DESIGN OF MULTIPLE ENROLLMENT BASED FINGERPRINT RECOGNITION SYSTEMS

By

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1.0 INTRODUCTION

Many organizations now days have embarked on using biometrics to authenticate individuals and validate or verify their identities. Distinct from traditional identification methods, which rely on what you know (for example a PIN, a Password) or what you have (like a key, a token), a biometric system makes judgments based on what you are, and thus meets more stringent security requirements, while relieving users from the burden of remembering passwords [1].

The use of fingerprints as a biometric characteristic is one of the oldest and widely used method for recognition because of their high distinctiveness and high performance [1], [2]. For example, in the field of forensics, fingerprint recognition has been (can be) important in corpse and terrorist identification, criminal investigation, parenthood determination etc. Its application is also evident in the government and commercial sectors most especially in the national identification cards, drivers' license, social security, boarder and passport control, computer network logon, ATMs and credit cards, physical access control, etc., [1], [31], [32], [33] to mention but afew. Fingerprint recognition has not only acquired a wide spread use but also triggers security concerns in terms of errors and its recognition performance.

1.1 Background

Enrollment using multiple fingerprint samples (multiple enrollment) is a solution that can help in extending the information of a single enrolled fingerprint image and also ensure the reliability of each fingerprint image [1]. Multiple enrollment can also improve the recognition accuracy of the fingerprint recognition system by lowering the error rates, allowing robustness by lowering the False Rejection Rates for low quality or worn-out fingerprint images and also make spoofing harder [1].

Acquiring accurate fingerprint images for recognition in a onetime capture is infeasible because not all the necessary and distinguishable fingerprint information may be collected. This can be due to a number of factors such as noise, errors in the feature extraction module, fingerprint displacement and rotation during the enrollment or capture stage, distortion, low quality fingerprint images, worn-out fingerprint images, partial overlap, finger pressure and skin condition [1], [23]; these decrease the recognition performance/accuracy and make it hard to relay on single enrollment where one fingerprint sample is collected per individual.

The above mentioned factors can lead to high false non matches where fingerprint impressions from the same finger (of an individual) are falsely rejected. They can also lead to high false matches for cases where fingerprint impressions from different fingers (of different individuals) are falsely accepted to be the same [34]. The high false non matches and high false matches bring about a poor performance in the entire fingerprint recognition system. More so, it would even be worse for fingerprint recognition systems that use single enrollment for fingerprint recognition; for instance if the singly captured fingerprint image falls under the fore- mentioned factors. However, with multiple enrollment in place, it is possible to acquire a better recognition performance through fusion of the multiple enrolled fingerprint impressions of each individual [1].

It is true that multiple enrollment can help in improving recognition performance in fingerprint recognition systems. The researcher in his master's thesis [38] already carried out a research to verify recognition performance improvement arising from multiple enrollment in comparison to single enrollment fingerprint recognition systems. We have however realized that there is still a challenge in developing usable, acceptable, implementable and robust [35] multiple enrollment based fingerprint recognition systems (algorithms) that can match only high quality fingerprints amongst the many enrolled fingerprint samples, with a high matching speed, little memory consumption but still maintaining a high recognition accuracy. These identified gaps make it almost impossible to implement multiple enrollment based fingerprint recognition systems in real-world applications. More so, most of the multiple enrollment based fingerprint recognition systems have been designed mainly based on minutiae approaches but not others such as correlation and pattern based approaches.

This research extends the researcher's MSc. project by studying the existing approaches to multiple enrollment based fingerprint recognition system design and proposing algorithm improvements for better implementation and deployment in real-world scenarios; based on the current advances in information technology.

The MSc. project aimed at finding out (i) the result or effect of using multiple enrollment in fingerprint recognition systems, (ii) whether the difference in fingerprint acquisition time would affect the with-in class variance of the multiple acquired fingerprint images and (iii) whether multiple enrollment done at different time intervals would affect the resultant recognition performance. Just like all the referenced literature, the masters project was based on minutiae fingerprint matching approaches, there was no focus on improving recognition accuracy, there was no check for computation/matching speed of the algorithms, memory consumption was not taken into account, and other fingerprint matching approaches where not considered. At the master's project, we also in the future work projected for ways of improving recognition accuracy by looking at good fingerprint images amongst the many copies collected. We couldn't find ways of achieving this and we therefore anticipate that the PhD research will find ways of achieving it.

This research will therefore build on the fact that multiple enrollment fingerprint recognition systems yield better recognition accuracy results compared to single enrollment fingerprint recognition system. However, based on the current technology advancements, this research will further extend the masters project by proposing an approach that would improve the recognition accuracy, improve matching speed, reduce memory consumption and also focus on design of multiple enrollment fingerprint recognition systems using other techniques rather than minutiae based ones alone.

1.2 Statement of the Problem

Using multiple enrollment can improve recognition performance in fingerprint recognition systems; but there are several technical and operational challenges to implementing multiple enrollment based fingerprint recognition systems. Multiple enrollment based fingerprint recognition systems currently still have low recognition accuracies, poor matching speeds, and consume a lot of memory making it difficult to implement them in real world scenarios. Also most of multiple enrollment based fingerprint recognition systems have been designed mainly based on minutiae approaches but not others such as correlation and pattern based approaches.

