Reduce Data Utilization Scheme for Biometric Hand Recognition using Six Features

S.Mohammed Basheer, Ms.Joy Robinson

Abstract— This system provides a novel method for Person verification using hand matching with improved performance in large hand pose variations. Normally hand recognition systems are too complex and needs more datasets and algorithms at each level of processing. The proposed approach introduces a reduced data utilization scheme of providing both identification and authentication from contact free hand images using pattern matching technique. A generic and secure approach is proposed to upgrade the already existing template based Eigen finger authentication towards Pattern matched recognition to reduce its complexity and data utilization. Here the proposed approach is a hand based biometric system which allows both user identification as well as authentication using six features of user hand. The features used here are Little finger, Ring finger, Middle finger, Point finger, Thumb and the Palm print. The method is well suitable for implementing hand based authentication over a wide variety of technologies such as embedded systems and mobile phone technologies which requires a minimized data utilization scheme to provide user authentication.

Index Terms—Contactless Imaging, Feature Classification, Feature Extraction, Finger Print, Hand Biometric, Hand Recognition, Palm Print, Pattern Matching.

1. INTRODUCTION

In recent years, much research has been made to the understanding of Biometric identification and authentication. Though there are many approaches proposed so far to provide authentication based on any one of the biometric traits, Finger print and palm print has been accepted as the most accurate and widely suited form in identification systems because of its ease of acquisition and further processing.

1) Finger Print: Peoples are using their fingerprints for personal identification for many decades. The matching factor and the accuracy level using fingerprints are relatively high compared with other biometric traits. A fingerprint is the pattern of ridges and valleys on the surface of a fingertip, the information of which is determined during the first seven months of fetal development. Even the Fingerprints of identical twins are different. The accuracy of the currently available fingerprint recognition systems is adequate for authentication systems involving a few hundred users. Recent techniques include using more finger print features from a single person to provide enhanced and additional information to allow biometric authentication a successful one. But the main issue in these approaches is they need a very large amount of resources like large databases, high level acquisition devices and processing kid.

2) Palm print: Palm print is considered as the next higher level biometric trait which provides much more accuracy in human authentication same as finger prints. Here there is a need to have more concentration in finding out the proper region of interest and edge detection and segmentation. Recent techniques include fusion of finger print and palm print features to allow authentication as more successful one. It has been proved that instead of using a single factor, fusion of two or more biometric traits can make authenticate a most successful one because of its improved accuracy.

As these are hand held devices, hand authentication factors such as Finger print, Palm print and hand gestures might be the suitable as one among the other Biometric trends. At present, approaches on palm print and finger print recognition deals with feature extraction, texture, 2D & 3D geometry and multiple representations. Nowadays, fingerprints of a small fraction of the population may be unsuitable for the automatic identification because of illness, genetic factors, ageing, environmental, or occupational reasons. Also another major problem is that this type of Hand recognition system requires a considerably large database to make it more accurate regarding its validation and verification. Another issue is that these systems could be only used in a complex system, as it needs to maintain a wide range of datasets in its database to make the authentication purpose much clearer and accurate. Now there is a need for these type of authentication systems to be used in small scale devices and embedded systems, which can maintain only a limited database. A systematic approach is needed to make way for new technologies for handling hand

- *S.Mohammed Basheer is currently working as an assistant professor in Department of Information Technology, SCAD College of Engineering and Technology, Cheranmahadevi, Tirunelveli, Tamilnadu, India. E-mail: basheer_s26@yahoomail.com*
- *Ms. Joy Robinson is currently working as a Head and professor in Department of Information Technology,SCAD College of Engineering and Technology, Cheranmahadevi, Tirunelveli, Tamilnadu, India.*

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authentication for limited range technology devices.

