ToF) Method

With the challenges of the stereoscopy sensors, other sensors such as the Time-of-Flight (ToF) were explored for accuracy and robustness. ToF sensors consist of a light source that emits a continuous waveform and a distinct imaging sensor that measures the phase shift of the received signal in each pixel (Blais, 2004; Konolige & Nüchter, 2016). The depth of the sensor at each location is proportional to the phase shift between the outgoing and returning signals. Moreover, 3D ToF cameras use highly sensitive, custom-made Complementary Metal-Oxide-Semiconductor (CMOS) or Charge-Coupled Device (CCD) image sensors and measure the ToF of an emitted light wave in the near-infrared spectrum. Most ToF sensors transmit only a single beam, thus range measurements are only obtained from a single surface point. As a result, 3D ToF scanners are usually preferred for measurements at longer ranges because its sensors can theoretically have constant range accuracy and constant precision in depth measurement no matter how far an object is, unlike triangulation sensors (Blais, 2004).

But ToF sensors cannot replicate the very fine precision of triangulation sensors for close objects, and hence are not used in close-range applications, such as small object reconstruction (Konolige & Nüchter, 2016). Limitations on the accuracy of these sensors are based on the minimum observation time (and thus the minimum distance observable), the temporal accuracy (or quantisation) of the receiver, and the temporal width of the laser pulse. In addition, the need for allocating a large portion of ToF sensors to the decoding electronics has made it a challenge to produce low-cost sensors at reasonable resolution. Hence, efforts to overcome these challenges with new innovations, such as the RGB-D, became appealing.

### 2.2.3 Red-Green-Blue-Depth (RGB-D) Camera Method

In recent times, there has been a resurgence in range-based sensing using RGB-D sensors that utilise structured light and cameras to generate dense range maps. These RGB-D sensors enabled a new generation of full model reconstruction systems with an arbitrary camera motion. Thus, the development of 3D RGB-D cameras has enabled the 3D tracking of full body models in large and partially occluded spaces, with ongoing improvements toward robustness in tracking (Kragic & Daniilidis, 2016). In addition, RGB-D cameras are a specific type of depth sensing devices which work in association with an RGB camera that can augment the conventional image with depth information (related with the distance to the sensor) in a per-pixel basis. The depth is a channel in which each pixel relates to a distance between the image plane and the corresponding object in the RGB image. Examples of the 3D RGB-D cameras include the Microsoft Kinect and Asus Xtion, which provide both colour and dense depth images.

#### 2.2.4 3D Laser Scanner Method

The laser scanner method is based on a similar principle of triangulation. It is the most widely used triangulation-based 3D scanner because of its simplicity and cost (Blais, 2004). The laser beam of the scanner is projected from a known position to a real-world object on a targeted surface, while the surface is monitored by a camera sensor from a second known position; resulting in the detection of a complete profile of points in a single frame. In other words, the laser system measures the range to points on objects within their field of view, as well as the bearing (angles) to those points within the instrument's coordinate frame. These systems usually output point clouds with 3D coordinates associated with each point. Knowing the relative positions and orientations of the laser and sensor allows the capturing of the 3D image geometry of the shape and/or appearance of the object at the targeted surface (Konolige & Nüchter, 2016).

The laser-based methods offer many advantages and have been known to be more reliable and accurate (Blais, 2004). This is because: they can easily generate bright beams with lightweight sources; infrared beams can be used unobtrusively; they focus well to give narrow beams; single-frequency sources enable easier rejection filtering of unwanted frequencies; single-frequency sources do not disperse from refraction as much as full spectrum sources; semiconductor devices can more easily generate short pulses (Christensen & Hager, 2016). In addition, laser scanner results in higher resolution and accuracy with a very large depth of focus defined by Gaussian beam propagation equations and a high power in small packages at the compromise of increased laser speckle noise (Blais, 2004). The use of laser scanner systems is rapidly gaining popularity due to its efficiency in capturing the existing conditions of an object in great details.

The characteristics of an optimal laser scanner or acquisition system include accuracy, speed, robustness and ease of use. Other characteristics to consider are the low cost of the system and the capability of capturing the colour properties of an object. In this study, the laser scanner method is the choice of acquisition because of the advantages it possesses. It can capture objects with good depth and intensity, saving the output as a point cloud.

## 2.3 Data Acquisition Techniques

The virtual acquisition of 3D data is accomplished with a variety of methods, techniques and algorithms, involving the use of both hardware and software components (Bi & Wang, 2010). Some hardware used include optical sensors (e.g. camera) and laser scanners. The optical sensors can be used as a single acquisition device (in the case of 2D images) or multi-sensor acquisition device. The multi-sensor acquisition setup consists of two or more optical sensors, or one optical sensor with another acquisition device/s (e.g. laser scanner). Sometimes, depth sensors are used in the multi-sensor acquisition setup for 3D texture acquisition as well. These sensors will need to be perfectly synchronised to avoid distortions and other irregularities. Acquiring the data with these sensors is done in two main parts. The first is the capturing of the image or data, while the second is the processing of the captured data with a software.

The software component consists of program interfaces for processing the acquired data. Usually, the software that is used with a data acquisition system is specifically written for the data acquisition hardware used. In other instances, the software is developed with a graphical interface such that program and subprogram structures and routines are represented by icons. Examples of such software include Cloud Compare and MeshLab. Both the hardware and software are synchronised during setup.

Furthermore, 3D data acquisition as applied in this study involves the two main parts mentioned above. That is, capturing the data and processing the data. Capturing the data simply involves translating a physical scene into digital machine-viewable format, while processing the data is a procedure that eliminates data adulteration – in the form of distortion, noise etc. – to give a fine data for further analysis. In addition, the application approaches of 3D data acquisition include acquiring 3D models from 2D data (such as photogrammetry), and directly acquiring the 3D models using tools and devices meant for such purpose. This has led to various studies yielding good 3D acquisition systems.

### 2.3.1 Structured Light

A structured light acquisition system comprises mainly of a projector and, at least, a camera. Acquisition is done by projecting known light patterns onto an object with the projector to obtain correspondences between projected and recovered patterns by the camera, and determine the 3D surface information of the object (Christensen & Hager, 2016; Konolige & Nüchter, 2016). To adequately reconstruct the geometry of the object's shape, the triangulation technique is used. In addition, the use of structured light in data acquisition is a popular approach that has been explored over the years.

Studies such as that of Gilboa *et al.* (2013), Grosman *et al.* (2008) and Ritz *et al.* (2012) used structured light in the acquisition of 3D data because of its ability to acquire an accurate depth image. While Grosman *et al.* and Ritz *et al.* used a two camera system, Gilboa *et al.* used a three camera system. The advantage of using more than one camera system is that it improves texture, depth and spatial resolution, which in turn improves the matching. To further improve the depth and geometry precision, Ritz *et al.* used a digital camera, a specialised industrial camera and a 1D mechanical lens shifter addon between the projector and the object. While the lens shifter contributed towards an improvement in resolution and depth precision, the addition of more equipment might increase system complexity, leading to a significant increase in the total cost of the system in general. In the case of Gilboa *et al.* with a projector and three camera system, two of the cameras were used to capture the geometry of the object while the third camera was used to capture the texture of the object. Just like the study of Ritz *et al.*, it improved depth and texture but leads to system complexity and high cost.

However, because of the susceptibility of structured light to environmental light interference, sensor readings and information could be distorted and lead to occlusion and other errors (Konolige & Nüchter, 2016). For this reason, structured light cannot be efficiently used in an outdoor environment. In addition, because some issues with cameras used in structured light are that there is often too little texture, especially indoors, to make reliable matches, more or better sensors are desired. This leads to several cameras being used to increase robustness and depth, often leading to a complex system setup. Thus, to solve these problems, other methods have been considered to improve the performance.

### 2.3.2 Time-of-Flight

The Time-of-Flight (ToF) technique measures the distance between a sensor and an object. It does this by emitting signals from the sensor towards the object, while the object reflects the signals back to the sensor. The time difference between the emission of the signal and the return of the reflected signal estimates the ToF. While different signals – such as sound, radio frequency and light among others – can be used, the use of light is focused on in this study.

Various studies have employed ToF. Among them are the studies of Cui *et al.* (2013), Reynolds *et al.* (2011) and Schober *et al.* (2017). Cui *et al.* and Schober *et al.* both used one ToF camera for acquisition while Reynolds *et al.* used two ToF cameras. The number of cameras used did not really affect the quality of data capture. Reynolds *et al.* used two ToF cameras with a supervised machine learning-based approach to improve depth accuracy. This approach used a random forest regressor to improve per-pixel confidence measure. However, the method may not be easily applicable to a wide range of object acquisition. This is because training a wide range of objects is required for supervised learning, thus raising a likelihood for complexity and poor resolution.

On the other hand, the study of Cui *et al.* reduced complexity significantly. Cui *et al.* used a ToF camera to capture images of an object and applied an approach that results in a high-resolution 3D depth acquisition. While this approach sufficiently improves the resolution of the image, the quality of the data and accuracy remains an issue. For instance, objects with specular surfaces returned poor resolution data after capture. Hence, Schober *et al.* attempted to solve this problem.

Schober *et al.* focused on a probabilistic approach that integrates ToF observations with that of previously captured information of an object using a dynamic ToF camera in real-time. The dynamic ToF camera uses different measurement patterns in two successive time steps and integrates multiple measurements in time to improve the depth accuracy. This approach deviates from the traditional operation of static ToF cameras which uses the same measurement patterns in each time step and uses the captured information only once to estimate depth. Thus, using the dynamic method seemed to improve computational and data acquisition efficiency. However, managing the camera motion and saving previously captured image stamps might affect computational efficiency and lead to system complexity.

In general, ToF sensors that use light are safe to the eyes and can attain higher speed and longer range. However, ToF sensors could be quite expensive, noisy and have low resolution. In addition, it is challenging to use them to acquire high-quality data as they have low spatial resolution and were not designed for such purposes, but for object detection and distance estimation. Hence, the laser scanner technique attempts to solve this challenge.

### 2.3.3 3D Laser Scanner

3D laser scanners based on triangulation are active scanners that use laser light to scan objects and the environment to capture information. The laser scanner projects a laser stripe onto the object and a camera monitors the object surface to locate the laser stripe. The location of the laser stripe differs as seen on the camera's field of view. Thus, the laser stripe, laser scanner and the camera form a triangle, from whence the name triangulation was derived. Knowing the length of one side of the triangle, the distance between the camera and the laser scanner and the angle of the laser scanner, other parameters can be determined that will aid the acquisition of a 3D geometry. These systems are very good and efficient methods to accurately acquire 3D point clouds of object surfaces (Konolige & Nüchter, 2016).

Because of the high accuracy derived in the acquisition process, laser scanning has become one of the standard optical measurement methods, offering advantages over other methods. The rapid progress of accurate and low-cost laser scanning systems has encouraged more studies in this domain (Christensen & Hager, 2016). Among a host of studies, those that have applied 3D laser scanners include that of Banerjee *et al.* (2013), Chen *et al.* (2013), Díaz-Marín *et al.* (2015) and Isa and Lazoglu (2017). These studies used a 3D acquisition system that comprises of a camera and a laser scanner to acquire point cloud data of an object surface. While the accuracy of the acquisitions was good, the accuracy of the laser acquisition system depends on an accurate calibration of the camera and laser scanner.

Generally, the technique used for 3D data acquisition depends on the accuracy and distance capability required by the device or sensor. For short distances of about a few inches, structured light could be used. Where high accuracy is a requirement, the laser triangulation technique is usually preferred. However, where the distance is beyond the range that triangulation can effectively work with, ToF with some system modification is employed. In this study, laser triangulation is used for high accuracy since work is done within a short distance.

## 2.4 Pottery Reconstruction

Pottery preservation is an important process in the field of archaeology. This is because pottery, especially the excavated ones, inherently provide valuable data for archaeological studies (Stamatopoulos & Anagnostopoulos, 2016). In addition, due to the nature of the pottery with respect to how they were made, they possess properties that make them resistant to decay, wear and tear (Barclay et al., 2016; Stamatopoulos & Anagnostopoulos, 2016). Thus, archaeologists can recover pottery during excavation either as a complete pot or fragments, but hardly in their original state.

The preservation of pottery is mainly carried out either manually or digitally. The manual way involves physically reassembling the pottery and then drawing it. Drawing the pottery helps the architect to be able to reproduce any design on the body almost perfectly. But this leaves room for extrapolation to correctly reproduce the pottery design from observation. In addition, while the manual recovery makes the archaeologist’s work meaningful, it is nonetheless time and effort consuming (Barrère, 2016; Marchetti et al., 2017). As a result, technology approaches have been utilised to digitally preserve pottery. Such technologies include computer visualisation, computer graphics, digitisation, modelling and photogrammetry among others (Ch'ng, 2015; Maver, 2001). In this study, 3D digitisation has been utilised, while focusing in on 3D pottery reconstruction.