1.3 Research Questions

The main research questions we are interested in are:

- ✓ What are the current approaches being used in designing multiple enrollment based fingerprint recognition systems? *This question is important to achieve research objective 1. We shall carryout formative research to find out the state of the art in design of multiple enrollment fingerprint recognition systems. We shall be able to determine which techniques are available for integration for us to formulate our proposed approach. This* *question will also help in determining the challenges and requirements needed to design better multiple enrollment based fingerprint recognition systems.*

- ✓ How can we design multiple enrollment based fingerprint recognition systems to improve recognition accuracy/performance and matching speed, but reduce memory consumption? *This question aims at achieving objectives 2, 3 and 4. After attaining the challenges and necessary requirements, it will now be possible to design better multiple enrollment fingerprint recognition systems. A novel approach will be designed and later a multiple enrollment fingerprint recognition system implemented from the approach to test and validate its efficiency and effectiveness.*
- ✓ Would a particular fingerprint matching method/approach be a determinant for a higher improvement in recognition accuracy/performance, matching speed and low memory consumption in multiple enrollment based fingerprint recognition systems design? *This question also aims at achieving objectives 2, 3 and 4. There are three kinds of fingerprint matching methods one would implement in fingerprint recognition systems. This question will help in determining which method(s) perform(s) best when implemented in multiple enrollment fingerprint recognition systems. Knowing the best method(s) will later be important in formulating recommendations to designers of such systems. This is still part of testing and evaluating our approach.*

1.4 Purpose of the Study

The purpose of this study is to provide a novel multiple enrollment fingerprint recognition approach which will further improve recognition accuracy, the matching speed and reduce memory consumption in multiple enrollment based fingerprint recognition systems.

1.5 Specific Objectives

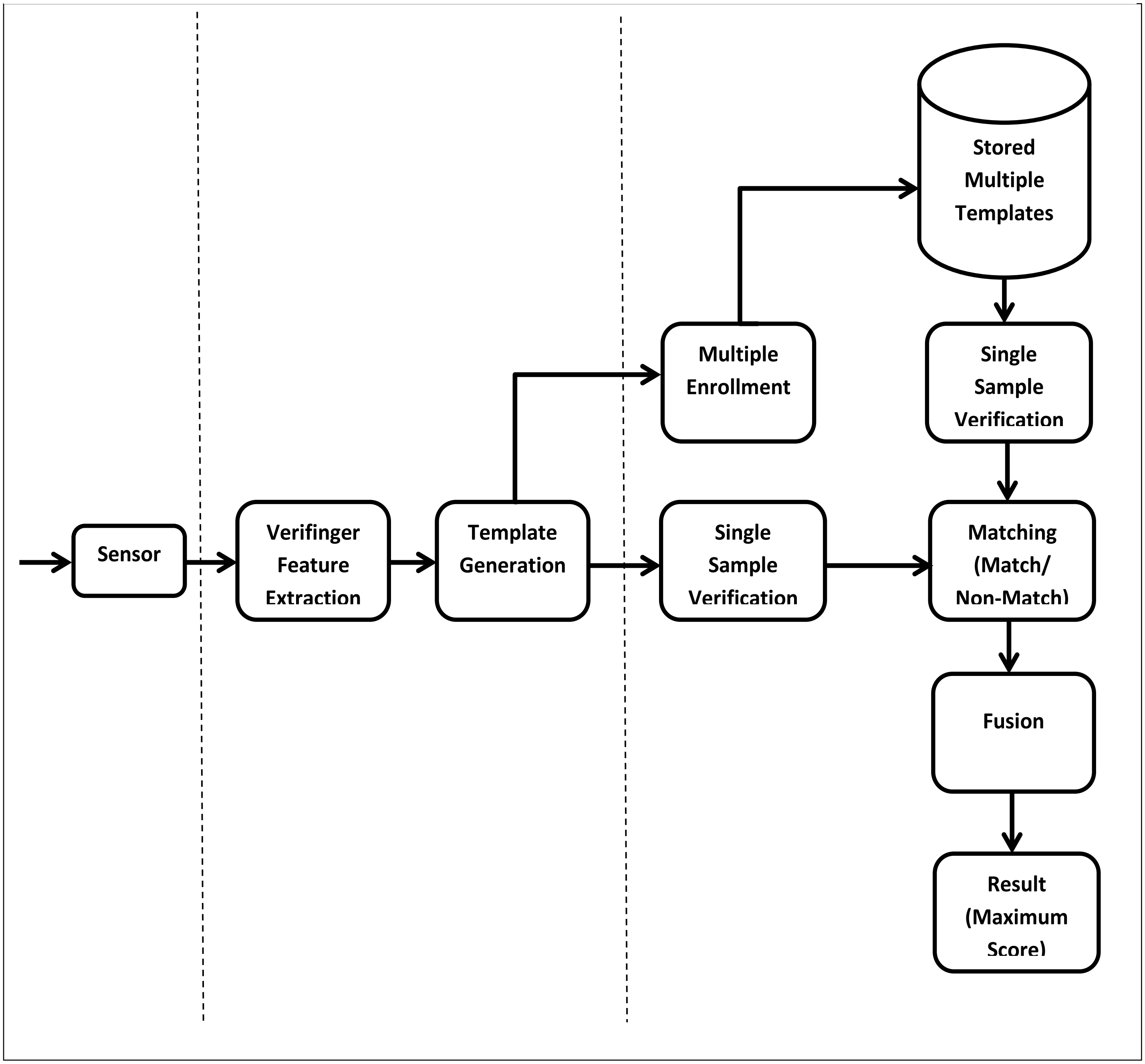
The specific objectives of this study are to:

1. Investigate techniques that will be used for integration to frame our proposed approach to designing of multiple enrollment based fingerprint recognition systems
2. Design a novel approach to multiple enrollment based fingerprint recognition systems design.
3. Implement a multiple enrollment based fingerprint recognition system from the approach.
4. Test and evaluate the approach for viability

1.6 Conceptual Framework

This section provides the proposed conceptual framework for this research. The general idea was adapted from [1].

Figure 1: Proposed conceptual framework (adapted from [1])



We have partitioned the conceptual framework into three phases; 1, 2 & 3. In each phase, there are different activities that take place as briefly described below:

Phase 1

In this phase, the individual presents a finger and his or her fingerprint biometric characteristic is captured, pre-processed (e.g. removing background noise, artifacts from sensor, etc.) and a fingerprint image sample/impression generated *(Input = finger, output = fingerprint image sample/impression)*

Note: *it is important to note that phase1 may not concretely be applied in this particular study, since the datasets were already acquired (the fingerprint image samples are already internationally available).*

Phase 2

In this phase, the acquired fingerprint image samples are input into a feature extraction tool (for example, Verifinger) which extracts the desirable matching features/characteristics (*feature set*) such as minutiae (spectral) points, loop, whorl, arc, and delta to generate templates (*often referred to as the reference*) that will be stored for future comparison (matching and verification). *(Input = fingerprint image samples, output = templates)*

Phase 3

In this phase, a number of activities take place;

One, the individual's biometric information is captured and stored in a process called enrollment. This is the process when the individual uses the biometric system for the first time.

Note: *For purposes of this study, multiple templates will be enrolled and stored.*

Two, is matching where the feature set (*of a claimed identity of a subject*) and the enrollment template (*pre-stored template of the same subject*) are compared by computing their similarity in terms of a matching score (*similarity score*). Based on a system *threshold*, if the two are similar (*score higher than the threshold*), a match decision is produced otherwise a non-match decision will be produced (*when the score is lower than the threshold*).

Note: *It is important to note that one by one sample is verified at ago. For the case of verification where multiple enrolled samples are considered, multiple scores are produced. On the other hand, verification where a single enrolled finger is considered, a single score is produced.*

It is still here where we expect to have only the good fingerprint images chosen for matching to improve recognition performance, matching speed and reduce memory consumption.

Three, is Fusion where the multiple scores generated after matching only the good multiple enrolled samples will be combined and the maximum score (best score) chosen.

Note: *It is in this phase 3 where the researcher will evaluate the improvement in recognition performance and matching speed as well as memory consumption in a multiple enrollment based fingerprint recognition system. The proposed algorithms design improvements will also be under this phase.*

1.7 Risk Assessment

Reputational Damage

This study will not cause any damage to public perception of the University because the research being carried out is ethical and meets both public and internal standards.

The research will also be of good quality, done within the agreed budget and completed on time. Therefore the reputation of the university will not be damaged

There will not be any falsification or fabrication of data and the research output will be of good quality to meet local and international research community standards. International secondary (already collected) data will be used.

Legal and/or financial liability

There will not be any kind of breach of the duty of care to the researcher leading to legal action or insurance claims being brought against the university.

If the researcher fails to deliver the work agreed with the funder (in this case the university), Legal and financial liability for breach of contract are assumed. However, the work will be completed on time and therefore, there will not be any breach of contract.

1.8 Significance of the study (Benefits)

This study will be significant in the following ways:

1. Firstly, this study will provide the state of the art overview about multiple enrollment fingerprint recognition system and areas that require future research and development in the field. Performance data about multiple enrollment fingerprint recognition systems will also be provided. This performance data can also be referenced for future research and development activities by other researchers.

2. This study will also be significant in proposing a novel multi-sample (multiple enrollment) algorithm that will further improve the recognition performance, matching speed and reduce memory consumption in multiple enrollment based fingerprint recognition systems.
3. Results from the study will provide recommendations to developers, decision makers and users on which fingerprint matching methods to use for design or select when implementing multiple enrollment fingerprint based recognition systems in real-world deployment situations.

2.0 LITERATURE REVIEW

2.1 Introduction

One approach that has often been applied to improve performance (matching accuracy) in fingerprint recognition systems is by fusion of multiple sources of biometric information with respect to multiple enrollment [1]. Not only that, but fusion with respect to multiple enrollment has been known to be important for cases where some of the fingerprint data is corrupted (e.g. due to certain reasons like finger displacement, finger rotation, non-linear distortion, partial overlap, fingerprint pressure and skin condition, noise resulting from remains or residue on the sensor platen coming from the previous fingerprint captures and lastly feature extraction errors). In such situations, other impressions of the same finger or different fingers could reliably be used for recognition.