2. Literature Review

There has been an increase in the use of digital image processing techniques for the authentication of hand surface after it was recommended as one of the method of the most successful biometric authentication systems. With this increase, more work have been done to improve some of the existing authentication methods while new methods have also been introduced in order to increase the level of security and the accuracy level of human biometric based authentic systems. The increase in the interest of hand surface authentication over contactless surface has made possible the consideration of 3D hand geometry and 3D palm print features [1]. Most of the work has been made in pose correction and altering over large pose invariance's. Image segmentation has been made possible after necessary mapping of 3D hand images into 2D hand image which has been previously captures from a 3D digitizer [1]. The experiment of Vivek kanhangand works with dynamic fusion of palm print image and hand gesture. It has been successfully proved that hand identification is possible in contactless pose invariance's. The input user image will be in a 3D format, which could be mapped into 2D form. Then the image will be pose normalized after necessary preprocessing of the input image. After hole filling the input image, it could be matched with either one of the 5 different hand poses described in [1]. His experiment result in this dynamic fusion produced only 0.28% of EER. This could be a well constraint approach for recognition of contactless hand imaging after proper pose correction.

Most of the available work done can generally be categorized into 3D hand acquisition and pose correction. However only few works has been done in the detection of verification of user hand images. In this section, some of the past works on contactless pose invariant hand surface authentication are discussed. In [2], an improved unified framework for hand surface verification has been made. this paper also investigates the performance improvement that can be achieved by integrating five biometric features, i.e., 2-D palm print, 3-D palm print, finger texture, that are continuously extracted from the user's hand presented for authentication. The fusion of 3D and 2D hand geometry matchers proposed by Vivek kanganhad produced a performance of 2.3 (EER) which is really a successful factor in case of contactless hand image authentication. Also at the other hand, in [3], an online biometric system integrates finger-geometry features extracted from the four fingers and Eigen finger features extracted by means of the Karhunen-Loève (K-L) transform applied to the four finger strip-like regions produced an EER of 0.04% on a database of 1270 hand image datasets. But this performance for hand authentication is from a contact oriented hand image taken from an IR reading or a scanner. In [4], a very simple and efficient scheme for 3-D palm print recognition has been made. After calculating and enhancing the mean-curvature image of the 3-D palm print data, Extraction of both line and orientation features from it has been made.

The two types of features are then fused together at either score level or feature level for the final 3-D palm print recognition. The line feature extraction and orientation feature extraction from a 3D hand image proposed by Wei li is a well defined approach for improving efficiency in hand authentication regarding 3D palm print with less matching time. In [5], Ajay kumar proposed an approach for providing biometric authentication using the knuckle tips which can be used as key points for the image normalization and extraction of region of interest. In this approach the matching scores are generated in two parallel stages: (i) hierarchical matching score from the four topologies of triangulation in the binarized vein structures and (ii) from the geometrical features consisting of knuckle point distances in the acquired images. The weighted score level combination from these two matching scores are used to authenticate the individuals. He successfully proved a high level accuracy over hand authentication with using only a medium level database. In [6] David Zhang proposed an approach for online multispectral palm print system to meet the requirements of real-time applications. Here A data acquisition device is designed to capture the palm print images under Blue, Green, Red, and near-infrared (NIR) illuminations in less than 1 s. A large multispectral palm print database is then established to investigate the recognition performance of each spectral band. His experimental results showed that the Red channel achieves the best result; instead the Blue and Green channels have comparable performance but are slightly less probable to the NIR channel. After verifying the extracted features from

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different bands, He then proposed a score level fusion scheme to combine the multispectral information. He successfully determined that the fusion of 3 or more bands will not provide a good result compared to fusion of 2 bands.

