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Performance Analysis of ANN Optimized FT-PCA Human Palm Features

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ABSTRACT

The aim is to develop and test the performance of an image processing based Human Palmprint Recognition Application that was developed using combination of Artificial Neural Networks in combination with Fast Fourier transforms and Principal Component Analysis (ANN-FTPCA) techniques is accomplished. After the palmprint images are collected, the preprocessing of those palmprint images is one of the important phases in palmprint recognition systems. Instead of the large palmprint image, a small central sub-image is required for feature extraction. So, in the preprocessing scheme, the central region of interest (ROI) is extracted from the large palmprint image. Also sometimes, the palmprint images need enhancements. During the enrollment phase, multiple samples of palmprints per user are collected in regular intervals from three different databases, so each image from each database is different, as the palm's position suffers from a little bit of rotation and translation in every database. So, the central ROI generated each time will be different. But as the required area is of central sub-images generated from the preprocessing phase, it should be all similar. The developed system is used for human identification based on palmprints; there is a need for the development of high-quality classification methods and accurate feature extraction, which is very significant to execute the system in actual operating environment. The MLP neural network is used for feature optimization and matching to improve accuracy and recognition rate as in the speed of the application and the performance is evaluated on three palmprint databases CASIA, IITD and Poly U.

Introduction:

Palmprint recognition uses the palm region of a person as a biometric for identifying or verifying identity of the person. The palm is the inner surface of our hand from the wrist to the root of fingers. Earlier in *19th* century, in many instances, palmprint examination was the only method of distinguishing illiterate person from each other. But automated palmprint recognition is relatively young.Nowadays every mobile and computer has the feature of editing and enhancing an Image because Modern technology has made it possible to manipulate an image, we get clicked by applying filters, and can be made even more beautiful. The main concept behind this new feature of applying filters or editing an image is Image processing Digital image processing is an important technique using which we can manipulate a digital image through an algorithm using a digital computer. This algorithm takes digital images as input and produces the characteristics of images or parameters of an image as output [1].

Neural Networks are just called Artificial Neural Networks (ANN) are generally propelled by Biological Neural Networks that comprise the human cerebrum. An Artificial Neural Network is the assortment of nodes known as Artificial Neurons which are way more similar to the neurons in the human mind. An Artificial neural network contains layers of interconnected hubs or neurons. An artificial neural network trains the example information to distinguish the contrast between the anticipated yield that is we get by applying the algorithm and the targeted yield. That difference is known as an error. The network then adjusts its weighted probability itself to minimize the error. Progressive changes in the network will make the neural network produce an outcome that is path closer to the targeted result. After a necessary number of these changes, the training can be ended dependent on specific rules. Now a days everything has become handy from online shopping to handwriting recognition, in each of these neural networks has a prominent role to play. Neural Networks find a considerably great variety of applications in areas where traditional computers don't perform well [2].

Literature Review:

A. Nalamothu and J. Vijayapublish that palmprints have fascinated academics attributable to their steady and exclusive residences as biometric technology grows to be extra popular. Over fingerprints and facial biometrics, palmprints offer extra targeted characteristic statistics for reputation systems. This study paper ambition to offer a complete overview of numerous palmprint popularity methods, together with ROI extraction mechanism, characteristic extraction strategy, and matching systems, in addition to a top-level view of to be had palmprint datasets, for you to apprehend the cutting-edge developments and studies dynamics with inside the palmprint popularity area [3].

I. Păvăloi, A. Ignat, L. -C. Lazăr and C. -D. Niţăin this paper study the palmprint recognition problem using SURF (Speeded Up Robust Features) keypoints. The main setback when using SURF is that it computes, for the same set of parameters, very different number of keypoints for each image in the dataset, making the matching procedure inefficient. To solve this impediment, authors use an algorithm that tunes a SURF parameter for approximately computing the same number of keypoints for all the images in the dataset. This idea was tested on five palmprint datasets. The palmprint recognition results using this approach are very good, better than those obtained in two recent papers [4].