Pottery reconstruction is an approach towards pottery preservation that utilises image processing techniques for this purpose. Over the years, the virtual reconstruction of pottery has been studied using a variety of algorithms, techniques and methods. The various approaches work optimally for the scenario in which they are applied, but with the possibility of modifying them for other scenarios. While these approaches have significantly improved studies in their niche, there has been no "one-size-fits-all" solution. Thus, studies in this area is still an open issue.

The study on pottery reconstruction has improved over the years as a result of new and improved methods and approaches of inquiry and implementation. The study, which began with a tedious manual process, has progressed into an easier semi-automated and automated process that uses technology to attain its goals. It should be noted that to solve issues inherent in the manual process of pottery reconstruction, the virtual reconstruction of pottery needs to be done accurately for the reconstruction to be good enough for study and research purposes. This has directed the focus of the researches being carried out in this domain. Thus, technology methods mainly use 2D and 3D approaches.

### 2.4.1 Reconstruction in 2D

The reconstruction of 2D objects could be said to have been inspired by works on jigsaw puzzles. In fact, some methods used in the studies of Burdea and Wolfson (1989), Chung *et al.* (1998), Goldberg *et al.* (2004) and Nielsen *et al.* (2008), such as Euclidean transformation, matching, least squares estimation, neighbour and similarity search, are now used in 2D reconstruction but with a different perspective.

Because the reconstruction of archaeological pottery was a concern, many studies have attempted to solve this problem through automated methods and extraction of salient features and descriptors from pottery, with the aim of overcoming some of the practical problems related to the manual reconstruction. One of such studies is that of Smith *et al.* (2010) which investigated methods of classification and reconstruction of images of excavated archaeological ceramic fragments based on their colour and texture information. This was achieved by using Scale Invariant Feature Transform (SIFT) and a feature descriptor (Smith *et al.*, 2010).

Likewise, the study of Puglisi *et al.* (2015) proposed a system that uses SIFT but with a different approach. The system uses image processing techniques to automatically identify and analyse images of the structural components of pottery through “optical microscopy”. As a result, the suitable features can then be computed and analysed for classification purposes. Both Smith’s and Puglisi’s studies aim to segment the acquired images of thin artefacts and extract their features for classification. To achieve this, the authors chose to use SIFT feature point method, where the feature points are extracted and matched with related pairs (Puglisi *et al.*, 2015). While this system generally improves on the ones before it, it falls short in providing a high and acceptable accuracy.

Similarly, the study of Makridis and Daras (2012) explores the classification problem by focusing on a technique for accurate and automatic classification of pottery. The technique was implemented in four steps namely: feature extraction, feature fusion, feature selection and classification. This approach attempted to reduce the computational complexity problem with a “bag of words (BoW)” method that uses the features extracted from the images to create a “global descriptor” vector of the images (Makridis & Daras, 2012). However, while this approach demonstrates efficiency, how it reduces computational complexity and increases accuracy is not clear.

With these studies and more, it is apparent that 2D object reconstruction works well for low-level implementation when compared with 3D. Where fine details visualisation and finesse are concerned, 2D reconstruction may not be adequate. Thus, exploring 3D reconstruction to solve challenges that 2D reconstruction could not solve became desirable.

### 2.4.2 Reconstruction in 3D

One major goal in 3D reconstruction is to recover the geometric structure of an object from the captured images or point clouds (Moons, Gool, & Vergauwen, 2010). 3D reconstruction is the process of capturing the shape, orientation and appearance of an object. This can be done using different methods. As a result, there has been various studies on 3D reconstruction built on extracting and matching feature points with the goal of improving visualisation (Szeliski, 2011).

The studies of Belenguer and Vidal (2012), Hermoza and Sipiran (2018) and Roman-Rangel *et al.* (2016) are notable in this area. Hermoza and Sipiran focused on the problem of incomplete and damaged archaeological objects by applying a novel approach with machine learning methods to repair damages on symmetric and asymmetric objects, as well as improving the computational time to do such restorations. This was addressed by proposing a shape completion network. The 3D encoder of the shape completion network compresses the input voxel grid with a series of 3D convolutional layers, and then concatenates the compressed values with the embedded information about the input class label. The 3D decoder is thus able to predict the voxel output using 3D transposed convolutional layers (Hermoza & Sipiran, 2018).

A custom-built dataset comprising 3D scanned objects, 3D CAD objects and ModelNet dataset was used to evaluate the network model. The results showed an improvement in performance on different network settings against the test data and a significant reduction in output loss from the input loss. In addition, the network model could recover most of the missing information, even when more than half of the voxels were missing.

However, some unexpected shapes different from the original were reconstructed, and the amount of data used seems not to be adequate given the unexpected restorations. That some objects were restored to an unexpected form shows that more studies are required. Also, from the direction of the study, it will be difficult to reconstruct 3D data with precise geometric and photometric properties as the precision of the reconstruction is dependent on datasets.

Furthermore, Roman-Rangel *et al.* (2016) proposed a statistical descriptive approach using Histogram of Spherical Orientations (HoSO), a method for the automatic classification and analysis of 3D surfaces of pottery. This method analyses the external frontal view of the pottery alone, processes 3D data by using only the points coordinates without using colour, texture or faces, and efficiently encodes the information from the points coordinates. They posit that the advantages include substantial time reduction in pottery organisation and a simple method of acquiring the image (Roman-Rangel *et al.*, 2016). However, the approach does not seem to be robust and accurate for a large dataset.

Thus, a robust 3D virtualisation of pottery at a high accuracy is an interesting task for pottery reconstruction and digital preservation because the fine details could retain information about how the artefact was made, leading to an understanding and improvement in the reconstruction process. Notably, the classification stage makes reconstruction easier and achievable, with the reviewed studies focusing on automatic classification. However, how these automatic approaches fare with respect to classification, and reconstruction in general, requires validation.

Furthermore, the complexities inherent in 3D reconstruction depend largely on the approach followed and the assumptions made. For example, while a ToF acquisition system can be used to acquire excavated pottery, it is preferable to consider an acquisition system like laser scanner that can acquire objects accurately at the required distance. This is because an accurate acquisition with ToF will result in a complex system in addition to other issues. Thus, the reconstruction process should be simplified as much as possible by considering the methods used and techniques applied, as well as the type and size of the data used. As a result, this study investigates a path towards 3D reconstruction and digitisation of archaeological pottery with a high and improved accuracy as a goal.

## 2.5 Methods of Reconstruction

Over time, various methods have been used for the virtualisation of pottery. The initial methods may only have attained good results within their specific contexts, they nonetheless form the bedrock for further and more accurate methods. In addition, the improved methods are as a result of advancements in 3D acquisition and reconstruction procedures. With the advancement of these procedures come the challenge of large data processing and analysis. Besides, having more data presents an advantage of good visualisation of reconstructions of pottery. Some of the methods of pottery reconstruction include symmetry-based methods, template-based methods and feature-based methods among others.

### 2.5.1 Symmetry-based Reconstruction

Given a geometric object $S$ in a plane, a symmetry of $S$ is a function $f$ from $S$ to itself such that the distance between any two points $x$ and $y$ of $S$ is the same as the distance between the transformed points *f(x)* and *f(y)*, thereby preserving the distance between each pair of points (Gowers, Barrow-Green, & Leader, 2010). In essence, a symmetry of *S* is a function that preserves the structure of *S*, which is the distance between any two of its points.

Consequently, the symmetry-based reconstruction is one that estimates the symmetry plane of a defective object and replicates the complete part on one plane to the defective part on the other plane in an organised manner without changing the overall shape (Gregor et al., 2014). This is usually done to restore or repair objects with missing parts, either *a priori* or *posteriori*, without the need for external data. It leverages the symmetric nature of an object to synthesise the missing parts of the object by assuming the existence of one symmetry plane.

For example, the studies of Kampel and Sablatnig (2003) and Sablatnig and Kampel (2002) used the symmetry-based method. Kampel and Sablatnig focused on the virtual reconstruction of a rotationally symmetric pottery from a pottery fragment only. This approach attempts to estimate the correct orientation of the pottery fragment to get the exact position of the fragment on the original pottery. Two opposite views of the fragment (outer and inner) were captured with a projector scanner. The projector scanner used the shape from structured light method to acquire the geometric data for the purpose of registering them into a single fragment. According to the authors, the registration of the two views was done with the Iterative Closest Point (ICP) algorithm by estimating the transformation that minimises the mean square distances of the corresponding points between the surfaces of the two views (Kampel & Sablatnig, 2003; Sablatnig & Kampel, 2002). But how this was done with ICP is not clear.

While the registration of the inner and outer views of the fragment results in the extraction of the fragment profile for reconstruction of the pottery about the axis of rotation, it can be said that the alignment of the views was done based on the direction of the rotational axis of symmetry. Thus, an accurate reconstruction of the pottery fragment cannot be said to have been effected. This is because two views of a pottery fragment are not enough to accurately reconstruct it for visualisation as certain parts will have no data due to occlusion. But since the goal of the authors was to extract the profile, this limitation could be overlooked given this consideration.

Additionally, in the reconstruction of the pottery, the similarities of profiles were used to synthesise and completely reconstruct the pottery. However, the reconstruction of the pottery could only be performed if the type and class of pottery the fragment belongs to is known. This is a major concern for objects that are not symmetric in nature. Moreover, from the author’s conclusion, the registration error shows that more work is necessary. Hence, efforts to improve the outcome of their study with different data is and should be ongoing.

Furthermore, due to the challenges of symmetry detection inherent in incomplete geometry, Sipiran et al. (2014) proposed a vote-based algorithm that uses a heat diffusion function to detect symmetries in 3D shapes with missing parts, and then selects corresponding points across two surfaces of the 3D rigid object. The algorithm detects local features for symmetry detection of partial data and uses the features to depict the local geometry in a way that it can synthesise the missing data. It also detects symmetry planes by computing and validating the veracity of the symmetry planes. It does this by using the curvature in each point on the object’s surface to create a voting system, then computes a support system that will filter the points needed for voting for a plane.

The algorithm was tested with two sample points using the following criteria: points identified on both sides of the plane, points approximately equidistant from the plane, points orthogonal to the plane, symmetric normal and points geometrically similar. As demonstrated with 3D meshes, this method works best with objects that have features. This is because if features are not detected on both planes, correspondences cannot be established, and symmetric planes cannot be computed. However, the symmetries are estimated and not accurate. These observed challenges have led to the exploration of other methods of reconstruction such as the template-based reconstruction method.

### 2.5.2 Template-based Reconstruction

Unlike symmetry-based reconstruction that works with only symmetric objects, template-based reconstruction works with both symmetric and asymmetric objects. It is, to a large extent, based on the principles of template matching, which defines a measure or cost function to find similarity between portions of a template image with another target image. It then estimates the parameters that will transform the template onto the target in a way that will minimise the distance between them.

Template-based reconstruction is one that restores incomplete or defective objects by searching for a geometrically similar template from datasets in a database or repository (Gregor et al., 2014; Shu-Yu et al., 2015; Yin, Wei, Li, & Manhein, 2011; Zhang, Yu, Manhein, Waggenspack, & Li, 2015). The goal is to compute the similarity evaluation as an optimisation problem (Gregor et al., 2014). In searching for a geometrically similar model in the database, if an object is severely damaged to the point that significant parts are missing and the exact template object as the defective one is not available, the closest similar template is used (Yin et al., 2011). This is done by identifying and matching local features. However, a template having high geometrical similarity with the target is desirable. Some template-based reconstructions use one template only and discard the database because the target object that is meant to be reconstructed is known, along with its main features and information. Such single template reconstructions include the works of Du et al. (2016) and Yin et al. (2011). All these studies used the template-based method as part of a multipronged approach to reconstruction. They used information from complete and fractured surfaces of an object to reconstruct the fragments into a whole. In order to reduce high computational cost, the template-based aspect is done in two steps namely feature extraction and correspondence matching.

The feature extraction step involves detecting and extracting features from the surface of the object. The goal is to identify salient feature points and extract the features of these points. In a bid to discover the best approach to extracting salient feature points, different techniques and approaches have been explored. For example, Yin et al. (2011) extracted salient feature points using the slippage features, a feature detection technique. The curvature of the surface of the extracted features was computed to increase robustness in the presence of noise, thereby improving the matching process. Shu-Yu et al. (2015) used the Hough transform to identify feature points under noise and extract features to reduce computational complexities. On the other hand, Zhang et al. (2015) used the Intrinsic Shape Signature (ISS) detector to identify and extract feature points by computing the covariance matrix of the surface of the object because of its repeatability and efficiency. In the case of Gregor et al. (2014) and Du et al. (2016), a feature extraction algorithm based on Heat Kernel Signature (HKS) was used because of its flexibility and robustness. The algorithm extracts feature points that have the largest changes in HKS value, since the HKS energy changes according to Gaussian curvature. Each of these techniques and approaches possess advantages in their individual implementations, but limitations still exist. Thus, the various techniques have been explored.