Another approach has been proposed by Ajay kumar [7] to perform authentication from hand images using the triangulation and hand vein characteristics of human hand. This is a method of providing authentication from a contactless hand images from near infra red region with relatively less cost of processing. This schema is well suitable for implementing authentication for low end systems. The main theme behind this approach is the vein triangulation of humans varies depending upon the physical characteristics of a person such as temperature, hand pose, health conditions and thickness of the fat layer. Temperature, humidity and structure of venous characteristics also the other factors for providing uniqueness regarding hand vein authentication. He produced a promising experimental result of 1.14 as EER ratio when proper image acquisition and processing is followed. However this technique employs only for a fixed focus and cannot able to work under large pose variance. Paper [8] (Pre processing methodology applied to the hand correction of Radiographic images) describes a way of understanding the preprocessing of Input hand images, which is the first step for any Hand authentication schemes. Here it can be understood that it is possible to eliminate large intensity variation using the heel effect algorithm. This is a much useful method which allows us to reduce the non uniformity in the illumination of light intensity of the input image. It is possible to segment the hand image separately from the background by noise deduction procedures to subject the image into further processing. Also paper [9] describes the way of image acquisition using a simple mobile camera. It is possible to make an input hand image to be retrieved from a low level mobile camera instead of using a 3 D digitizer to perform preprocessing. This simple technique allows us to segment the hand images by classifying the input image into three boundaries- The finger area, Background and the Boundary. Next samir kumar bandyobadyay [10] and gholamreza amayeh [11] proposed some useful approaches in segmentation and edge detection of input images. Again Vivek kanganhad [12] produced an idea of pose normalization and correction of an input 3D hand image and also he describes in his paper about the finding of ROI of palm, which is a much needed level of template creation. Finally Hiroyuki Aritaki [13] described with his shape recovery algorithm about object acquisition from a 3D digitizer. Also Rishi R. Rakesh [14] proposed a much useful statistical approach of thresholding in edge detection of images. At last Nianjun Liu [15] applied active statistical model for hand gesture extraction and recognition. The rest of the paper is organized as follows. The methodology of the proposed hand image verification and authentication system is described in Section 3. Section 4 discusses the implementation procedures for hand image recognition. Section 5 discusses the experimental results and analysis of this reduced data utilization hand image recognition. Finally, conclusion is drawn in section VI which also includes suggestions regarding future work.

3. PROPOSED METHODOLOGY

The goal of image compression is to store an image in a more compact form, i.e., a representation that requires fewer bits for encoding than the original image. This is possible for images because, in their "raw" form, they contain a high degree of redundant data. Most images are not haphazard collections of arbitrary intensity transitions. Every image contains some form of structure. As a result, there is some correlation between neighboring pixels. If one can find a reversible transformation that removes the redundancy by de-correlating the data, then an image can be stored more efficiently. The Karhunen-Loève Transform (KLT) is the linear transformation that accomplishes this. Now consider the Karhunen-Loève Transform *(KLT),* which is closely related to the Principal Component Analysis *(PCA)* and widely used in data analysis in many fields.

3.1 CALCULATION OF KLT

The calculation of the KLT is typically performed by finding the eigenvectors of the covariance matrix, which requires an estimate of the covariance matrix. If the entire signal is available, as is the case for coding a single image, the covariance matrix can be estimated from n data samples as,

$$Q_n = \frac{1}{n}\sum_{i=1}^{n}(x^i - \overline{x})(x^i - \overline{x})^T$$

Where $\mathbf{x}_i$ is the $\mathbf{i}$'th row of the sample matrix. If only portions of the signal are available, care must be taken to ensure that the estimate is representative of the entire signal. In the extreme, if only one data vector is used then only one nonzero Eigen value exists, and its eigenvector is simply the scaled version of the data vector. For typical images, it is rarely the case that their covariance matrix has any zero Eigen

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values. For a data vector of dimension N, a good rule of thumb is that at least $10 \times N$ representative samples from the various regions within an image be used to ensure a good estimate if it is not feasible to use the entire image. To calculate the KLT of an image, the covariance matrix is first estimated. The estimate is calculated from the set of sequential non overlapping blocks for the image.

3.2 Eigen Fingers and Eigen Vectors

In image processing, processed images of faces can be seen as vectors whose components are the brightness's of each pixel. The dimension of this vector space is the number of pixels. The eigenvectors of the covariance matrix associated with a large set of normalized pictures of faces are called Eigen faces; this is an example of principal components analysis. They are very useful for expressing any face image as a linear combination of some of them. In the facial recognition branch of biometrics, Eigen faces provide a means of applying data compression to faces for identification purposes. Research related to Eigen vision systems determining hand gestures has also been made.