For multi-biometrics, Anil et al [20] classify fusion into three levels;

(i) Fusion at the feature extraction level, where a new feature vector is generated from a combination of feature vectors (with a similar type of measurement scale) extracted from different biometric indicators, is used for matching,

(ii) Fusion at the matching score level, where the resultant matching scores can be combined to verify the truthfulness of a claimed identity and

(iii) Fusion at decision level where each of the biometric systems provides its own recognition decisions which are later voted upon to get a majority vote for making the final recognition decision. The other classification is Fusion at image level (see [1] for details).

Carrying out fusion with respect to fingerprints depends on the type of biometric fusion scenario and the choice of information source to be used. [1] provides 5 different biometric fusion scenarios with the respective information sources: (i) is Multiple Traits, where other biometric characteristics such as iris, ear, or face can be combined together with fingerprints, (ii) is Multiple Fingers of the same person, where two or more fingers of the same person can be combined, (iii) is Multiple samples of the same finger acquired using different sensors, whereby different sensors are used to collect fingerprint data of the same finger and later combined, (iv) is Multiple samples of the same finger, where multiple enrolled fingerprints of the same finger are combined and lastly (v) is Multiple representations and matching algorithms, where different approaches to feature extraction and/or matching of fingerprints are combined. For this PhD research project our focus is on Fusion at matching score level and we shall use information from multiple fingers of the same person.

Fusion at score level entails combining the resultant matching scores into one to verify the truthfulness of a claimed identity. We choose it because among all the fusion implementation levels (fusion at feature-level, score-level and decision-level), it is fusion at score level that can easily be used in all the above mentioned biometric fusion scenarios. More so, it has been widely embraced and known to have the most significant tradeoff between effectiveness and ease of fusion [1]. Although implementation of fusion at score level seems more significant, the generated scores in some cases maybe non-homogenous hence requiring normalization. The most common techniques that have been used for normalization in fusion at score level are Sum Rule, Max Rule and Min Rule. The AND Rule, OR Rule and Majority Voting techniques are also commonly applied to better realize fusion at decision level [26].

As earlier mentioned, fusion can be carried out based on the information source chosen. The source of information we choose for fusion for this research is multiple fingers of the same person, where two or more fingers of the same person are combined. For this case of fusion, it is required to choose which fingers to be used from both hands and also in what order the users would present them at enrollment and verification. For example in the FVC2000 Fingerprint Verification Competition [23], up to four fingers were collected from each person; taking the forefinger and middle finger of both hands. The following order was used during the acquisition: first sample of left forefinger, first sample of right forefinger, first sample of left middle finger, first sample of right middle finger, second sample of left forefinger, second sample of right forefinger . . . , etc., up to 8 samples per person.

Another good example regarding multiple fingers of the same person, is the SAS-DB2 fingerprint database (of University of Twente, Netherlands) that constitutes 12 samples per volunteer coming from six fingers; the pointing finger (or forefinger), middle finger and the ring finger of both hands. During the literature search it has been noted that the ordering left-right first sample, left-right second sample . . . , have seemed to be the commonly used sequence during acquisition of multiple samples from the multiple fingers.

Fusion using Multiple fingers of the same person, does not only achieve a higher recognition accuracy, but the fingerprint recognition system also becomes more difficult to fool [1]. For instance, during verification the user is often required to present his fingers in the same sequence as he did during enrollment. Based on the examples we have discussed above, this would not only require the intruder to get the four or six fingers, but also to know the correct sequence in which they should be presented at the fingerprint reader. This makes spoofing quite harder than when a single finger is used. Also on the other hand, if one of the samples from the given finger(s) is/are corrupted, the other(s) can reliably be used for recognition. Fusion at score level has been the most popularly used [36], [37] implementation level for multi-finger recognition systems; although it is also possible to fuse multiple fingers at other levels. Recognition systems using multiple fingers have also mainly been deployed at border control and in the law enforcement agencies of different governments across the globe.

2.2 Related Work

Studies from different researchers in [17], [18], [21], [22], [25], and [27] show that a better recognition performance is attained when fusion of multiple sources of information is used than when a single source is used. Hybrid biometric systems like one in [19] which uses the face and fingerprint as primary traits together with gender, ethnicity, and height as the soft characteristics, also shows a significant recognition performance improvement. In their research "decision-level fusion in fingerprint recognition" [24], Prabhakar and Jain also show that if different fingerprint matching algorithms are combined (four algorithms were used), the overall performance is increased. Not only that, but they also show that combining multiple impressions or multiple fingers improves the verification performance of the fingerprint recognition system.