N. A. A. Khalid, M. I. Ahmad, T. H. Mandeel, M. N. M. Isa, R. A. R. Ahmad and M. Z. Nayef Al-Dabaghin this paper propose new technique to extract the Region of Interest (ROI) of palmprint biometric image while removing the distortion between images such as translation or rotation during ROI extraction. A similarity measure known as Enhanced Correlation Coefficient (ECC) is used in the proposed approach for better ROI extraction and image alignment, which helps to evaluate and determine the distortion. The objective of image alignment approaches is to find the deformation or transformation that minimizes the incongruities between images. After applying ECC algorithm the Region of Interest (ROI) is extracted from the palmprint by using Moore neighbours algorithm, on the other hand, to verify and validate the efficacy of the recommended method the PolyU palmprint dataset II was used [5].

B. Zhang, Z. Song, W. Zhang, X. Shuai and J. Qianpropose an improved local non-negative matrix factorization (LNMF) algorithm for palmprint recognition to solve the problem regarding the high requirements of palmprint image preprocessing. First, the Fisher discriminant criterion is integrated into the non-negative matrix algorithm of the target function, using the gradient descent method. To solve the drawbacks of the traditional algorithm, the LNMF algorithm does not contain class information affecting the recognition rate, and finally, it chooses the appropriate classifier for matching. Experiments on two databases are conducted, and the results show that the proposed method has very high recognition rates on the two databases. In a comparison with other algorithms, the current algorithm achieves a higher recognition effect [6].

L. Fei, B. Zhang, Y. Xu, C. Tian, I. Rida and D. Zhangpropose a simultaneous heterogeneous palmprint feature learning and encoding method for heterogeneous palmprint recognition. Unlike existing hand-crafted palmprint descriptors that usually extract features from raw pixels and require strong prior knowledge to design them, the proposed method automatically learns the discriminant binary codes from the informative direction convolution difference vectors of palmprint images. Differing from most heterogeneous palmprint descriptors that individually extract palmprint features from each modality, our method jointly learns the discriminant features from heterogeneous palmprint images so that the specific discriminant properties of different modalities can be better exploited. Furthermore, authors present a general heterogeneous palmprint discriminative feature learning model to make the proposed method suitable for multiple heterogeneous palmprint recognition [7].

A. Wirdiani, D. Putra, M. Sudarma and R. S. Hartatipropose that palmprint identification is widely used as biometrics because palms have unique and different characteristics of each person. The changes that occur in palm lines are relatively small. The data acquisition process is relatively easy and has small risks associated with the radiation effects. The palm characteristics must be processed before they can be used in biometric systems. The stage of the palmprints identification system is the enrollment and the identification stage. The preprocessing and the feature extraction method are affected to the recognition results. This paper uses a Gaussian filter for preprocessing, feature extraction using Laplacian of Gaussian and Canny edge detection, while the classification method uses Support Vector Machine and CNN [8].

N. A. A. Khalid, M. Imran Ahmad, T. H. Mandeel and M. N. M. Isapresent a combination of LBP with KAZE feature detection to extract the features exist in palm image after applying the LBP. KAZE feature detection is able to select the most discriminant features which produce better class separation in the feature space. KAZE is used to select the most dominant features exist in LBP image descriptor. A serious issue in developing automatic palmprint verification systems is the accurate and robust palm image cropping and feature extraction in order to produce high recognition accuracy. Feature extraction such as local binary patterns (LBP) can be used to describe palm image texture characteristics since the palm print image has a rich number of texture features. Using LBP only to represent a local feature is not enough information to categorize the palmprint image [9].

Methodology:

The processing level includes image acquisition level, feature extraction level, match score level and decision level. The basic level of processing is same for all the biometric system. The complexity lies in the implementation of processing using different approaches and methods. A biometric system which uses a palm print of a person for authentication/verification is shown in figure below.

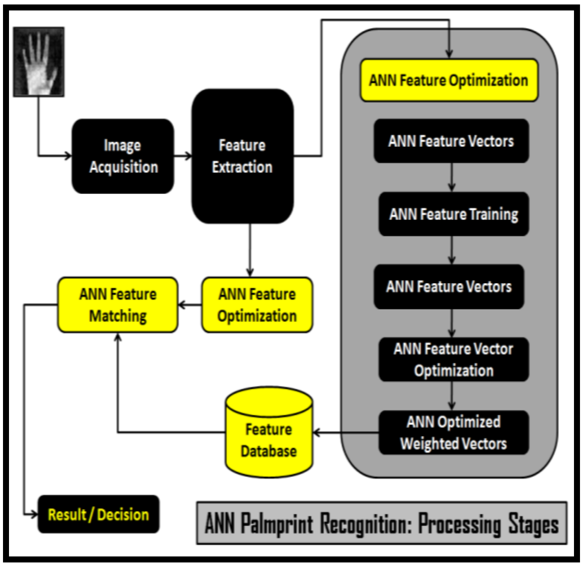

Fig 1_Palmprint Recognition System: Processing Stages

Stage/Level 1: Palmprint Image Acquisition Level

It is the first step in any biometric system where the image of palm is captured for person identification. In this system the palmprint image source is from a readily available palmprint databases like CASIA Palmprint Database, PolyU Palmprint Database and IIT Delhi Palmprint Database.