4. Implementation

4.1 Hardware and Software Configuration:

Our detailed evaluation methodology has been instrumented by a simulation on the IDL software to quantify and analyze the palm and finger feature comparison with the dataset for both matched and unmatched input user hand images. To begin with, the input and the dataset features have to be compared in a separate manner. Further performed an analysis and test samples have been made for palm features of input image versus that in the dataset already stored. The same procedure needs to be done for finger features also. All software components were compiled using a standard IDL built on the IDL toolkit for opportunistically architecting finger and palm feature pairs.

This approach explores a study of replacing existing template based authentication technique using an improved pattern matching based process. The block diagram of the approach has been given in figure 1. The proposed approach is divided into a cycle of nine phases: Preprocessing, Image segmentation, Normalization, Finger sub image extraction, Eigen finger and palm extraction, Feature Extraction, Feature Classification, Authentication and Analysis. Preprocessing phase makes the acquired image suitable for feature extraction. In sixth and seventh phase, the feature points are located and extracted features are put in the storage device. In the final step, textures of hand image are compared with the stored template.

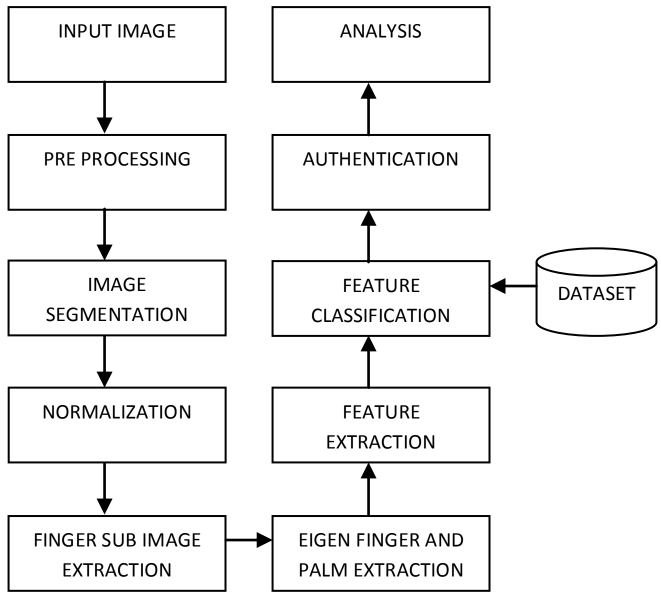

Figure 1: Block diagram of phases of hand image authentication.

4.2 Preprocessing:

The 3D hand image acquisition has been made using any one of the low level digitizer is done. This image acquisition setup is simple. Only the users will be requested to place their hands near the digitizer. The initial stage preprocessing includes necessary gray conversion, noise reduction and texture correction which have been made from the continuous images acquired from the 3D digitizer. The Received 3D Image must be converted into a 2D image using one of the contactless pose invariant approach [1] which will be pose corrected and mapped, so that it could be matched with the Dataset already exists in the Database. The figure 2 shows the initial stage preprocessing of an input image. Here the conversion of the input image into gray scale has to be performed to precede further level of processing.

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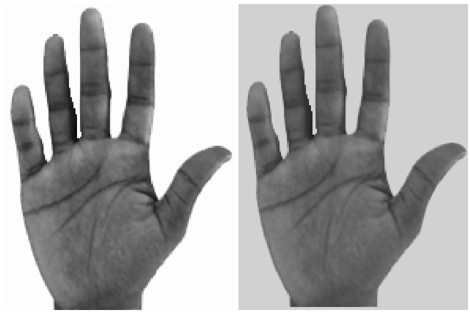

Figure 2: An Input hand acquisition image (Left) with its Gray Scale conversion (Right).