Chunxiao, Yin, Jun, and Yang [14] in their research propose a method that implements score level fusion using multiple fingerprint impressions for fingerprint verification to improve performance. Multiple samples of the same user's finger are enrolled and stored as templates for future reference; that is matching to generate matching scores. At the time of verification, the distance from the test fingerprint (claimed identity) and the centroid of reference fingerprints (stored templates) is computed in a multidimensional space. For comparability and matching, they measure the centroid of all the vertices for a given polyhedron and those vertices that are closer to the center of the polyhedron are said to match better than all the others. The distance output is considered as the final score level fusion result. Our research also proposes multiple enrollment of multiple fingerprint sample of the same person while implementing score level fusion. However, we will not compute the centroid but rather focus on comparison of basic fingerprint patterns and features such as the arch, whorl, delta and loop as well as spectral minutiae; between the previously stored template and a candidate fingerprint. It is the generated multiple scores that we will fuse by taking the maximum as the final result.

In their research "Decision-Level fusion in fingerprint verification" [9], Prabhakar and Jain combine four fingerprint matching algorithms (three minutiae-based and one filter-based matcher) to improve accuracy. They carryout multiple enrollment by combining two fingerprint samples of the same finger or different fingers to verify the effectiveness of their proposed scheme. The matching scores generated from the four different fingerprint matchers (algorithms) are then combined and the lowest False Rejection Rate for a certain False Acceptance Rate is Chosen. Prior to the time of combining the matching algorithms (matchers), they use a feature effectiveness approach which implements a matcher selection pattern that measures how well the two imposter and genuine pair classes are separated with respect to a certain feature vector in a dimensional space. They later perform an exhaustive search of all feature subsets and obtain the best feature subset. The final decision is arrived at by using a likelihood ratio L whereby, for high values of L, impostors are identified and for low values of L, genuine people are identified. Similarly, our research proposes selection prior to matching but by automatically assigning/allocating a certain weight in cases where (during fingerprint matching) a poor quality fingerprint image is realized (a low weight value is assigned) and in cases where (during fingerprint matching) a good quality fingerprint image is realized (a high weight value is assigned). This would imply that it is only those fingerprints assigned a High weight value that would be chosen during the matching (fusion) process to improve both accuracy and matching speed as well as reduce on memory consumption. Compared to their work which assesses multiple matchers using decision level fusion to generate a final decision/result, our research focuses on evaluation of a single matcher and implementing score level fusion to generate a final result. Lastly, although both works assess minutiae matching algorithms which use general minutiae as a distinguishing feature to be extracted; our research will specifically focus on use of spectral minutiae.

Luca and Fabio in their research [10] fuse multiple fingerprint sensors (optical and capacitive sensors) for fingerprint verification. Each sensor is subjected to fingers whose fingerprint images are captured; processed and distinguishable features are extracted. The extracted feature sets are matched and two matching scores (each resulting from each sensor) are generated. It is these two scores that are combined to acquire a fused matching score. To attain a final decision, this score value is evaluated based on a certain acceptance threshold, and a claimed identity is accepted (as a genuine user) or rejected (as an impostor) if the score is above or below that acceptance threshold, respectively. This research takes on a similar idea but will rather apply it to the genuine scores after already computing the impostor scores. Amongst the genuine scores generated, the algorithm will choose High weight scores from the genuine ones rather than also taking on the Low weight scores. This will be possible basing on a given score threshold. It is important to note that, we will not classify the low weight scores as impostors, because they are part of the genuine scores. In this case our aim will be to achieve further accuracy improvement in recognition (from fusion and then choosing High value scores). Also, their research focuses on using minutiae as distinguishing features to evaluate the accuracy improvement of imaging sensors by fusing optical and capacitive sensors. This research will however use Spectral Minutiae, to evaluate the recognition accuracy improvement in multiple enrollment based fingerprint recognition systems.

To improve performance and robustness of a fingerprint matcher, Luca and Fabio in [11] further provide a perceptron based fusion technique whereby after enrollment, matching takes place with the help of multiple fingerprint matchers, which then generate a set of the multiple verification scores. It is these multiple scores that are input to the perceptron which later fuses them to have a maximum separation between the genuine users and the impostors. The idea here is borrowed for our research whereby, we will fuse multiple verification scores but ones coming from a singer matcher and mainly those that would have been assigned high weight values during the matching stage.

Jain, Umut, and Ross [12] provide an automated template selection methodology that performs clustering to pick a template set which best characterizes the variability and typicality amongst the stored multiple fingerprint images. During the clustering process, a dendrogram which is in form of a binary tree whose nodes form clusters (representing fingerprint impressions), is output. It is from these clusters that the fingerprint samples with the minimum average distance from the other fingerprint samples are selected. Furthermore, the fingerprint samples are categorized basing on their average distance score in relation to other fingerprint samples and selection of those samples that display supreme likeness (those with the smallest average distance score) with all the other fingerprint impressions is done. With this technique, selection and ranking are based on Average Distance from the other impressions and then choose impressions with least average distance and uses minutiae as the fingerprint matching distinguishing feature. Our research proposes to implement the same idea of selection from many but rather by simply selecting the best matching scores (among others) that are above a certain reasonably good threshold. The fingerprint matching distinguishing feature to be used is spectral minutiae rather than 'normal' minutiae.