For correspondence matching, Yin et al. used the spin image technique to compute and describe the surface geometry with surface normals on the extracted features. Feature points on the template and target objects with similar spin images and similar principal curvatures tend to be corresponding points. Thus, a coarse matching between corresponding points is effected by transforming the template object to the target object. Shu-Yu et al. used “the thresholding of the Otsu algorithm” to improve accuracy, while Zhang et al. used the Signature of Histograms of OrienTations (SHOT) shape descriptor to compare feature points on the surface of the template and target objects. In addition, Zhang et al. used the RANSAC algorithm for correspondence matching to pair detected corresponding feature points on the template and target objects by computing the Euclidean distance between corresponding points. Gregor et al. and Du et al. used the HKS algorithm to describe the objects’ salient features. Two points are correspondent if their HKS curves match well, which means that their treads are nearly equal. The variance of the Euclidean distance of corresponding pair of points is finally used to evaluate the differences between two HKS curves, to find the closest curve or the best match for a given point. In all these cases, the point pairs without similarity are removed because they are not corresponding pairs.

Furthermore, the use of machine and deep learning in template-based reconstruction attempts to solve some problems inherent in the afore-discussed studies. The studies of Dai et al. (2017), Hermoza and Sipiran (2018) and Yang et al. (2017) used Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) to reconstruct damaged objects in their approach. The idea was to develop a shape completion network (3D encoder and 3D decoder) that represents 3D objects as a voxel grid, and an adversarial network architecture (generator and discriminator). To train the network, pairs of complete objects were captured while fractured objects were simulated from the complete objects. The simulated fractured object then served as input while the network predicts the complete object as output. To improve the restoration process, the completion network loss and the adversarial loss were combined during training to aid the outputs of the network.

The main strength of this approach is the improvement in performance and computational time to do restorations. The network can predict accurate 3D shapes and structures with fine details (Hermoza & Sipiran, 2018). Also, it can learn 3D shape restoration using an end-to-end completion method. This leads to an improvement in accuracy for shape retrieval tasks (Yang et al., 2017). However, the accuracy of the reconstruction itself needs improvement because unexpected shapes different from the original template were reconstructed. Also, a large amount of dataset is required because the performance and evaluation of the network relies on having a large amount of data. The data used in these studies are synthetic datasets from virtually scanned 3D CAD models instead of real-world datasets (Hermoza & Sipiran, 2018; Yang et al., 2017). This makes it hard for the network to work accurately with real datasets with features. To then improve the performance, it might require low resolution data. Increasing the output resolution might result in significant increase in computational costs, making the optimisation of the training process more difficult (Dai et al., 2017).

While template-based reconstruction has its strong points, it also has some limitations. For example, for template-based reconstruction to have a good output, it has to be used in conjunction with other techniques or methods. This might lead to system complexity. Although, it can be used alone, but only for a low-level output. Another major challenge with template-based reconstruction is that it requires a high computational power, which can be time-consuming. As a result, other approaches of reconstruction are being explored.

### 2.5.3 Feature-based Reconstruction

Feature-based reconstruction is one that extracts an object's features, such as shapes, edges, textures, colours, keypoints, to match with a target object in order to restore the complete object. The features provide rich information that can help in distinguishing between object surfaces and used as descriptions for matching and alignment. Feature-based reconstruction involves feature detection, feature extraction, feature description, correspondence matching and registration. These steps are exhaustively discussed in chapter four of this thesis.

Some of the studies discussed in the template-based reconstruction also applied feature-based reconstruction alongside. They include Shu-Yu et al. (2015), Yin et al. (2011) and Zhang et al. (2015). Feature-based reconstruction is robust and efficient. However, its main limitation is that it cannot work efficiently when an object's surface have fewer features than required.

## 2.6 Chapter Conclusion

This chapter presents a detailed review of archaeological pottery reconstruction, providing a comprehensive overview of state-of-the-art in acquisition methods, acquisition techniques and methods of performing pottery reconstruction. The use of state-of-the-art methods to acquire object data is quite accurate but only within their context of usage and makeup. While some methods can acquire objects at a distance accurately, they fall short in doing same for objects in proximity. However, each method provides different and unique benefits in their distinct and dynamic scenario. This unique benefit is dependent on the acquisition technique(s) used. The acquisition techniques reviewed were structured light, time-of-flight and 3D laser scanner. One or more of these techniques are applied in data acquisition to have robust data for processing. But it is not always the case as the accuracy and robustness of the data is dependent on the quality of the equipment used and the accuracy of the calibration done.

Furthermore, the data reconstruction approaches were discussed based on 2D and 3D reconstructions. The techniques and approaches used, as well as the data differ significantly in some cases. In addition, the methods of reconstruction as classified in this thesis were discussed. They are symmetry-based, template-based and feature-based reconstructions. Their strengths and limitations were presented based on previous work in the areas. While some of the reconstruction methods work well in a given scenario, they nonetheless have unique challenges. For example, symmetry-based reconstruction can only successfully reconstruct symmetric objects and failing if the object is not symmetric. It is on this background that a discussion of 3D acquisition of pottery is based. This is discussed in the subsequent chapter, chapter three.

# CHAPTER 3: 3D DATA ACQUISITION OF POTTERY

## 3.1 Introduction

Building from the background on archaeological pottery reconstruction in chapter 2, this chapter outlines the data acquisition approach and the techniques used. It presents the acquisition system and its specification and how the technical details may determine a lot of the data output. It culminates with the data that was acquired for this study.

To this effect, the chapter begins with an outline of the acquisition system, stating the laser scanner and camera, as well as the setup employed, in section 3.2. This is followed, in section 3.3, by the discussion of the calibration of the various components and devices of the acquisition setup. At this point, presenting the process involved with acquiring data with the acquisition system is provided in section 3.4. The chapter ends with a conclusion in section 3.5.

## 3.2 The Acquisition System

The data acquisition stage is critical to the entire stages of a 3D reconstruction task. At this stage, objects are scanned and virtualised into 3D point clouds. The precision of the process goes a long way to determine the accuracy of further procedures such as reconstruction and reassembly. Virtualising objects to reflect majority of its original information is important in carrying out studies. As noted by Gilboa *et al.* (2013), when objects are virtualised without key information, data may be lost. In addition, it is important to use the right instruments and tools for this process. Some tools are good for virtualising objects just for visualisation purposes. Others will require that the fine details of the objects be captured, thus enhancing analysis and further processes. Using appropriate tools and instruments is good for the acquisition process as it could lead to a high accuracy virtualisation output. As a result, laser scanners are widely used to acquire data with high accuracy within an acceptable distance. The laser scanners will generate dense unstructured point clouds of an object. To attain the virtualisation process in this study, a low-cost off-the-shelf acquisition setup, consisting of a line laser, RGB camera, Arduino UNO and other embedded devices and components, was used.

### 3.2.1 Z-laser Line Laser and Mercury RGB Camera

The line laser used is a standard and focusable Z-laser Z15M18S3-F-640-LP60 series with an output power of 15mW, wavelength of 640nm, intensity control of 32 steps and an LP60 optics that projects a single line optical pattern. The projected optical pattern has a homogeneous distribution of intensity along the line. The intensity can be adjusted by means of a simultaneous analogue modulation and digital Transistor-Transistor-Logic (TTL) trigger with a switching frequency of up to 1kHz. This allows an adjustment of the intensity and switching of the laser at intervals. The use of TTL modulation promises a convenient and standardised method for switching or triggering the laser on and off, thereby yielding clean data.

Additionally, a compact Mercury RGB camera MER-231-41U3C-L with resolution of 1920x1200, frame rate of 41 frames per second (fps) at full resolution and power consumption below 2.5W, was used. The camera is equipped with an infrared filter with a cut-off frequency of 700nm, making it easier to synchronise the camera with the line laser via a software. In addition, the camera is precise in operation with extremely low noise and perfect colour conversion.

### 3.2.2 Acquisition Setup

The line laser and the camera can be mounted in four ways namely ordinary, reversed-ordinary, specular and look-away (SICK, 2011), as shown in Figure 3.1. The ordinary setup has the camera mounted perpendicular to the object mount while the laser is mounted at an angle to the side. This method has the highest resolution but results in miss-registration during operation. On the other hand, the reversed-ordinary setup has the laser mounted perpendicular to the object mount while the camera is mounted at an angle to the side. This method does not result in miss-registration but has a slightly lower resolution than the ordinary setup. Another setup is the specular one that has both camera and laser mounted on opposite sides of the normal. Because it requires less illumination than the other setups, it can be used to capture objects with dark or dull surfaces quite well during operation. Lastly, the look-away setup has both camera and laser mounted on the same side of the normal, unlike the specular one. This method is useful in the avoidance of unwanted reflection. However, it requires more illumination than the other methods, as well as resulting in a lower resolution.

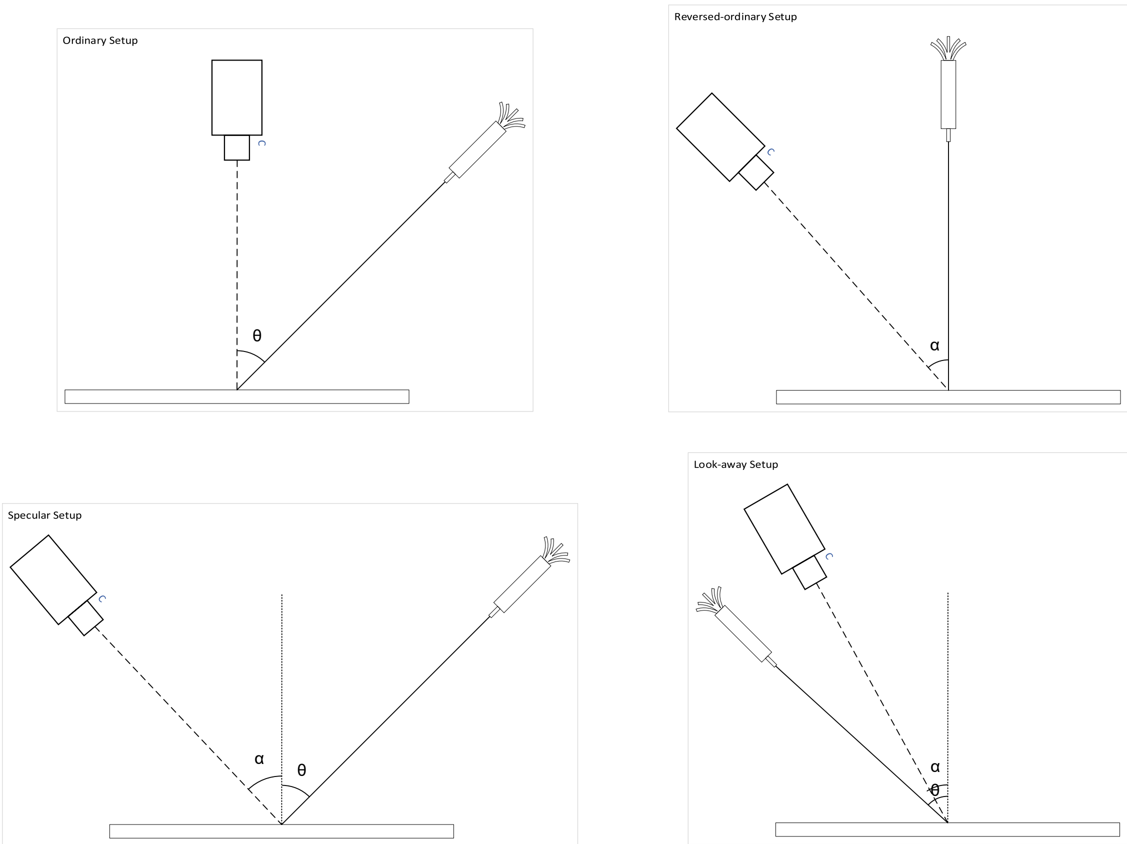


**Figure 3.1: Main setup orientations for the camera and laser**

In this study, the reversed-ordinary setup, shown in Figure 3.2, was adopted since a better accuracy in registration is desired. As the lowered resolution does not impact the registration, the setup then allows for flexibility resulting in an improved pottery virtualisation and registration process.