Stage/Level 2: Palmprint Image Pre-processing Level

Palm images acquired are pre-processed to extract its features. The principal lines are significant and minutiae and textures are used as unique information in forensic.The pre-processing steps involve converting the image to binary, extracting the region of interest and segmenting, key point detection and establishing the coordinating system. Centre of palm is used as region of interest in many methods as it covers most of the palm features and has unique texture for each person. To extract the centre of palm image first it has to be aligned and oriented to crop the centre portion. In key point extraction the valley points from middle finger, ring finger, little finger and the line joining these are taken as orientation and a centre portion of palm image is found and a circular or a squared portion of defined size is cropped.

Stage/Level 3: Palmprint Image Feature Extraction using FT-PCA

Feature extraction of ROI of an image is to locate the points those lie along boundaries i.e., set of pixels that either separate object from one another or change in the surface geometry of an object. The two types of boundaries can be step edges or crease edges. Step edges identify the discontinuity in depth and can be identified by a gradient magnitude. Palm features may also include texture information which can be extracted using statistical measures and wavelets. Palm shape feature includes global features and local features like boundary segments are extracted using Hough's transform which transforms Cartesian to parametric.

Algorithm for Palmprint Feature Extraction using Fourier Transform - Principal Component Analysis (FT-PCA)

Principle component analysis is a statistical method that is used in the field of pattern recognition and/or image compression. PCA is also a powerful technique for data compression since; it can reduce the number of dimensions significantly, particularly for high dimensional images. Basic steps for feature extraction from 2D images are as follows:

Step 1: Select and Read the Images

In the first stage, palmprint images are taken from a dataset of L images. Each image has two dimensions which are N and M. Then the images are converted into a vector shape.

Step 2: Calculating Mean Center of Dataset

In this stage, the mean of the input dataset is calculated.

Step 3:Subtracting Mean from the Vectors

In this stage, the calculated mean is subtracted from each image in the dataset. The goal of this operation is to remove constant component and deal with the maximum directions of in variance in the database.

Step 4: Compute the Covariance Matrix

Following the mean-subtracted dataset, the covariance matrix C is calculated.

Step 5: Computation Eigenvalues and Eigenvectors of the Covariance Matrix

Eigenvectors of the covariance matrix are computed to find the principal bases of variation. Since the covariance is typically square, eigenvectors and eigenvalues can be computed from $CV = \lambda V$, the solution of which can be obtained using the factorization of equation.The diagonal matrix λ keeps the eigenvalues and V is the matrix of corresponding eigenvectors. If the dimensions of C arePxP, this procedure computes P eigenvalues and the same number of eigenvectors, one for each eigenvalue.

Step 6: Sort the Eigenvectors in Decreasing Order of Their Eigenvalues

Eigenvectors are sorted in decreasing order of their eigenvalues.

Step 7: Determining Principal Components

After sorting the eigenvalues, eigenvectors corresponding to the highest eigenvalues represent principal components of the dataset. Simply, a number, K, of eigenvectors corresponding to the largest eigenvalues are considered C to build the projection matrix of PCA.

Step 8: FT- Principal Component Enhancement from Spatial to Frequency Domain

Fourier Transform is one of the most popular and useful transforms in image processing applications. The major applications involve image enhancement and feature extraction. In this palmprint recognition, Fourier Transform can be used in feature extraction as there exists few correspondences between palmprint features on a spatial domain image and those on a frequency domain image. In general, the stronger the creases are on a spatial domain image, the less compact the information is on a frequency domain image. And if a palmprint image in the spatial domain has a strong line, in the frequency domain there will be more information in the line perpendicular direction. In this palmprint recognition system, as feature extraction is conducted in the frequency domain, it is important that similar palmprints resemble each other when converted into frequency images.