Chunyu and Zhou in their research [16] perform multiple enrollment for fingerprint verification by combining the chosen multiple fingerprint samples through using a combination of feature fusion and decision fusion. The results show a performance improvement. However, matching speed, as well as memory consumption are not taken into account. Also, they are focusing on use of minutiae based matching where they record all the minutiae's appearances as well as their positions. Our approach aims at using score level fusion rather than feature or decision level fusion, matching speed and memory consumption will also be tackled. Although a minutiae matching method will be tested, a non-minutiae based matching method will also be deployed to investigate performance improvements, matching speed, memory consumption as well as possibilities for implementation assessed for real world deployment..

Younhee Gil et al [39] also perform multiple enrollment by using multiple snapshots of a fingerprint to extend the fingerprint's reliability as well as its information for better recognition accuracy. The results show a performance improvement by using their approach. However, matching speed, as well as memory consumption are not taken into account. Also, they are focusing on use of minutiae based matching. Our approach will take into account the matching speed as well as memory consumption. Although a minutiae matching method will also be tested, a non-minutiae based matching method will also be deployed to investigate performance improvements, matching speed, memory consumption as well as possibilities for implementation assessed for real world deployment.

2.3 Research Gap

A lot of research that has been done relating to multiple enrollment has mainly focused on combining multiple fingerprint matchers (algorithms), like in [9], [11], [13], [14], [15], [24], and in some cases combining multiple fingerprint sensors, like in [10] to achieve better recognition accuracy; rather than concentrating on single fingerprint matchers focusing on multiple enrollment of fingerprints. Others like [12], [17], [18], [19], [21], [22], [25], and [27], have focused on fusion of multiple sources of information to improve recognition performance. From the analysis of the previously done research related to multiple enrollment, some of the researchers have implemented decision level fusion in fingerprint verification; whereas the majority has implemented score level fusion and others have tried to combine the two in some cases. From the literature searched, it is evident that there is a lot of interest in combining multiple sources of biometric information to improve the recognition accuracy.

However, on top of the avenues for improving recognition accuracy, little research has concretely concentrated on improving the matching speed of such multiple source based biometric systems, usability, memory consumption and acceptability. Although multi-modal, multi-sensor, multi-matcher/algorithm based fingerprint recognition systems somehow improve the recognition performance, their implementation, usability, high memory consumption, poor matching speed and acceptability in real-world deployment situations still remains a challenge; it would require more costs to acquire the necessary extra computational resources, implement as well as convincing and training users to adapt to them. The analyzed recognition accuracies from the current researches are also still low. Also according to our analysis, researchers have not concretely recommended which fingerprint matching methods work best when multiple enrollment is deployed in real world scenarios.

2.4 Proposed Possible Solution

The gaps presented in the section above are a driving force to our research; where we intend to take a closer study on existing biometric systems (mainly fingerprint biometric systems) that use multiple sources of biometric information (concentrating on multiple samples of fingerprints of the same individual like in [12], [16] and [39] to evaluate their performance (recognition accuracy), matching speed, acceptability, usability, and memory consumption.

Our research study proposes a novel multiple enrollment fingerprint recognition approach which will further improve recognition accuracy, the matching speed and reduce memory consumption in multiple enrollment based fingerprint recognition systems. This approach will focus on selection prior to matching by automatically assigning/allocating a certain weight in cases where (during fingerprint matching) a poor quality fingerprint image is realized (a low weight value is assigned) and in cases where (during fingerprint matching) a good quality fingerprint image is realized (a high weight value is assigned). This would imply that it is only those fingerprints assigned a High weight value that would be chosen during the matching (fusion) process to improve the recognition accuracy, matching speed as well as reduce on memory consumption. Score level fusion will be implemented to generate final results.

Our approach will focus on performance and accuracy evaluation of both minutiae-based and pattern-based fingerprint matching methods to realize which method performs better when multiple enrollment is deployed. Rather than using multiple matchers, multiple modals, or multiple sensors; a single matcher, sensor and modal (multiple fingerprint samples) will be used to allow for acceptability, usability and easier implementation.

3.0 METHODOLOGY

3.1 Introduction

This study will concurrently adopt two research approaches; (i) being the exploratory research method [29], where different fingerprint matching methods (such as pattern-based matching method, minutiae-based matching method etc.) will be tested to check which method performs better when multiple enrollment is deployed in real systems. This research method will first be used find out more information about the chosen matching methods and to better understand the problem as well as testing our concepts. The reason we deploy it first is to find a clear basis for us to have a more conclusive research. It is from the thorough formative research analysis in this method that we will be able to draw conclusions about the requirements needed in structuring our approach. This will help us answer the first research question, achieve the first objective as well as guide research question two and research objective two. (ii) The design science research methodology [30], where a prototype multiple enrollment based fingerprint recognition system (algorithm) will be developed as our proposed novel artifact to implement the proposed approach. This methodology will be important in verifying our approach to designing multiple enrollment based fingerprint recognition systems. We cannot simply assume that our theoretical approach to designing multiple enrollment based fingerprint recognition systems would produce expected results without practical verification. It will therefore help us fulfill research question 2 and 3 as well as help in achieving objectives 2, 3 and 4. It is for this reason therefore as to why we will use the design science methodology.

3.1.1 The Design Science approach

The design science methodology research approach whose main goal is to create or contribute to new and interesting design science knowledge in a chosen area of study has been widely used.