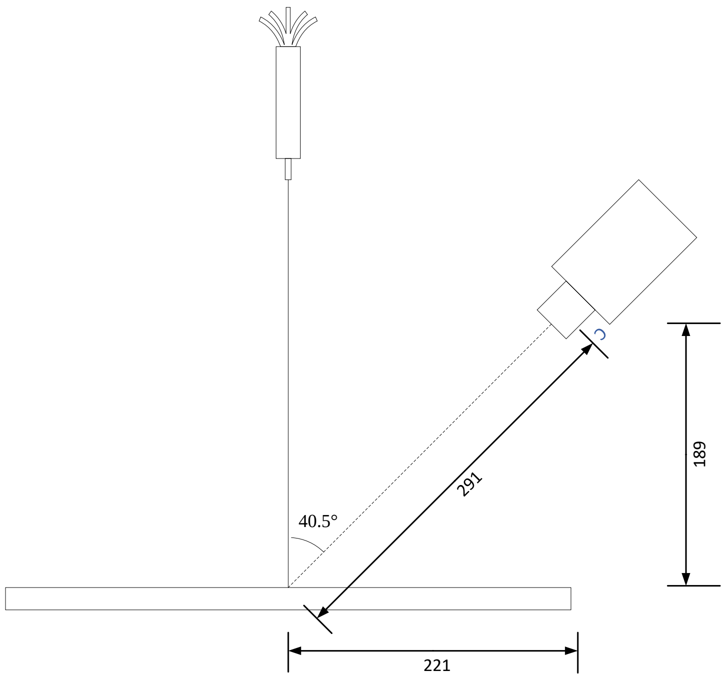


**Figure 3.2: Reversed-ordinary setup for the camera and laser**

A representation of the acquisition setup is shown in Figure 3.3. The setup, which was used for a different project in our research group, was modified to suit its use in this study. The line laser and the camera were mounted on an aluminium frame, with the line laser perpendicular to the horizontal sliding table while the camera was set up at an angle and facing the sliding table. The sliding table is driven by a stepper motor beneath it. The stepper motor, camera and line laser were synchronously controlled by the Arduino circuitry. The camera and the Arduino circuitry were connected to a laptop via USB, with illumination positioned in a way that it does not flash into the lens of the camera. While illumination was provided by a lamp, it was ensured that the setup was in a controlled light room or environment and not directly under sunlight, as sunlight can influence the quality and accuracy of the scans, leading to noise and occlusion. Exposure to uniform and homogeneous light is preferred. But for the system to work synchronously, it had to be calibrated first, as this would also simplify the reconstruction process.

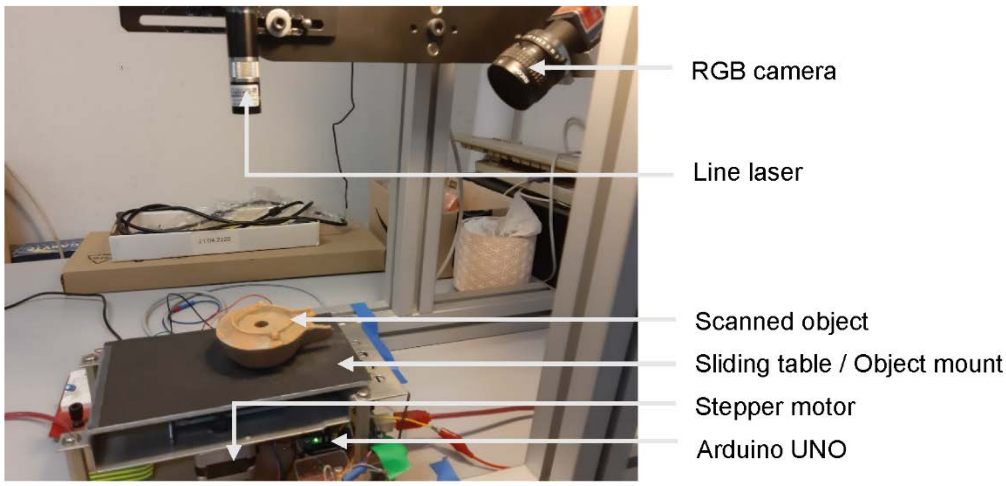


**Figure 3.3: Data acquisition setup**

## 3.3 Calibration

Camera calibration is the process of estimating some desired parameters of a camera to capture accurate images. To estimate these parameters, 3D world points and their corresponding 2D image points are required. These correspondences can be gotten by using multiple images of a calibration pattern, such as a squared checkerboard or circular chessboard. The camera parameters can be estimated with the correspondences. The desired parameters to be estimated include camera intrinsics, extrinsics and distortion coefficients. These parameters are used to correct lens distortion, measure the size of an object in world units, or determine the location of the camera. To evaluate the accuracy of the estimated parameters, the relative locations of the camera and the calibration pattern can be plotted, the reprojection errors and the parameter estimation errors can be estimated. Then, the calibrated camera can be used to acquire images of different views for 3D reconstruction.

To calibrate the system, a 1920x1200 pixels Mercury U3V camera, a cyclic chessboard pattern and a sawtooth image were used to estimate camera intrinsics, extrinsics and lens distortion parameters using the Brown's distortion model (Brown, 1966). Twenty chessboard images and four sawtooth images were captured with the camera and saved in PNG format, ensuring that they are within the working distance of the camera and not blurry. This is because the precision of the calibration depends on the camera parameters. The input parameters include the camera pixel resolution, working distance (WD), focal length, field of view (FOV) and angle of view (AOV), derived using the following equations:

$$\textbf{Sensor area width (mm)} = \boldsymbol{image\ width * pixel\ size} \tag{3.1}$$

$$\textbf{Sensor area height (mm)} = \boldsymbol{image\ height * pixel\ size} \tag{3.2}$$

$$\textbf{FOV W (mm)} = \boldsymbol{image\ width * pixel\ resolution} \tag{3.3}$$

$$\textbf{FOV H (mm)} = \boldsymbol{image\ height * pixel\ resolution} \tag{3.4}$$

$$\textbf{AOV W (°)} = \boldsymbol{2tan^{-1}(\frac{FOV\ W}{2WD})} \tag{3.5}$$

$$\textbf{AOV H (°)} = \boldsymbol{2tan^{-1}(\frac{FOV\ H}{2WD})} \tag{3.6}$$

where FOV W is the width of the field of view, FOV H is the height of the field of view, AOV W is the width of the angle of view, AOV H is the height of the angle of view and WD is the working distance from the lens to the object.

A developed calibrator adapted from the approach of Heikkilä and Silvén (1997), Scaramuzza and Siegwart (2007), Urban *et al.* (2015) and Zhang (1999) was used to estimate the desired values of the input parameters. To compute the intrinsic parameters, the chessboard images were added to the calibrator, ensuring that the width and height of the pattern and image, as well as the distortion coefficient types were inserted (2 radial and 2 tangential coefficients). The radial and tangential distortions can be computed using equations (3.7) and (3.8) respectively (Heikkilä & Silvén, 1997; Z. Zhang, 1999):

$$\begin{bmatrix} \delta u_i^{(r)} \\ \delta v_i^{(r)} \end{bmatrix} = \begin{bmatrix} k_1 \\ k_2 \end{bmatrix} \begin{bmatrix} \tilde{u}_i r_i^2 & \tilde{u}_i r_i^4 \\ \tilde{v}_i r_i^2 & \tilde{v}_i r_i^4 \end{bmatrix} \tag{3.7}$$

$$\begin{bmatrix} \delta u_i^{(t)} \\ \delta v_i^{(t)} \end{bmatrix} = \begin{bmatrix} p_1 \\ p_2 \end{bmatrix} \begin{bmatrix} 2\tilde{u}_i \tilde{v}_i & ({r_i}^2 + 2{\tilde{u}_i}^2) \\ ({r_i}^2 + 2{\tilde{v}_i}^2) & 2\tilde{u}_i \tilde{v}_i \end{bmatrix} \tag{3.8}$$

where $k_1$, $k_2$ = coefficients of radial distortion; $p_1$, $p_2$ = coefficients of tangential distortion; $u$, $v$ = image coordinates; $\tilde{u}$, $\tilde{v}$ = image projection; $\delta u$, $\delta v$ = $u - u_0$, $v - v_0$; $u_0$, $v_0$ = image centre/principal point; $r = \sqrt{\tilde{u}^2 + \tilde{v}^2}$; $i$ = number of the images (i.e. 1, 2, 3, …).

The calibrator detects the centre of each circular pattern for all the images (see Figure 3.4) and computes the reprojection errors (see Figure 3.5). Three images were discarded for having high reprojection errors while 17 images were used to compute the intrinsic parameters.

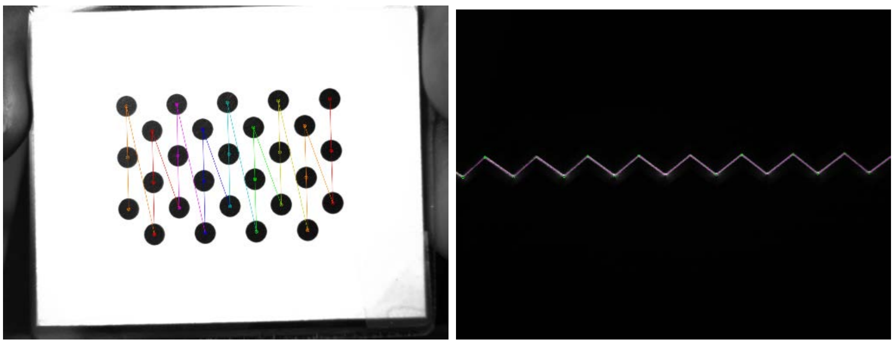

**Figure 3.4: Projected points on the chessboard and sawtooth images**

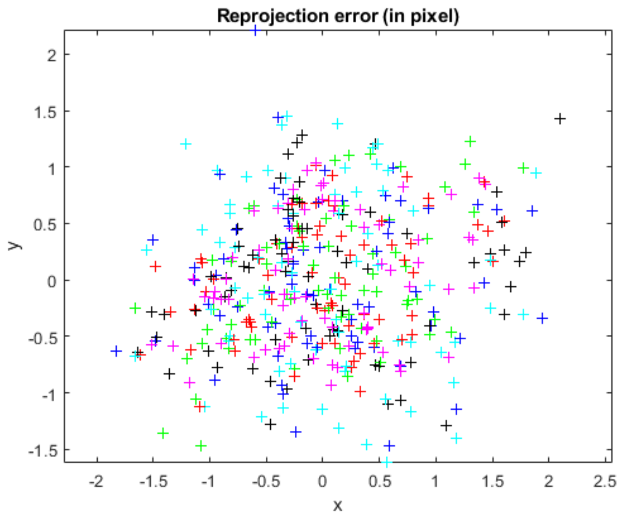


**Figure 3.5: Computed reprojection error in pixels**

With the intrinsic parameters computed, the report was exported as an XML file and added to the calibrator along with the sawtooth images to compute the extrinsic parameters. The pose estimation parameters (width and height of sawtooth) were inserted. The calibrator detects the tangents of the sawtooth images (see Figure 3.4) and computes the extrinsic parameters. The calibration report was exported as an XML file, which contains the computed parameters.

The computed parameters include the orientation of the camera at 40.5°, the baseline at 221mm, the height of the camera to the sliding table level at 189mm and the working distance, which is the distance between the lens and the object mount, at 291mm (see Figure 3.2). Also, the Root Mean Squared Error (RMSE), which is the metric used for the reprojection error, along the $X$ and $Y$ coordinates of the image are 0.0015mm and 0.0009mm respectively. The mean RMSE of reprojection is 0.0018mm. As a rule, the mean reprojection errors of less than 0.2mm are considered acceptable. These parameters are used to compensate the effects of lens distortion during the pottery scanning process.

## 3.4 Acquiring the Pottery

With the calibration completed and the line laser and camera synchronised, the system was ready for acquiring the data. It was ensured that the laser line was parallel to the edge of the sliding table as it reduces distortion and aids the alignment process. The goal was to acquire the pottery's geometry as the sliding table moves from one end to another in order to get every viewing angle as much as possible as shown in Figure 3.6.

**Figure 3.6: Samples of the scanned pottery**

Placing the pottery on the object mount, multiple exposures of the pottery's complete surface were acquired using the acquisition setup with a 16GB RAM Core i7-6500U laptop @ 2.50GHz. The scanning and the conversion of the data to point cloud was carried out by a script written for the virtualisation software of the camera. Due to occlusion occurring, many exposures of different viewpoints were acquired so that the occluded parts will be compensated for after registering the point clouds. While many exposures were acquired, about 24 were used for the reconstruction process. An illumination source was directed at the pottery at about 400mm distance to ensure that colour and shape information were well captured.