4.3 IMAGE SEGMENTATION:

The proposed approach also has been focused to follow the concepts of image segmentation and pose normalization from acquired hand images. Image segmentation is the next phase in our methodology, which includes allowing the acquired images to encounter necessary illuminations with noise removal. Figure 3 shows the Segmented Image which has been done using IDL Toolkit.

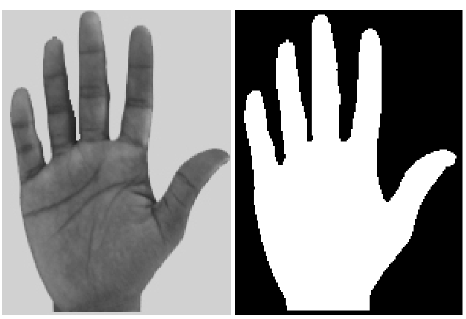

Figure 3: The subjected Input Image after performing Image Segmentation.

4.4 NORMALIZATION:

The next phase is the Normalization of the input image. This phase will be needed in the case of invariance in the poses retrieved from the input image. A 3D set up has been made to extract the data points from the region around the center of the palm. The orientation of the normal vector is then calculated and altered relative to the acquired dataset images. A sample pose correction of an input image is given in figure 4.

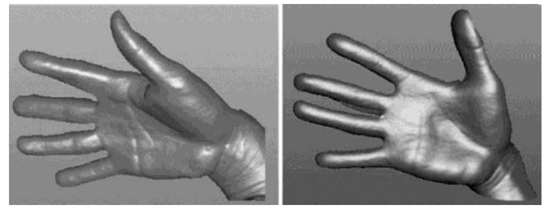

Figure 4: Pose corrected (Normalization) input image.

Normalization must be considered to ensure invariance to perform slight changes. One of the approaches [19] proposes a normalization scheme based on the finger length, dividing each extracted feature by their corresponding finger length. Lengths are measured in terms of Euclidean distance between the corresponding tip points to the bases of the finger.

4.5 FINGER SUB IMAGE EXTRACTION:

The approach suggest to follow the concepts of contour following algorithm [3] to perform finger sub image extraction which allows us to extract the hand image alone from the overall acquired input image. This would help us to perform boundary selection to ease the midpoint plotting for each finger at the next level of processing. The outer boundary detection of the hand image could be performed by subjecting the image to be binarized using global thresholding procedures. By doing this way a hand contour image has to process it to the next level of finding midpoint predictions. The contour image resulted by edge aided segmentation have been shown in the figure 5.

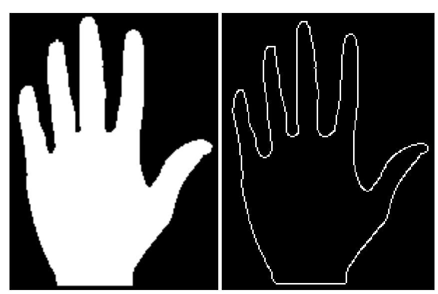

Figure 5: Edge aided Segmentation image after normalization.

4.6 EIGEN FINGER AND PALM EXTRACTION:

This efficient technique has been taken into account for more précised feature extraction from the Eigen finger and the palm extraction from the contour hand image. The next step will be finding the line of symmetry for each finger. From the

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acquired image with midpoint plotting, the necessary and needed region of fingers and palm could be then extracted to get a pattern, which could be further matched with the stored dataset of hand images. Totally 9 points have been plotted from the contour image.

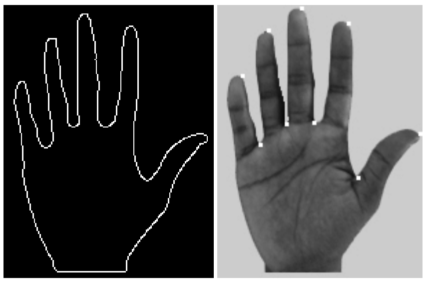

Figure 6: Hand contour image with relevant mid points.