By creation of knowledge, the methodology focuses on design of novel or innovative artifacts for examples algorithms, human or computer interfaces and systems. The approach mainly uses mathematical and computational methods to evaluate the quality and effectiveness of the designed artifacts; in some cases empirical methods are used. Our research/study will focus on the design of an approach with improved algorithms based on existing ones for better implementation of multiple enrollment based fingerprint recognition systems in real world applications. The effectiveness of the proposed theoretical approach to designing multiple enrollment based fingerprint recognition systems will have to be evaluated through design of an artifact. This therefore qualifies the design science research approach as appropriate in the context of our research. The Design Science approach takes on five steps of which our research shall follow as explained below:

A. **Step1: Awareness of the problem.** It is at this stage that the challenge or problem is identified to drive formulation of a better approach or solution. In the problem statement section, our study has already identified the challenges/problems at hand and proposed a better approach to designing multiple enrollment based fingerprint recognition systems. We will have a variety of methods used as well as literature searched for a good benchmark and kick off. The result at this phase is the requirements needed for us to be able to formulate a different and better approach to multiple enrollment fingerprint recognition systems design.
B. **Step2: Suggestion**. In this step, a noble solution/approach either an improvement (new solutions for known problems), invention (new solutions for new problems) or exaptation (non-trivial extension of known solutions for new problems) to address the challenge or problem is formulated. In the context of our study, improvement is applicable since a new

solution to a known problem has been proposed. The result of this stage is the proposed approach to multiple enrollment fingerprint recognition systems design.

C. **Step3: Development**. From the designed approach in step 2 above, we will implement an artifact that we will later use to check its viability. In this step therefore, the proposed solution will be actualized and implemented as explained in section 3.3. The result of this phase is an artifact representing a multiple enrollment fingerprint recognition system.
D. **Step4: Evaluation.** After developing the artifact, it is at this stage that experiments will be set up, data analyzed, processed and the performance, speed and memory consumption of algorithms tested and evaluated as explained in section 3.4 through section 3.6. This phase's results are recognition performance, matching speed, memory consumption and non-minutiae method comparisons.
E. **Step5: Conclusion.** After carrying out all the experiments, conclusions will be drawn and reported as explained in section 3.7. The output of this phase will be research papers as well as a final PhD Thesis.

3.2 Study Population and sample size determination

This research will be carried out based on study populations that are represented in form of datasets. These datasets are in form of fingerprint image databases of which we will need to identify. The next section provides a detailed explanation of how the database identification process will be carried out.

3.2.1 Fingerprint Database Identification

In this study, we will have to identify the fingerprint databases to use for our experiments. In this process, we will mainly focus on the following features to identify the suitable databases to use: (i) whether the database consists of multiple enrolled fingerprint image samples, (ii) whether it is large enough and well representative (heterogeneous), (iii) whether it has commonly been used internationally in the Biometrics research field, and (iv) it should not be too old (preferably not more than 15years). This process will be important in this study before we begin any analysis. Some example existing international commonly used fingerprint databases are: UPEK Fingerprint Database, CASIA Fingerprint Image Database, FVC 2006, FVC 2004, FVC 2002, FVC 2000, MCYT-Fingerprint 100, ATVS, Biometrix, Neurotechnologija, Innovatrics etc., to mention but a few. It is from the above list that we will identify the suitable databases as per our desired features. The source/owners of the databases will have to be contacted for full access to conduct our research.

Once the databases are identified and known, organized and data stored, the sample size to use for the experiments will then be determined based on the size of the databases.

It is therefore important to note that there will be no data collection, since it is the already existing international fingerprint databases that will be used.

3.3 Research Design

To better realize the effectiveness of our proposed approach to designing multiple enrollment based fingerprint recognition systems, all experiments will be compared with the existing reported multiple enrollment based fingerprint recognition systems. From this perspective, our research will first carry out a formative research on most of the existing reported multiple enrollment based fingerprint recognition systems, perform multiple enrollment experiments based on the identified databases, and later compare our findings/results with those of the existing multiple enrollment fingerprint recognition systems. With this, we will be able to identify variations and later make concrete performance evaluations which will generate proper recommendations on how to best design multiple enrollment based fingerprint recognition systems.

3.3.1 Approach Design and Implementation

After designing our approach, we will implement a multiple enrollment based fingerprint recognition algorithm and then use the existing methods to carry out the experiments. Different comparisons will be done based on the database used. For the different databases containing a certain number of fingers with a given number of samples per finger, each comparison will be done based on a number of fingerprints that will be selected from the dataset; with some as the *reference* fingerprints and others as the *test* fingerprints. Score level fusion based on the Max Rule in [26] then followed by taking the maximum score amongst the attained values, will be performed.

Two categories of multiple matching will be carried; (i) Multiple Genuine Pair Matching and (ii) Multiple Impostor Pair Matching.

In multiple matching category (i), a certain number of fingerprints of the same person each as a *reference* will be chosen matching each of them with a selected sample of that person as the *test* fingerprint. For any given image samples per person, we will establish relative permutation sets for multi-sample enrollment and single-sample verification.