## 3.5 Chapter Conclusion

In this chapter, the data acquisition approach employed in this study to acquire the pottery was discussed. Since the nature of the problem under investigation pertained to technical innovations, the acquisition system is a bedrock of the whole reconstruction process. The laser scanner and camera used for the acquisition were presented, along with their specifications. The laser scanner technique was chosen for this study because of its accuracy and robustness in proximity. The setup of the equipment was discussed, highlighting the various parts that make the setup. In addition, the four various setups that can be used for the line laser and the camera to be mounted for laser scanner acquisitions were highlighted. They are the ordinary, reversed-ordinary, specular and look-away setups. The various setups were explained and the choice of using the reversed-ordinary setup was highlighted. Furthermore, to be able to carry out experiments, a calibration of the system was necessary, highlighting the various steps in the process. This therefore paved the way for acquiring the pottery used in this study. Multiple views were acquired, ensuring that there was appropriate illumination. Thus, the registration of these views are implemented and presented in the following chapter, chapter 4.

# CHAPTER 4: REGISTRATION OF POTTERY ACQUISITIONS

## 4.1 Introduction

This chapter focuses on 3D registration of pottery point clouds in relation to object pose, transformation and reconstruction. While different methods exist to register point clouds, only the methods relevant to this study are considered. The scope of this work is on rigid alignment of 3D geometry of pottery. The geometric and photometric information of the pottery point cloud were considered in the registration process. The remaining sections follow with a presentation of the process of registration from a general point of view and narrows it to its specific use with point clouds in Section 4.2. This is followed by a description of the methods applied in point cloud registration in section 4.3. Section 4.4 highlights the registration process and experiment which involves data processing, feature detection and extraction, feature description, correspondence estimation and registration, as well as the results of the experiment. Section 4.5 discusses the evaluation and results of the previous section. The chapter ends with the summary and conclusion in section 4.6.

## 4.2 Point Cloud Registration

The study on point set registration has significantly progressed over the years using various methods. While much of the interest in the study is linked to the works of Besl and McKay (1992), Chen and Medioni (1991) and Wolfson (1990), its origins can be linked to works such as that of Arun et al (1987), Horn (1987), Huang et al (1986), Lin et al (1986) and similar works before theirs, as expected, due to increase in knowledge. These studies are either non-iterative (for example, Lin et al. and Arun et al.) or iterative (for example, Huang et al. and Besl and McKay). While non-iterative methods are computationally faster and less sensitive to parameter settings than iterative methods in general, its accuracy and performance is still an open issue when compared with iterative approaches during the registration process. Hence, studies on the iterative methods have gained more interest in point set registration.

Registration is the process of transforming datasets into a common coordinate system, allowing useful integration and alignment of the relative pose between the datasets. The datasets can be 2D or 3D datasets such as images, triangular or polygonal meshes, volumetric data and point clouds. Suitable datasets are used in various experimentations with volumetric data mainly used in medical imaging. On the other hand, point clouds are a collection of data points in a given coordinate system, while meshes are derived from point clouds and connectivity information between the points. Registration is a technique that is applied in various fields such as medical imaging, architecture and image analysis (such as image restoration, scene reconstruction, shape retrieval and cultural heritage reconstruction). Since this study focuses on works done with 3D point clouds, the discussion will be mainly on point cloud registration.

Point cloud registration is the process by which point set data or point clouds are spatially transformed into a common coordinate system. It is also referred to as point set registration. The registration can be attained by determining and applying the transformation that aligns the point clouds into a common coordinate system. For the alignment to be robust, the point clouds should substantially overlap and possess common features in the areas of overlap. Detecting these features will require methods such as nearest neighbour search to establish correspondences between keypoints or feature descriptors of the point clouds. The features can then be extracted for registration purposes.

Furthermore, there are two types of registration that can be performed on point sets, namely rigid registration and non-rigid registration. A rigid registration is one that transforms a point set, at a given location and orientation in space, to another point set's location and orientation without changing the distance between any two points of a point set. The ICP algorithm is the most popular and accurate method for rigid registration. On the other hand, a non-rigid registration is one that nonlinearly transforms a reference point set to a target point set by deforming the target point set to align with the reference point set. In this study, the focus is on the rigid registration of point clouds of a pottery.

### 4.3 Methods of Performing Registration

Point cloud registration can be categorised into two methods namely coarse registration and fine registration. Coarse registration returns a rough and fast initial alignment of the input point clouds without prior proximity assumptions of the point cloud positions (Díez, Roure, Lladó, & Salvi, 2015). This involves processes such as feature detection, feature description and correspondence search. On the other hand, fine registration assumes that the input point clouds are roughly aligned and fine-tunes the alignment between the point cloud coordinate systems, thus reducing the proximity error to as close to zero as possible (Elbaz, Avraham, & Fischer, 2017).

Furthermore, there are generally two approaches to performing 3D alignment namely, local registration and global registration. Local registration estimates a transformation that aligns two point clouds around overlapping regions with very minimal error. It is sometimes also referred to as pairwise alignment. On the other hand, global registration estimates transformations that align multiple point clouds into an object, while the alignment error between two point clouds are minimised by sharing the error among the whole point clouds.

These approaches of point cloud registration rely on the accuracy of the scanners to capture point clouds with less distortion and noise so that the rate of convergence of the point clouds would be optimal. Capturing these point clouds is attained by scanning the visible part of the target object. Hence, occlusion occurs due to the blocking of certain parts of the target object from the scanner.

To solve this problem, multiple scans of the target object are made from different views and aligned together in a common coordinate system by registration. Performing registration of the point clouds require an estimation of the transformation parameters, and the application of these parameters in a coarse registration. Both coarse and fine registration can be applied in local and global registration. In registering point clouds, accuracy is an important consideration because an inaccurate alignment will result in a wrong impression.

## 4.4 The Registration Process

The goal of the registration process is to find the correspondence, rigid transformation and best alignment between point clouds. Given two point clouds, model $P = \{p_1, p_2, \ldots, p_m\}$ and target $Q = \{q_1, q_2, \ldots, q_n\}$, in 3D space which contain $m$ and $n$ points respectively. If $p \subset P$ and $q \subset Q$ are the overlapping points between the two point clouds, then a rigid transformation $T$ applied to $P$ such that the distance between $P$ and $Q$ is minimised, results in the best alignment between the point clouds and is expressed as:

$$\mathbf{y = Rx + t} \tag{4.1}$$

where $x \in p$, $y \in q$, $R$ is the 3x3 rotation matrix and $t$ is the 3x1 translation vector.

A rigid registration can thus be found by minimising the following objective function or error metric:

$$\sum_{i=1}^{M} ||\boldsymbol{T}\boldsymbol{p}_i - \boldsymbol{q}_i||^2, \quad \boldsymbol{q}_i = \underset{\boldsymbol{q} \in \boldsymbol{Q}}{\arg\min} \, ||\boldsymbol{T}\boldsymbol{p}_i - \boldsymbol{q}|| \tag{4.2}$$

where $p$ is the model point set and $q$ is the target point set.

The registration process can be achieved with different techniques and methods as discussed by Bellekens *et al.* (2015) and Tam *et al.* (2013). But the most popular method that has formed the foundation for more improved ones is the ICP algorithm (Besl & McKay, 1992). However, it tends to be susceptible to local minima. Rusinkiewicz and Levoy (2001) categorise the ICP process into selection of points, matching of points, weighting of corresponding pairs, rejecting pairs, error metric and minimisation of the error metric. This categorisation represents the stages point clouds must go through during registration. The only difference would be the approach and methods applied. For example, the approach applied on two point sets that are roughly aligned would be different from the ones that are not roughly aligned. Hence, coarse registration is employed to first roughly align point clouds in this study.

In addition, because of the differences in objects to be registered – such as their geometry – and the unique challenges that befall them, as well as the huge point sets that might be involved, it is usually difficult to develop a "one-size-fits-all" solution for point cloud registration in general. Hence, certain works are refined or improved to suit the needs of the data that is involved (Glira, Pfeifer, Christian, & Camillo, 2015; Rusinkiewicz & Levoy, 2001). This has led to this study's implementation with C++ and the Point Cloud Library (PCL), among others. The following sub-sections discusses the coarse registration steps, shown in Figure 4.1.

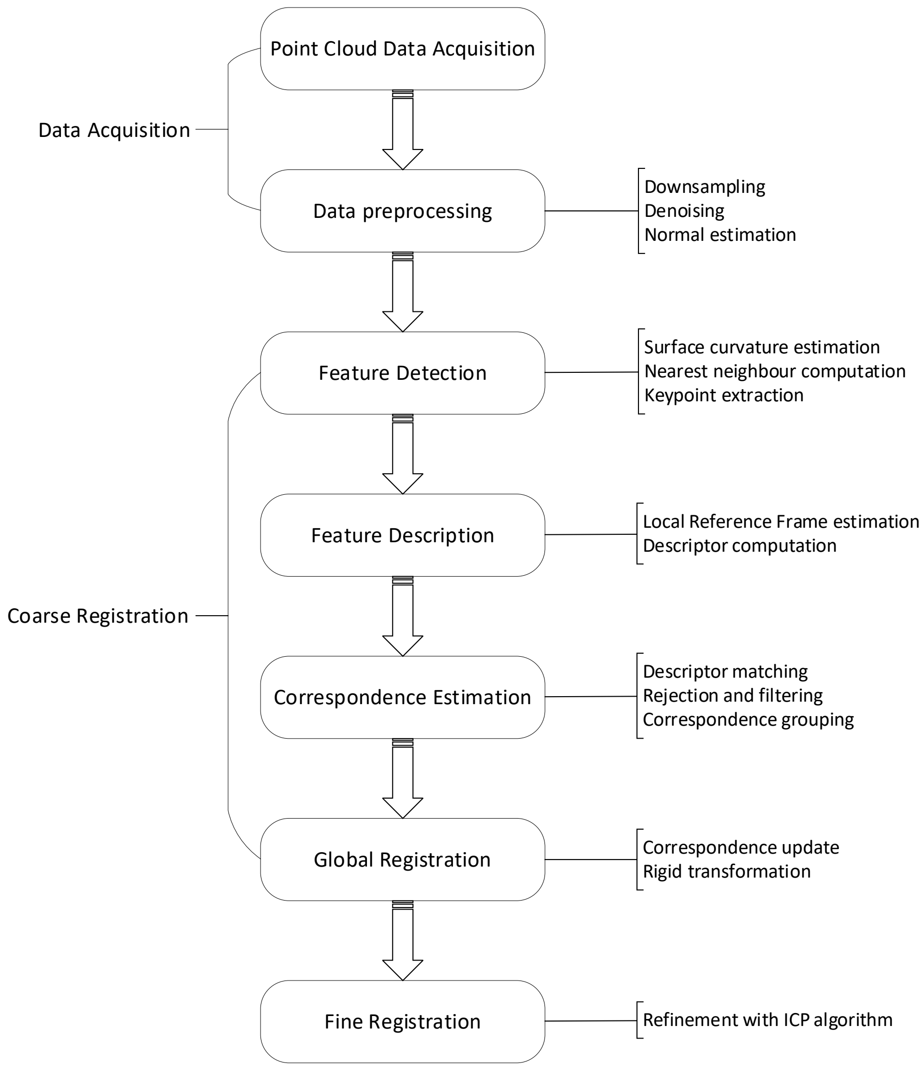


**Figure 4.1: Flow diagram of the registration method**

### 4.4.1 Data Processing

The scanned point clouds, from section 3.4, were processed with the publicly available CloudCompare software to obtain cleaner point clouds. The denoising and segmentation of the point clouds was carried out to remove unusable parts of the cloud, such as background points that were not part of the pottery itself, from the useful pottery part. In addition, the number of points of the point clouds were reduced by down-sampling. Down-sampling of the point clouds was based on space sampling, ensuring that the points are uniformly distributed to get a good estimation that contains only inliers. This was to ensure that points that do not have finite normal and enough neighbours in a certain radius (outliers) were removed. The outliers were removed based on the number of neighbours around a point and within a radius of 0.2mm.

Also, normal of the point clouds was computed for surface correspondence, thus ensuring a better alignment process. This was achieved using the Principal Component Analysis (PCA) algorithm (Shlens, 2014). The algorithm was used to determine the normal vectors of the point clouds because PCA can analyse the variation of points in three directions *x*, *y*, *z*. The normal vector corresponds to the direction with minimum variation. To estimate the normal vector, the covariance matrix, $M_{cov}$, can be calculated from the following equation:

$$\boldsymbol{M_{cov} = \frac{1}{k} \sum_{i=1}^{k} (p_i - \widetilde{p})(p_i - \widetilde{p})^T} \qquad \textbf{(4.3)}$$

where *k* is the number of nearest neighbours in the vicinity of $p_i$ and $\tilde{p}$ is the mean or centroid of all *k* neighbours denoted as:

$$\boldsymbol{\widetilde{p} = \frac{1}{k} \sum_{i=1}^{k} p_i} \qquad \textbf{(4.4)}$$

Nearest neighbour search is an optimisation problem which finds the set of nearest points *k* that is in proximity to a given point according to its Euclidean distance metric. The Euclidean distance is the straight-line distance between two points in Euclidean Space and is the square root of the sum of the squared differences of the points which can be represented as:

$$\boldsymbol{\sqrt{\sum_{i=1}^{n} (p_i - q_i)^2}} \qquad \textbf{(4.5)}$$

The k-nearest neighbours can be found by computing the Euclidean distance of the model point from a set of target points. The target points are then arranged in an increasing order of distance and the nearest neighbours determined based on the *k-th* minimum distance. The value of *k* is chosen based on the number of points within a certain radius from the model point, in this case between 0.1mm and 0.3mm. In this study, the FLANN library which performs fast and approximate nearest neighbour searches in high dimensional spaces was used in C++ to compute nearest neighbours.