4.7 Feature extraction:

Now the next step is to use the K-L transform method, which is a well efficient technique for feature extraction in biometrics. The basis vectors of the K–L transform are calculated by finding the largest m eigenvectors of the covariance matrix of the set of images. In the case of finger-strip images, eigenvectors will be called as Eigen fingers. The subspace spanned by these eigenvectors is referred as the finger-space. In our system, five finger spaces are created, one for each finger considered. The finger-spaces using the training set of our database, consisting of 9 images of 3 persons has been calculated. A sample feature extraction from our dataset has been given in the figure 7.

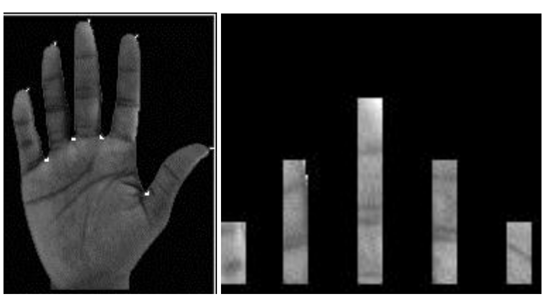

Figure 7: Finger features extracted from an input hand image.

4.8 Feature classification:

The acquired finger and palm features must be separately distinguished with its uniqueness in characteristics accordingly to perform matching the input image with that of the appropriate dataset image. Totally the input image has been classified into six features - five finger features and a palm feature. A sample set of six features including the palm print of an input hand image has been illustrated with the finger geometry measurements taken from the hand contour in figure 8.

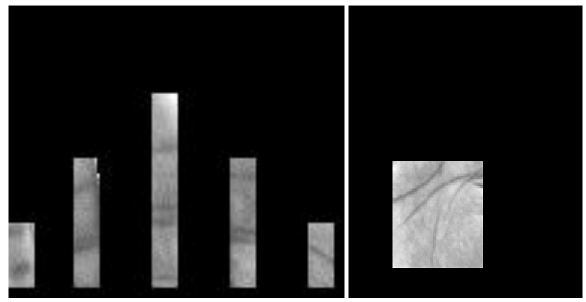

Figure 8: Six features extracted from an input hand image.

The next step is to combine and compare the extracted features as a whole where the process, so called feature classification could be made. This can be processed by the Karhunen-Loève (K-L) transform techniques. Seven measurements (six widths and length) are taken for each of the considered fingers. Thus, the finger-geometry template extracted from each sample consists of a 35-component vector G, in the case when five fingers are considered.

4.9 Authentication and analysis:

There is a need to use these six features as a whole to represent whether the samples matches with the dataset images. Though the input image have been separated into six features, it need to be classified as two main parts 1) A combination of extracted five finger features and 2) Palm feature. An analysis module could be followed which will detect whether these features match with either one person's hand image of the dataset images. By this way it can be easy to find out whether the input features are matched with the dataset images or not. Also Analysis has been produced for these two classifications to find out the variance with the other dataset images of remaining hand images of other persons. This has been explained in the next section.

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5. Experimental Evaluation and Result

The images acquired for a contactless hand image is taken from the commercial 3D digitizer as described in the previous sections. After subjecting the input images into the several phases of processing, then the comparisons of the extracted features will be calculated with that of the hand images previously stored in the datasets. We then go for the common strategy of variance (σ^2) which is a measure of how far each value in the data set is from the mean using the formula,

$$\sigma^2 = \frac{\sum (X - \mu)^2}{N}$$

The variance (σ^2) is defined as the sum of the squared distances of each term in the distribution from the mean (μ), divided by the number of terms in the distribution (N). Also the Standard deviation (represented by the symbol σ) is to be calculated, which shows how much variation or "dispersion" exists from the average (mean, or expected value) using the formula,

$$\boldsymbol{\sigma} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{N}} \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{N}} (\boldsymbol{x}^{\boldsymbol{i}} - \boldsymbol{\mu})^{\mathbf{2}}}$$

The input hand image will be compared with that of dataset with all its five fingers and the palm features. The analysis will produce the deviation result of the input image with the hand images of other persons stored in the dataset. This will be very helpful in the case of predicting the situation where same user will be giving various inputs with different pose variances. The process had been demonstrated by an analysis of 9 different hand images of 3 different persons.