In multiple matching category (ii), we will choose a sample of an identity (individual) in a given database and match it with the selected multiple enrollment samples of the different identities (individuals) of the same database.

VeriFinger extractor will be used to extract all the minutiae templates from all the fingerprint images in the identified databases. All experiments and algorithms will be implemented in MATLAB, and on a chosen operating system.

3.4 Data Analysis

We will first study the data, describe it, make models and later analyze it using both the pattern-based matching method [3], [4], [5] focusing on the arch, whorl, and loop as the fingerprint matching features and the minutiae-based matching method (such as Traditional minutiae-based matching [6], Spectral Minutiae-Based Matching [7], etc.) using minutiae points as the fingerprint matching features during the analysis. These methods/techniques have been chosen for implementation in this research because of their popular use [1], [5]. These methods have been known for better performance in the fingerprint field. Not only that, but they are also quite easy to understand as well as to implement in fingerprint recognition systems.

3.5 Performance Metrics and Comparisons

It will be important to measure how correctly the new approach to multiple enrollment fingerprint recognition system design will accurately match the fingerprints originating from the same individual but avoid incorrectly matching fingerprints originating from different individuals.

This study will focus on the following accuracy indicators for comparisons: False Acceptance Rate (FAR); the probability of a false match error happening, False Rejection Rate (FRR); the probability of a false non-match error happening and the Equal Error Rate (EER); one where the FAR and FRR become identical (equivalent). In our accuracy indicators we will consider use of percentages basing on the data we will generate from the experiments. We will also use the genuine and Impostor histograms as well as the Detection Error Tradeoff (DET) curves [28] to compare the performances of the multiple enrollment fingerprint recognition systems.

The processing time, template size as well as the memory consumption will also be used as performance indicators in this study. To better realize the effectiveness of our approach, our experimental results will be compared with the existing multiple enrollment based fingerprint recognition systems.

3.6 Testing Strategy

We will test our approach by performing comparisons amongst the genuine recognition attempts and the impostor recognition attempts to determine the improvements in the recognition accuracy, speed and memory consumption reduction. All the testing will be done at the researcher's site using the researcher's hardware. All evaluations will be done in a fully controlled environment so that all input and output processes are thoroughly monitored. For practicality reasons in our testing strategy, we will try to enforce a limit on the maximum response time of the algorithms in the approach for enrollment and comparisons. The testing strategy discussed above will help us monitor and evaluate all the speed (processing time), performance and accuracy as well as memory consumption indicators as already discussed above.

3.7 Reporting

We will communicate the research results both during and after the analysis and testing have been done. It is at this stage that we will interpret and present our results. We will mostly present the results in form papers in scientific journals or as presentation talks in research seminars, workshops and conferences or to colleagues in organized colloquia. However, reports will periodically be prepared, submitted to supervisors for the University to carry out progressive assessment and guidance. Finally, a PhD thesis will be compiled containing all the information about this research study and submitted for public defense.

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APENDICES

5.1 Appendix 1: Work plan and Timeframe

ACTIVITY PLANNED/ MONTH	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT
YEAR ONE 2014/2015												
Feasibility Study and information gathering												
Concept Paper Development/Submission												
Literature (Related Work) Search and gathering												
Proposal Development/Submission												
Experiment One Setup and implementation												
1st Research Article Writing/Submission												
2nd Research Article Writing/Submission												

Progressive Report writing/Submission												
Proposal Defense												
Experiment Two Setup and implementation												
3rd Research Article content compilation												
Progressive Report writing/Submission and Year Two Plan Review												

ACTIVITY PLANNED/ MONTH	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT
YEAR TWO 2015/2016												
3rd Research Paper writing/submission												
Experiment Three Setup and implementation												
4th Research Article content compilation												
4th Research Article writing/submission												
Progressive Report writing/Submission and Year Three Plan Review												

ACTIVITY PLANNED/ MONTH	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT
YEAR THREE 2016/2017												
Verification Experiment Setup and implementation												
5th Research Article content compilation												
5th Research Article writing/submission												
PhD Thesis content compilation												
PhD Thesis content Writing and Submission												
PhD Thesis Presentation Preparation												
PhD Defense												

5.2 Appendix 2: Budget

No.	Item	Quantity	Unit Price (Shs)	Amount (Shs)
1	Personal Computer/Laptop	1	1,500,000/=	1,500,000/=
2	Digital Persona U.are.U. 4500 Fingerprint Scanner	1	100$ (260,000/=)	260,000/=
3	Transport to and fro Kampala (Supervisor meetings and workshops)	6 times per Academic Year (Total 18 times)	50,000/=	900,000/=
4	Accommodation while in Kampala	2 nights per visit (2*6*3 = 36 nights for 3 years)	120,000/=	4,320,000/=
5	U.S.B flash disk	1 (8 Gigabytes)	100,000/=	100,000/=
6	Printing & Binding			1,000,000/=
7	Communication and Internet (modem subscriptions)			1,000,000/=
8	Publication costs for papers (2 per year)	6	150$ (390,000/=)	900$ (2,340,000/=)
9	Functional Fees	3	1,302,000	3,906,000
10	Miscellaneous			500,000/=
			Total	**14,826,000/=**