By using PCA to perform eigen decomposition on the covariance matrix of equation 4.3, three eigenvalues, $\lambda_1$, $\lambda_2$, $\lambda_3$, and their corresponding eigenvectors, $e_1$, $e_2$, $e_3$, were obtained. Hence, the eigenvector corresponding to the smallest eigenvalue estimates and represents the surface normal vector $n_i$ at point $p_i$. Algorithm 4.1 shows how the normals are computed with PCA.

**Algorithm 4.1: Principal Component Analysis**

```
Input: d dimensional point cloud, number of neighbours
  Output: vector normal
  Initialize: vector normal, vector neighbours, vector neighbours mean, covariance matrix
  For each point p in P:
      Extract the neighbours using nearest neighbour search – (equation 4.5)
      Calculate the centroid of the neighbours – (equation 4.4)
      Compute the covariance matrix – (equation 4.3)
      Compute eigenvectors and corresponding eigenvalues – (equation 4.6)
              Sort eigenvectors by decreasing eigenvalues
      Extract the normal
  Return Normals
End
```

### 4.4.2 Feature Detection

While the oil lamp, vase with design and vase without design were processed, only the oil lamp and vase with design were used for further work as the vase without design had no feature on its surface that could be detected. Feature detection involves selecting repeatable and salient feature points (keypoints) of 3D point clouds that are more distinct than other points based on the geometry, colour and curvature of the surface normal. The keypoints, which describe geometrical shapes based on information around the points, are detected from the source and target point clouds. The surface curvature of the point cloud is used to estimate the keypoints that characterise the point cloud's surface. The change of surface curvature $C_\lambda$ is estimated from the eigenvalues as follows:

$$\boldsymbol{C_\lambda = \frac{\lambda_1}{\lambda_1+\lambda_2+\lambda_3}} \tag{4.6}$$

where $\lambda_1 < \lambda_2 < \lambda_3$

To calculate the surface curvature, a quadratic surface is fitted to the nearest neighbours in the vicinity of $p_i$, for example. The maximum and minimum of the normal curvature $k_1$ and $k_2$ at a given point $p_i$ on a surface are called the principal curvatures of the surface, which are in the principal directions. The mean curvature $H$ of the surface at $p_i$ is the arithmetic mean of the principal curvatures, while the total or Gaussian curvature $K$ is the (square of the) geometric mean of the principal curvatures. The relationship between $H$ and $K$ in relation to $k_1$ and $k_2$ is represented by:

$$\boldsymbol{H = \frac{1}{2}(k_1 + k_2)} \tag{4.7}$$

$$\boldsymbol{K = k_1 k_2} \tag{4.8}$$

With some algebraic manipulations, equations (4.7) and (4.8) can be written as a quadratic equation as follows:

$$\boldsymbol{k^2 - 2Hk + K = 0} \tag{4.9}$$

The quadratic equation has solutions as follows:

$$\boldsymbol{k_1 = H + \sqrt{H^2 - K}} \tag{4.10}$$

$$\boldsymbol{k_2 = H - \sqrt{H^2 - K}} \tag{4.11}$$

For the point $p_i$, keypoints are computed with the eigenvalues and eigenvectors derived from PCA, in the neighbourhood of $p_i$ with radius $r_i$. The largest value of the RGB components is computed by finding the products of two curvature to get the local maxima. With the local maxima of the curvature obtained, the keypoints were computed as shown in Figure 4.2. Table 4.1 shows the number of keypoints detected on the vase and oil lamp pottery.

**Figure 4.2: Detected keypoints based on the principal curvature of the vase and pottery surface normal**

**Table 4.1: Registration values (keypoints, correspondences, time) of the vase and oil lamp**

| Point Cloud | Number of Geometric Points | Number of Keypoints | Number of Correspondences | Matching Time (sec) |
|---|---|---|---|---|
| Vase Scan 1 (V1) | 250570 | 4813 | 850 | 1470.59 |
| Vase Scan 2 (V2) | 255224 | 5180 | | |
| Oil Lamp 1 (P1) | 249929 | 5477 | 1490 | 1950.84 |
| Oil Lamp 2 (P2) | 276882 | 3402 | | |

In essence, by analysing nearest neighbours around the point of interest $p_i$ within a certain radius $r_i$ and curvature threshold $C_\lambda$, the principal curvature for all points were computed and the covariance matrix established as stated in equation (4.3). For the oil lamp for example, the curvature was computed using points in a radius of 0.8mm, and local maxima within a radius of 1mm. these values were chosen based on the distance between the points after downsampling the point clouds.

### 4.4.3 Feature Description

Having computed the keypoints, local descriptors are required for correspondence determination and matching. The descriptors should be inherently descriptive and robust. Thus, they are computed using the neighbourhood features in the vicinity of the detected keypoints, as shown in Figure 4.3. The corresponding keypoints of two point clouds would then have matching descriptors in proximity. The keypoints are found on both views with descriptor distances (Euclidean distance) smaller than a threshold. The keypoints that had small distances compared to most keypoints are not considered. For example, two keypoints with few points around them will both have descriptors full of zeros but are not necessarily the same keypoint. Also, empty descriptor spatial bins were not considered when computing descriptor distances, mostly because it should make this step a little more robust to occlusion.

**Figure 4.3: Computed description based on detected keypoints**

The eigenvalues and eigenvectors derived via decomposition earlier, describe the neighbourhood features of the keypoint that were computed using the 3D SHOT descriptor (Salti et al., 2014). SHOT is chosen for its robustness and performance (Alexandre, 2012; Salti et al., 2014). A Local Reference Frame (LRF) is computed for the keypoints at a radius of 4mm. The normal at the keypoint was used as Z axis of the LRF, the X axis as the principal curvature direction, while the Y axis is the cross product of the Z and X axes. This leaves the problem of "inverted" reference frames since curvature directions do not truly have a sign. However, the sign of the axis was chosen as the one where points are further away from the tangent plane defined by the normal at the keypoint. This approach results in 20% of the keypoints with reference frames inverted and, on average, 1.5° of error on the Z axis and 7 – 8° on the X and Y axes. These increases of views have a very small overlap area with large occlusion. For the oil lamp, the local reference frame was computed using points around the keypoint with a maximum distance of 1.2mm. this value was chosen based on the distance between the points after downsampling of the point clouds. For the sherd, the number of keypoints to be extracted were increased.

### 4.4.4 Correspondence Estimation

Correspondence estimation involves identifying regions of two point clouds that correspond to each other. With the descriptors computed from the keypoints of the point clouds, they are compared with their Euclidean distance and matched to establish point correspondences using nearest neighbour search in the feature space of the keypoints. Also, angular vectors between the normal of the descriptors are defined and correspondences are clustered into groups. Because of the existence of poor or no matches and wrong correspondences, a matching criterion is used to reject these correspondences. This is achieved through RANSAC-based filtering. The filtering approach usually improves the convergence rate of the point cloud during registration. Tables 4.1 and 4.2 show the derived values of the correspondence grouping, filtering and overlap of the point cloud of the vase with design and oil lamp pottery.

**Table 4.2: Values for the correspondences, filtering and overlap of the vase with design scans**

| Group | After Grouping | After Filtering | Outliers (%) | Overlap (%) |
|---|---|---|---|---|
| 1 | 831 | 737 | 27 | 49 |
| 2 | 783 | 680 | 32 | 49 |
| 3 | 778 | 683 | 28 | 49 |
| 4 | 763 | 636 | 35 | 49 |
| 5 | 738 | 649 | 26 | 49 |
| 6 | 688 | 605 | 48 | 47 |
| 7 | 668 | 589 | 50 | 47 |
| 8 | 585 | 511 | 53 | 45 |
| 9 | 533 | 467 | 58 | 39 |
| 10 | 520 | 433 | 60 | 43 |

| | | | | |
|---|---|---|---|---|
| 11 | 478 | 416 | 58 | 38 |
| 12 | 435 | 365 | 66 | 35 |
| 13 | 428 | 350 | 67 | 35 |
| 14 | 405 | 347 | 51 | 46 |
| 15 | 389 | 340 | 52 | 46 |
| 16 | 376 | 314 | 72 | 30 |
| 17 | 368 | 314 | 72 | 32 |
| 18 | 333 | 264 | 65 | 44 |

**Table 4.3: Values for the correspondences, filtering and overlap of the oil lamp scans**

| Group | After Grouping | After Filtering | Outlier (%) | Overlap (%) |
|---|---|---|---|---|
| 1 | 1477 | 1344 | 24.10 | 75.20 |
| 2 | 1477 | 1343 | 25.64 | 75.18 |
| 3 | 1476 | 1342 | 24.24 | 75.21 |
| 4 | 1476 | 1303 | 25.82 | 75.17 |
| 5 | 1475 | 1341 | 24.26 | 75.18 |
| 6 | 1474 | 1271 | 24.57 | 75.22 |
| 7 | 1473 | 1337 | 24.31 | 75.18 |
| 8 | 1473 | 1338 | 24.43 | 75.18 |
| 9 | 1473 | 1338 | 24.13 | 75.21 |
| 10 | 1473 | 1336 | 24.91 | 75.20 |
| 11 | 1473 | 1336 | 25.51 | 75.18 |
| 12 | 1473 | 1233 | 24.44 | 75.15 |
| 13 | 1472 | 1274 | 23.49 | 75.15 |
| 14 | 1472 | 1332 | 24.49 | 75.18 |
| 15 | 1472 | 1335 | 24.18 | 75.14 |
| 16 | 1472 | 1339 | 24.35 | 75.18 |
| 17 | 1471 | 1334 | 24.27 | 75.20 |
| 18 | 1471 | 1309 | 24.27 | 75.19 |

About 1,000 correspondences were established before filtering between views with large overlaps for both the vase and the oil lamp. After filtering, the correspondences for the vase became 649 while that of the oil lamp became 1274, with about 150 correspondences being correct. Likewise, about 400 correspondences are established between views with small overlaps, with about 6 – 7 correspondences being correct. To attempt to improve this, some geometry consistency criteria is imposed by forcing the same distances between correspondences to create groups from them. For example, for two point pairs $(p_i, q_i)$ and $(p_j, q_j)$, distance $d = ||p_i - p_j|| = ||q_i - q_j||$ for the pairs to be valid. By creating all the possible groups with about 1,000 correspondences, this step becomes slow. Hence, the best correspondences were used to create a completely new group and then look for compatible correspondences among the others. With this, if there are some correct correspondences, there should be at least a couple of them among the best correspondences. Figure 4.4 shows correspondences between point clouds of the vase with design and oil lamp pottery.