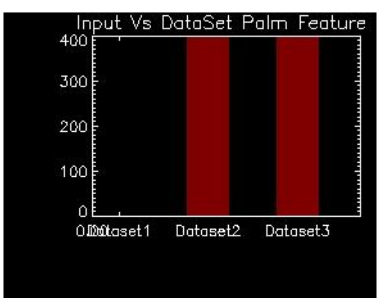

Figure 9: The results were produced using IDL toolkit for the analysis of variance between palm features of user and dataset hand images.

The experiments and the analysis of hand authentication have been performed using IDL 6.5 Toolkit. The variance measurements of the input hand image and the dataset images have been given in the figures 9 and 10.

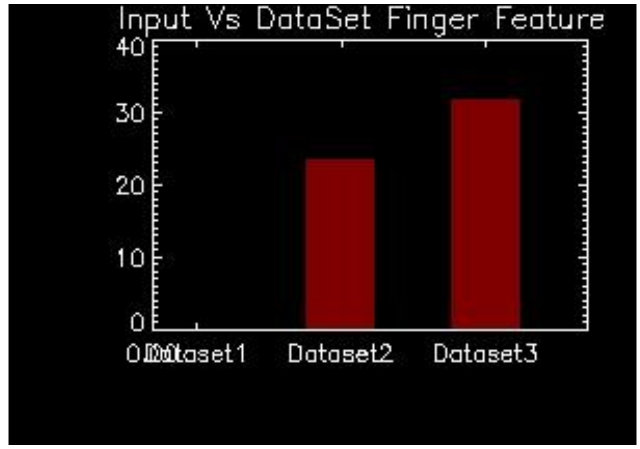

Figure 10: The results were produced using IDL toolkit for the analysis of variance between finger features of input and dataset hand images.

5.1 Experiments:

The Measurements of variance between the palm (Figure 9) and finger images (Figure 10) of Input hand image and that of the dataset images has been made. Here an efficient and very useful positional based identification of hand image has been made (figure 11). The above mentioned analysis is much helpful for determining the impression of hand images. This will ensure the level of normalization made from the image acquisition step. The placed hand image in 3D space has been deduced to 2D impress of X, Y coordinates. The length, width and positional measurements have been identified very clear in the analysis given below.

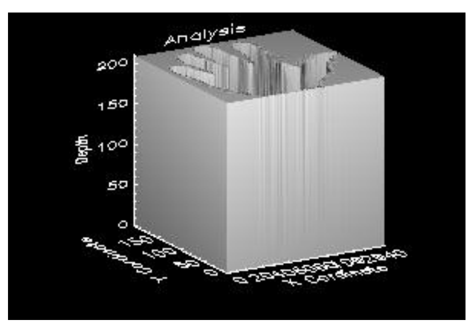

Figure 11: The analysis for hand image identification based on its impression and position

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6. Conclusion and Future work

In this paper a study of an adaptive and efficient approach for Contactless Hand image identification and authentication. A pattern based approach has been proposed here for the purpose of biometric hand authentication. Efficient results have been made comparative to the template based previous approach. Authentication experiments were conducted on a database consisting of two mutually exclusive sets: a data set and an input set. The data set consisted of 9 visual hand-images of 3 persons. The results show the feasibility of performing identification and authentication of hand acquisition image with reduced data utilization scheme. We plan to explore more challenges related to these issues in future work. Further we decided to test the system on a large database to be collected over a longer period of time. The major disadvantage of the proposed approach is its utility the use of commercial 3-D scanner. Slow acquisition speed and size of this scanner make it infeasible for any online biometric applications. As part of our future work, an alternative to the 3-D imaging technologies that can overcome these drawbacks. We also try to precede the biometric authentication into a technological and commercial level methodology for small scale systems like mobiles and embedded systems in the future.

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