Stage/Level 4: ANN Feature Optimization

Neural networks, like human beings depend on the idea of learning in order to achieve any task. Here is designed a multilayer MLP artificial neural network for recognition of off-line digitized palmprints. The main reasons for the widespread usage of neural networks (NNs) in pattern recognition are their power and ease of use. A simple approach is to firstly extract a feature set representing the palmprint with several samples from different subjects. The second step is for the NN to learn the relationship between a palmprint and its class (either "genuine" or "forgery"). Once this relationship has been learned, the network can be presented with test palmprints that can be classified as belonging to a particular subject. NNs therefore are highly suited to modeling global aspects of palmprints. The proposed ANN consists of input variables, hidden neurons, and output variables and it is designed to recognize one palmprint at a time. Back propagation algorithm along with MLP is used for training. First, an input/output database is created manually for training and testing the ANN for palmprint images which are belong to same person but signed different time. Each input vector consists of seven moment invariants obtained for a palmprint. Different moment invariant vectors are produced for each palmprint. These vectors are divided into two sets each containing three vectors. These sets (3 input vectors) are used in the training of ANN and the other set (remaining 3 input vectors) is used for testing. Additionally, also produced here are other extra properties for a palmprint called feature vectors.

Training the ANN

The network weights and biases are initialized. The system behaves as a neural network classifier using the nnet command in MATLAB.The training process requires a set of examples of proper network behavior network inputs p and target outputs t. The training proceeds in MATLAB using the nntool command. During training the weights and biases of the network are iteratively adjusted to minimize the networkperformance function net.perform. The default performance function for feed forward networks is mean square error (MSE), the average squared error between networks outputs a and the target outputs t. Now we need to train the network in order to obtain the correct weights such that the network behaves as an efficient classifier.

Stage/Level 5: ANN Matching and Decision making

In this stage, the ANN is applied for recognize the features that has been extracted and saved in a database. The ANN that suggested is the most general used supervised learning of neural network. The system process obtains one model from each training image by testing each input image against all the models inside the database and the model close to the input image using Mean Square Error (MSE) criterion indicates the recognized person. The ANN Classifier used is nearest neighbors' distance-based classifier based on Mean Square Error (MSE) which will form the basis for weighted features vectors. The distance based nearest neighbors neural net classifier is trained using a Multi-Layer Perceptron (MLP).

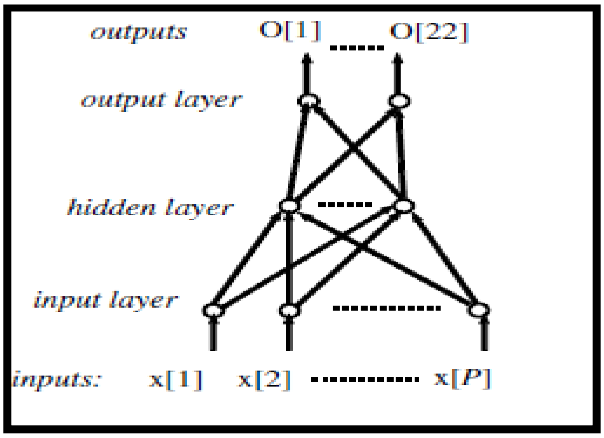

Fig 2_Multi-layer Perceptron (MLP) Architecture

Multilayer perceptron neural network (MLPNN) is considered as a widely used artificial neural networks architecture in predictive analytics functions. The architecture of an artificial neural network, that is, its structure and type of network is one of the most important choices concerning the implementation of neural networks as forecasting tools. The design of MLPNN is motivated by the structure of a biological neuron system capable of parallel processing like a human brain, but the processing elements of this machine learning tool has gone far from their biological inspiration. For this reason, MLPNN have been successfully used by most of the researchers in the field of forecasting, science and engineering to predict the behavior of both linear and nonlinear systems without the need to make assumptions that are implicit in most traditional statistical approaches.

ANN based Decision Making

Features extracted are stored in the database as templates. Each template is unique and has salient features of the image under consideration. When the query image is processed for verification / authentication, the features are compared with the stored template using matching techniques. Match scores are estimated using a threshold and final decision is taken to accept /reject the query image. Classifiers are designed based on three different approaches namely concept of similarity, probabilistic, or a geometric approach.