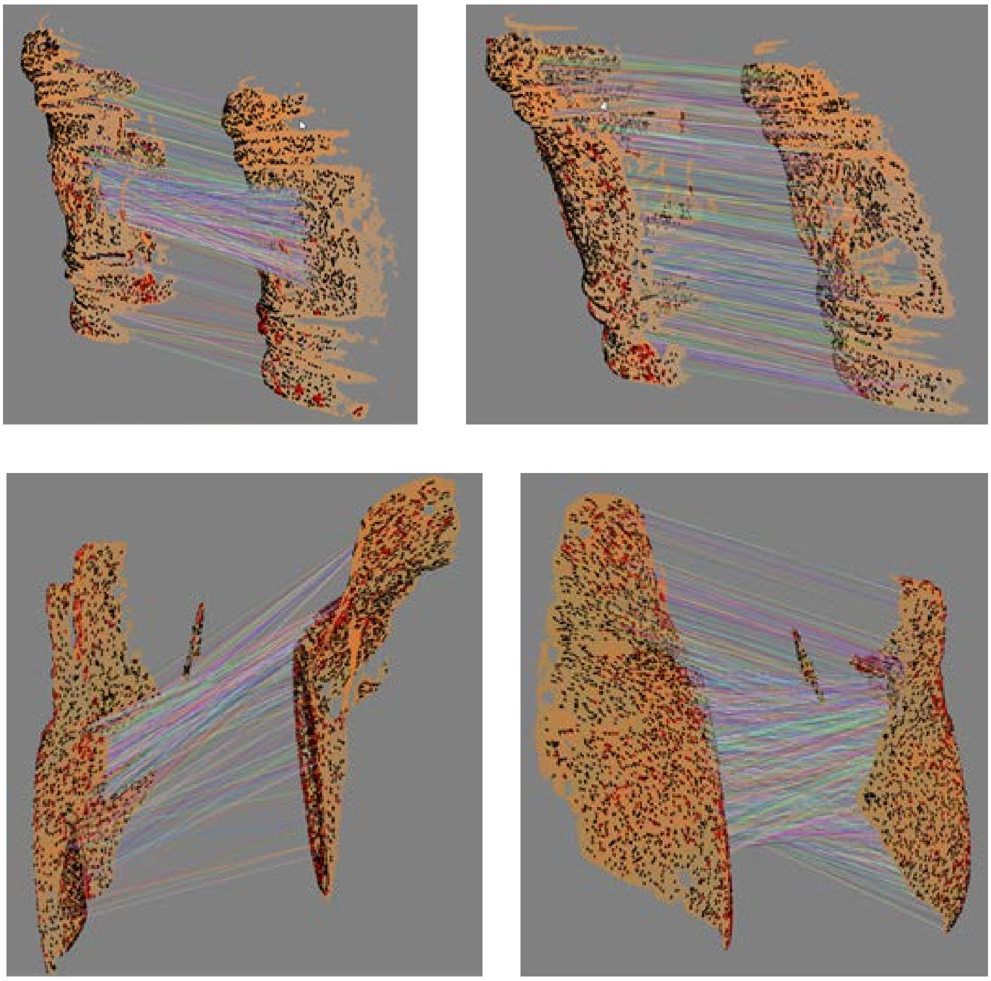

**Figure 4.4: Correspondences between the vase and oil lamp point clouds**

### 4.4.5 Global Registration

With correspondences established, the point clouds are roughly aligned. In other words, a global registration that transforms and aligns all point clouds into an object was made. Thus, the alignment error between two point clouds are minimised by sharing the error among the whole point clouds. The ICP algorithm is used to do a fine registration on the pairs of point clouds. Figures 4.5 and 4.6 show two pairs of point clouds and their pairwise registration. Figure 4.7 shows a global registration of all point clouds of the vase with design, oil lamp pottery and its potsherd.

**Figure 4.5: Point cloud data of the vase and oil lamp pottery**

**Figure 4.6: Pairwise registration of the vase and oil lamp point clouds**

**Figure 4.7: Global registration of vase, oil lamp pottery and its potsherd**

## 4.5 Evaluation and Discussion

While one solution may not solve all problems, as stated earlier, this work intended to bridge a gap that exists specifically with archaeological pottery. As was seen from the extraction of keypoints from the vase, lamp and its sherd, flexibility played a role. When present parameters did not satisfy the same goal for lamp and sherd, the parameter was adjusted so that more keypoints could be extracted from the sherd, as much as possible. This section presents an evaluation of the results of the registration of the pottery.

### 4.5.1 Dataset

Synthetic datasets were not considered in this study since the study is geared towards a specific challenge existing in the archaeological domain. Moreover, there has been a lot of studies with synthetic dataset. It thus bodes well to focus on the data type that will suit this study. The datasets used in this study are real 3D point cloud data obtained from two vases and an excavated pottery. While the vase without design underwent preliminary processing, feature points could not be extracted from it. The C++ program terminated without an output. On the other hand, the vase with external design was used for this study, as well as the excavated pottery and its sherd. Figure 4.8 shows a plot of outlier against correspondence group with percentage of outliers detected and removed.

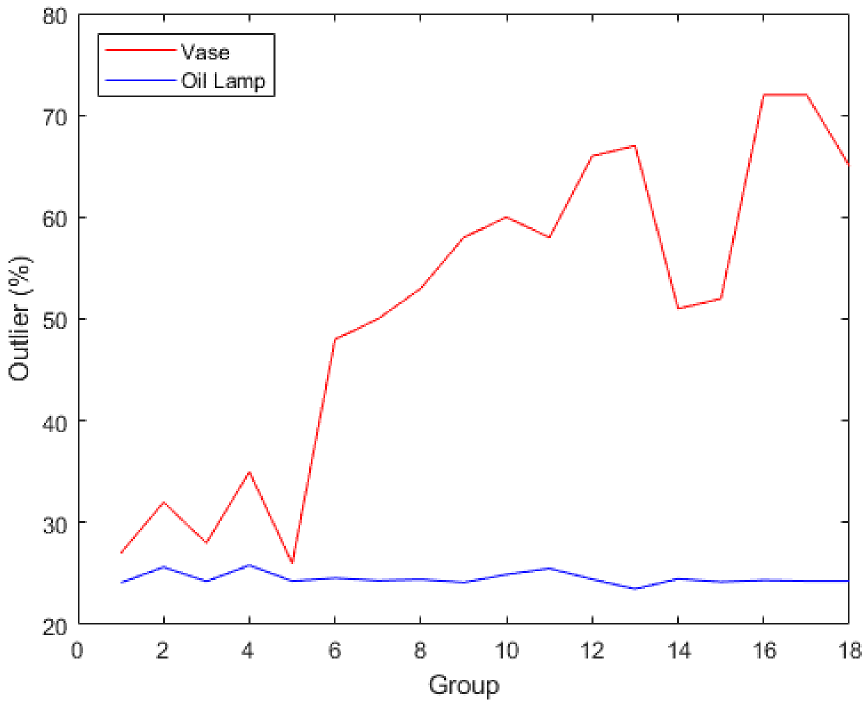


**Figure 4.8: Plot of Outlier against Correspondence Group showing percentage of outliers detected**

From Figure 4.8, it can be seen that a large percentage of outliers were detected and eventually removed from the vase, while the oil lamp's outliers have a low percentage detected. This will affect the number of correct correspondences that would be computed, with the oil lamp having a better chance than the vase based on the graph. Over 50 scans each of the vase with design and oil lamp pottery were acquired. About 16 scans of the vase with design and 24 scans of the oil lamp were used eventually for the registration experiment. Likewise, about 30 scans of the potsherd were captured while 12 were used for the registration experiment. The reduction in the quantity used was also due to occlusion, noise and inadequate illumination for the pottery during acquisition.

Some of the very problematic acquisitions were not used at all while others were used because the errors were due to the angle of acquisition, which can only be resolved by getting a better camera lens. Figure 4.9 shows some blurry acquisitions and one lacking adequate illumination. These kinds of acquisitions make the keypoint extraction and description estimation stages quite challenging, which reduces accuracy and robustness. To then improve the acquisitions, the position of the lighting was adjusted, the parameters of the camera setup were adjusted, and the calibration redone.

**Figure 4.9: Poorly illuminated and blurry point clouds**

Given that the captured point clouds range between 385,968 and 1,594,059 points, which was too large for further work due to computation limitations, it was pertinent to downsample the point clouds for further studies and analyses. Hence, the point clouds were downsampled to an average of 245,000 points for all the point clouds using an iterative spatial method.

### 4.5.2 Registration Accuracy

Figure 4.10 shows the registration results of the pottery and its sherd. While the potsherd used all 12 point cloud scans, the pottery did not use all of its own. Although 24 pottery point clouds were applied, 6 were removed due to misalignment while 18 were used for registration. Despite that, the coarse registration completed accurately so that the fractured areas could be viewed and used for further studies. This is important for pottery reassembly purposes. A fractured surface that is well registered such that the fine details of the ridges, corners and cracks are visible will make it easier to perform an accurate reassembly process. Notwithstanding, the accuracy could still be improved with higher resolution camera lens and calibration accuracy. Table 4.4 shows the computed average values of the reference frame and alignment errors of the vase and oil lamp after coarse registration.

**Table 4.4: Average reference frame and alignment errors after coarse registration**

| Point Cloud | X (mm) | Y (mm) | Z (mm) | Alignment (%) |
|---|---|---|---|---|
| Vase | 0.2110 | 0.2002 | 0.0573 | 18.55 |
| Oil Lamp | 0.1665 | 0.1578 | 0.0349 | 21.83 |

From Table 4.4, the average reference frame error of the vase is higher than that of the oil lamp. This has probably affected the global registration of the vase as seen in Figure 4.7. The global registration of the vase could not be completed with all the point clouds. The scans of the inner part of the vase could not register with the outer part. Hence, only the outer part of the vase was registered. Solving this problem will require using a higher resolution camera and possibly considering a more complex setup that will capture the inner part of the vase with an improved accuracy. In addition, the alignment error of the oil lamp is higher than that of the vase. This is because the number of correspondences computed for the oil lamp is almost double that of the vase, as seen in Table 4.1.

**Figure 4.10: Registered point clouds showing the fractured areas**

Furthermore, another factor that contributes to an improved registration process is the overlap between point cloud pairs. Figure 4.11 shows a plot of overlap against correspondence group showing percentage of overlap between point cloud pairs of the vase and the oil lamp. While the oil lamp has a relatively high overlap that improves correspondence estimation and registration, the vase has a relatively low overlap. This shows that the same parameters that worked for the oil lamp might not be enough for the vase. Hence, the system should be improved in such a way that will make it flexible for parameter adjustments. While this will improve the accuracy, it might increase the system complexity.

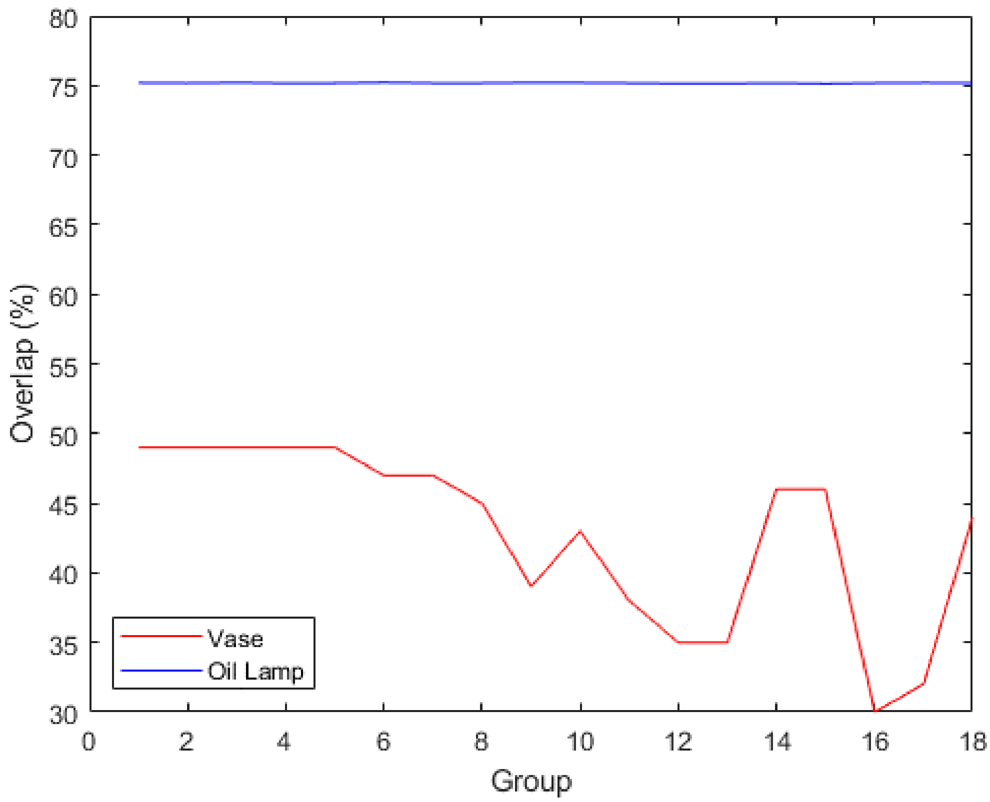


**Figure 4.11: Plot of Overlap against Correspondence Group showing percentage of overlap between point cloud pairs**

### 4.5.3 Performance Comparison with the Oil Lamp

A laptop running Windows Operating System (OS) with 16GB RAM Core i7-6500U @ 2.50GHz and another with Ubuntu Linux 19.10, 8GB RAM Core i5 @ 1.90GHz were used for the experiment. In addition, cmake was installed to configure and generate the source code on Microsoft Windows. The original source code written in C++ used the Microsoft visual studio compiler. On Ubuntu Linux, the open source clang compiler was used.

For the pairwise registration of Figure 4.6, the registration process of the oil lamp completed in 223 seconds on an Ubuntu Linux laptop and 1950 seconds on a Windows laptop with an accuracy of 0.08 mean-squared error. The registration process of the vase completed in 1470 seconds on a Windows laptop with an accuracy of 0.14 mean-squared error. Compared with the method of Lei et al. (2017), which completed in 1,116 seconds with the same pair of point clouds (see Figure 4.12), the time complexity is tolerable.