Patterns that are similar are assigned with a class. Based on the similarity of feature vector and the template, each sub system calculates its own matching score value. These individual scores are finally combined to obtain a total score which is then passed to the decision module. Euclidean Distance is used to compare the feature vectors. Euclidean Distance is calculated by summation of squared difference between two feature vectors. The weighed vectors are optimized feature vectors which enhance the performance of the system by increasing accuracy and recognition speed. The recognized id is shown according to the values returned on the basis of training done by ANN. An error-control learning system detects and possibly corrects the errors that occur when weighted features are transmitted through multiple layers of a MLP. To accomplish this, the MLP transmits not only the informative features, but also one or more redundant features. The MLP uses the redundant features to detect, and possibly correct, whatever errors occurred during transmission in hidden layers to the output layer of the neural network thus increasing the accuracy and speed.

Results and Discussions:

The Performance Analysis is done by statistical and graphical comparison and evaluation of parameters like Euclidean Distance, %Accuracy, %Error, Accurate and In-accurate matches. These parameters belong to the ANN-FTPCA technique for one-to-many (1: N) matching criteria and one-to-one (1: 1) verification criteria for a total of 480 input palmprint images including 160 images from each of three databases namely CASIA Palmprint Database, IIT Delhi (IITD) Palmprint Database and Hong Kong PolyU Segmented Palmprint Database respectively.

Analysis Graph 1: Comparison of Euclidean Distances (ED) (1: N Matching)

The **Euclidean distance** or **Euclidean metric** is the "ordinary" straight-line distance between two points in Euclidean space. The Euclidean Distance corresponds to the nearness of the input palmprint image to be matched to the palmprint image stored in the database. For exact match the ED value should be 0 theoretically but this value changes according to form of input image and can attain higher thresholds.

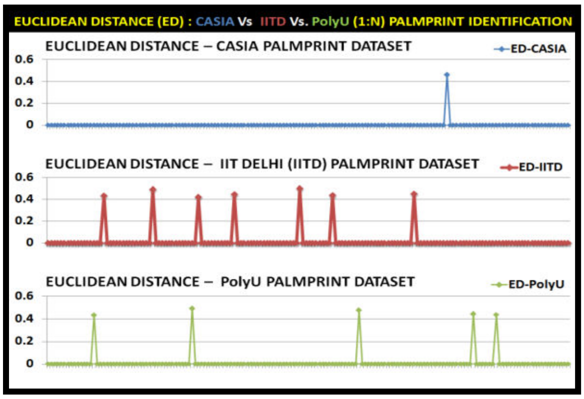

Fig 3_Euclidean Distance (ED) Comparison and Evaluation

The ED Values are calculated and recorded for 160 images of CASIA Palmprint Database are 0 for 159 images and exceed 0.4 which is the threshold for no match for 01 image. For 160 images of IIT Delhi Database the ED values are 0 for 153 images and exceed 0.4 which is the threshold value for no match for 07 images. For 160 images of Hong Kong PolyU Palmprint Database the ED values are 0 for 156 images and exceed 0.4 which is the threshold value for no match for 04 images.

Analysis Graph 2: Application Performance Evaluation %Accuracy (1: N Matching)

The graph analyzes the performance of the application on the basis of palmprint images correctly matched and incorrectly matched. The % accuracy on the basis of number of imaged matched is calculated and show in the graph.

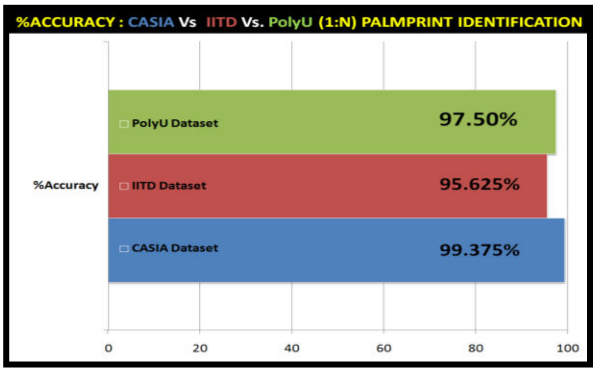

Fig 4_Performance Comparison and Evaluation (%Accuracy)

The CASIA Palmprint Database Dataset1 has 159 correct image class matches out of 160 leading to a high % accuracy performance of 99.375%. The IIT Delhi Database has 153 correct image class matches out of 160 leading to a slightly lower % accuracy performance of 95.625%. The Hong Kong PolyU Database has 156 correct image class matches out of 160 leading to a slightly higher % accuracy performance of 97.50% than IITD Palmprint Database and slightly lower % accuracy than CASIA Palmprint Database. The ANN-FTPCA palmprint recognition application shows considerably better performance when tested on CASIA Palmprint Database (Dataset1) and PolyU Palmprint Database (Dataset3) than IITD Database (Dataset3) with %accuracy deficit rate of 0.625%, 4.735% and 2.50% respectively.