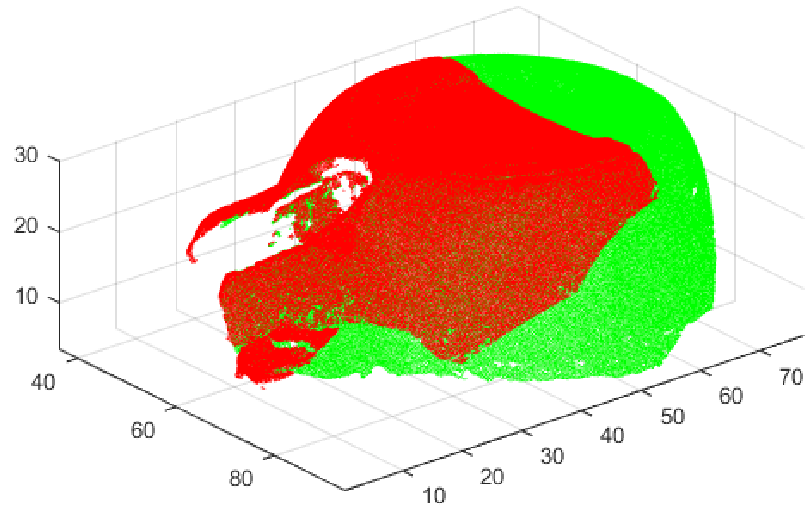


**Figure 4.12: Pairwise registration of two point clouds using Lei et al.'s method**

In addition, from applying the method of Cirujeda et al. (2015) (see Figure 4.13), it can be seen that though their method worked for their study, it did not attain accurate result with the data used in this study.

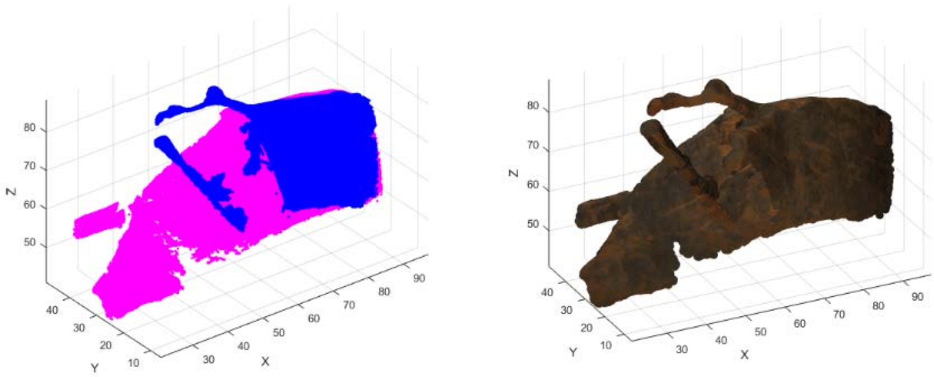

**Figure 4.13: Pairwise registration of two point clouds using Cirujeda et al.'s method**

Furthermore, the global registration of the whole point cloud took 192 minutes to complete on Windows. This prompted a need to improve the efficiency of the C++ code and make it compatible with both Windows and Linux, since it was initially written for Windows alone. The following optimisations were made on the code:

- C++17, optimization flags and extra warning flags were added to the cmakelists file.
- ConfigMap was optimised by removing redundant member functions and changing ConfigMap copies to immutable references. All ConfigMap repeated copies were removed as well.
- "Include" guards were added for header files.
- Windows and Linux compatibility was added.
- String copies was minimised by using string_views.
- Vector copies was replaced with const references.
- Move return semantics (copy elision) for vectors was added.
- Header file declaration signatures was changed to match equivalent definitions.
- Redundant std::endl output was replaced with std::cout with \n.
- Eigen vector copies were optimised, as well as other optimisations.

After making these optimisations to the code, global registration of the point clouds was run on Windows and Linux OS. On Windows, global registration completed in 168 minutes, and 90 minutes on Linux. This was a marked improvement as compared with Windows. Thus, performance across platforms have been improved. Although, this will need more testing and validation.

## 4.6 Chapter Conclusion

This chapter discussed the point cloud registration process, the findings and evaluation of the study, as well as their implication on archaeological pottery reconstructions, especially in relation to existing literature and knowledge. The registration process, which involve data processing, feature detection, feature description, correspondence estimation and global registration, was clearly discussed. The findings show that the use of real 3D dataset can attain impressive results when used with the right tools. High resolution lenses and accurate calibration help to give accurate results. The results obtained are useful for further studies such as 3D pottery reassembly. In addition, while the accuracy attained in the study is generally acceptable, there are rooms for improvement still. This will help in managing the local minimum problem to a reasonable extent as a result of doing a coarse registration, which improved efficiency and robustness. However, the performance of the hardware and software shows that the time complexity of this study needs improvement and will be an area of focus on subsequent studies. The conclusion of this thesis is presented in the following chapter, chapter 5.

# CHAPTER 5: CONCLUSION

The process of virtualising artefacts using point cloud data was presented in this chapter. The artefact was acquired as point cloud and pre-processed to have a clean cloud. The pre-processing step includes segmentation, normal computation, down-sampling and boundary point computation. Thereafter, keypoints were detected and extracted from the point clouds, and descriptors computed using point and colour information. The approach presented in this paper focuses on improving accuracy and optimising the cost function to have an optimal result for the pottery's profile. However, while the final registration for the pottery was successful, it was observed that the robustness of the descriptor dropped due to occlusion.

## 5.1 Introduction

The aim of this study was to investigate and evaluate a means of reconstruction of archaeological pottery considering accuracy and robustness as important metrics. The accuracy and robustness of such reconstruction is important in the archaeology discipline. The study focused on reconstructing an archaeological pottery clearly showing the geometric and radiometric properties of the surfaces and fractured faces required for easy further analysis. Thus, this study undertook to develop and evaluate an approach towards solving the archaeological pottery reconstruction challenge. In carrying out the study, coarse registration of point clouds using detected keypoints and estimated descriptors was chosen as a notable direction. Coarse registration of point clouds demonstrates that using object features to approximate a rough alignment of point clouds can be beneficial with archaeological pottery. The registration experiment and evaluation showed that adopting coarse registration in the overall process of accurate point cloud registration, especially for archaeological pottery, is a promising direction. Hence, further work in this research area stands to solidify the gains made in archaeological reconstruction and reassembly researches.

In this final chapter, section 5.2 summarises each chapter by stating the goals and the outcomes discussed in each chapter. This is followed by the unique and specific contributions made to this research in section 5.3. The areas for future work, that could provide the next steps along the path to an improved reconstruction and reassembly of archaeological pottery, concluded this chapter and thesis in section 5.4.

## 5.2 Summary of Chapters

In general, cultural heritage is an area of study that interests humanists. But this area of study should interest every discipline as it has to do with the roots of human origin in most cases. The study and understanding of cultural heritage have helped in the evolution of the way of life of a people, as people appreciate the past and innovate to preserve this legacy. Specifically, and with respect to archaeology, the preservation of archaeological artefacts is an important study. Because these artefacts tend to undergo both natural and human threats, governments around the world have gotten involved with the preservation of the artefacts. One of these artefacts is pottery. It attracts the attention of archaeologists because it carries significant archaeological value for studies. Thus, the recovery of pottery from archaeological sites and its preservation is paramount for archaeologists.

In recovering archaeological pottery, various methods have been adopted. They include manual methods, which is time and effort consuming, and technological approaches, which has provided new layers for archaeologists to carry out productive work. In addition, various technological approaches have been carried out. They include symmetry-, template- and feature-based approaches among others. Because symmetry- and template-based approaches hardly reconstruct pottery with its surface features, feature-based approach has attracted attention. The feature-based approach has the potential to handle the limitations that exist in other approaches. This is because it has the potential to reconstruct objects with their surface features with the advantage of accuracy and robustness.

These highlights were presented in details as a background to the research problem that was presented in chapter 1, highlighting the limitations and challenges that exist in archaeological pottery reconstruction and reassembly. This led to the research problem statement, which highlighted the problem, its impact, the hypothesis and the gap that the research intends to investigate. The hypothesis for this study is that archaeological pottery can be accurately reconstructed virtually with existing and new knowledge. Validating will therefore require the investigation process. Following, the aim of the research, as well as the rationale for the research were presented. The research delineation and contributions were also highlighted. Furthermore, the important terms and concepts prevalent in this thesis were clarified and explained, leading to the elaboration of the layout of this thesis. This introduction in chapter one laid a good foundation for the existing literature that was reviewed.

Chapter 2 covered a detailed review of archaeological pottery reconstruction, providing a comprehensive overview of state-of-the-art in acquisition methods, acquisition techniques and methods of performing pottery reconstruction. The use of state-of-the-art methods to acquire object data is quite accurate but only within their context of usage and makeup. While some methods can acquire objects at a distance accurately, they fall short in doing same for objects in proximity. However, each method provides different and unique benefits in their distinct and dynamic scenario. This unique benefit is dependent on the acquisition technique(s) used. The acquisition techniques reviewed were structured light, time-of-flight and 3D laser scanner. One or more of these techniques are applied in data acquisition to have robust data for processing. But it is not always the case as the accuracy and robustness of the data is dependent on the quality of the equipment used and the accuracy of the calibration done.

Furthermore, the data reconstruction approaches were discussed based on 2D and 3D reconstructions. The techniques and approaches used, as well as the data differ significantly in some cases. In addition, the methods of reconstruction as classified in this thesis were discussed. They are symmetry-based, template-based and feature-based reconstructions. Their strengths and limitations were presented based on previous work in the areas. While some of the reconstruction methods work well in a given scenario, they nonetheless have unique challenges. For example, symmetry-based reconstruction can only successfully reconstruct symmetric objects and failing if the object is not symmetric.

Chapter 3 discussed the data acquisition approach employed in this study to acquire the pottery. Since the nature of the problem under investigation pertained to technical innovations, the acquisition system is a bedrock of the whole reconstruction process. The laser scanner and camera used for the acquisition were presented, along with their specifications. The laser scanner technique was chosen for this study because of its accuracy and robustness in proximity. The setup of the equipment was discussed, highlighting the various parts that make the setup. In addition, the four various setups that can be used for the line laser and the camera to be mounted for laser scanner acquisitions were highlighted. They are the ordinary, reversed-ordinary, specular and look-away setups. The various setups were explained and the choice of using the reversed-ordinary setup was highlighted. Furthermore, to be able to carry out experiments, a calibration of the system was necessary, highlighting the various steps in the process. This therefore paved the way for acquiring the pottery used in this study. Multiple views were acquired, ensuring that there was appropriate illumination.

Chapter 4 presented the core of this study, which is the registration of the pottery acquisitions, by building on what was done in chapter 3. The chapter began with a general discussion on point cloud registration and climaxing with the coarse and fine methods of performing registration. While these methods can be used independently, they can also be used complementarily as applied in this study. The registration process began with the pre-processing of the data. This involved downsampling, denoising and normal estimation. The normal estimation was done using the PCA algorithm. The normalised data was then used in the feature detection stage. The feature detection stage involved surface curvature estimation, nearest neighbour computation and keypoint extraction. The surface curvature estimation was done using the eigenvalues obtained from the normal computation. Estimating the surface curvature of the point cloud aids the keypoints extraction process. Thus, by analysing the computed nearest neighbours around a point of interest, the keypoints were computed.

The computed keypoints were then used in the feature description stage for correspondence determination and matching. This stage involved estimating the LRF and computing the descriptor itself. Having computed the descriptor, the descriptors were matched using a distance threshold. The descriptors were filtered using RANSAC and outliers were removed. This made the correspondence grouping more efficient, and thus the correspondences were established between the point clouds. Correctly establishing correspondences make for an easier transformation of the point clouds, thereby minimising the distance errors between them. The transformation of the point clouds is the highlight of the coarse or global registration. Fine registration with the ICP algorithm was then used to obtain a finer result.

## 5.3 Future Work

A significant body of knowledge dealing with the issues and challenges of pottery reconstruction has emerged. These works focused on several issues related to accuracy and robustness of point cloud acquisition and registration. Various design complexities, hardware and software level analyses, tests and evaluation have been undertaken to consolidate these works. This research has provided a groundwork for studying more efficient ways and methods of virtual pottery reconstruction. Hence, this section describes the future research possibilities that will extend and improve the results of this research.

In this study, the various approaches necessary for virtual reconstruction of archaeological pottery have been presented. Some of the approaches have limitations that will be considered for future work. Firstly, the acquisition system will be upgraded with a lens with a higher resolution. This is to ensure that point clouds are captured without in such a way that the registration process will not be restricted in distance minimisation.  In addition, the algorithm will be improved and extended to accommodate multi-system usage. Consideration will also be given to using it with synthetic data, and more data will be used for validation. Finally, a major future work will be to reassemble the potsherd and the pottery to form a whole piece.

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