Analysis Graph 3: Application Performance Evaluation %Error (1: N Matching): CASIA Database (Dataset 1) Vs. IITD Database (Dataset 2) Vs. PolyU Database (Dataset 3)

The comparison graphs of the testing of ANN-FTPCA Palmprint Recognition Application on the three datasets created from three databases CASIA Palmprint Database, IITD Palmprint Database and PolyU Palmprint Databaseare compared and depicted graphically in figure below. The graph analyzes the performance of the application on the basis of palmprint images correctly matched and incorrectly matched. The % error on the basis of number of imaged matched is calculated and show in the graph. The CASIA Palmprint Database Dataset1 has 01 incorrect image class matches out of 160 leading to a lowest% error performance of

0.625%. The IIT Delhi Database has 07 incorrect image class matches out of 160 leading to a slightly higher %error performance of 4.375%. The Hong Kong PolyU Database has 04 incorrect image class matches out of 160 leading to a slightly lower % error performance of 2.50% than IITD Palmprint Database and slightly higher % accuracy than CASIA Palmprint Database. The ANN-FTPCA palmprint recognition application shows considerably better performance when tested on CASIA Palmprint Database (Dataset1) and PolyU Palmprint Database (Dataset3) than IITD Database (Dataset3).

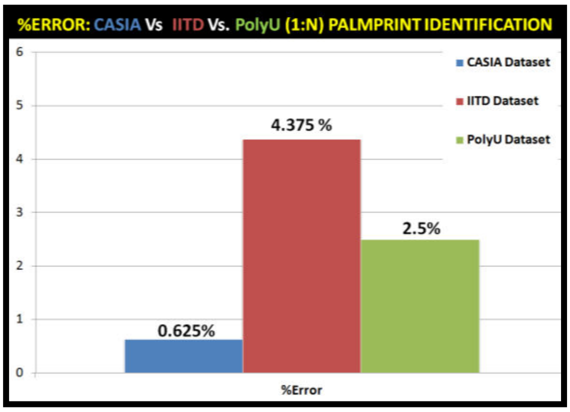

Fig 5_PerformanceComparison and Evaluation (% Error)

Analysis Graph 4: Application Performance Evaluation Accurate Matches Vs. Inaccurate Matches (1: N Matching)

The CASIA Palmprint Database Dataset1 has 159 accurate image class matches out of 160 and 01 inaccurate match. The IIT Delhi Database has 153 accurate image class matches out of 160 and 07 inaccurate matches. The Hong Kong PolyU Database has 156 accurate image class matches out of 160 and 04 inaccurate matches.

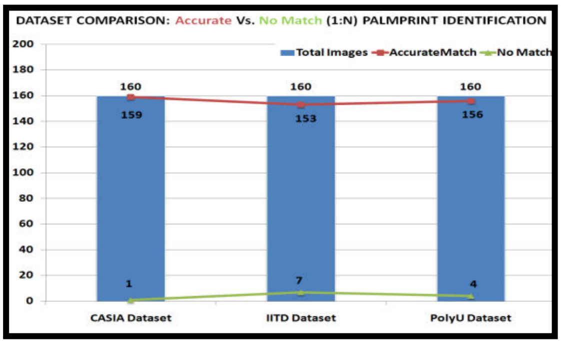

Fig 6_PerformanceComparison and Evaluation(Accurate Vs. Inaccurate Matches)

ANN-FTPCA Palmprint Recognition (1:1 Matching): Performance Analysis

The one-to-one (1:1) palmprint verification the each dataset from each of the three databases is of 48 images with 24 images of left hand palm and 24 images of right hand palm. The application is tested for the same by matching images from the same palm with one another and matching palmprint images of different palms with one another and recording the results.

Analysis Graph 5: Comparison of Euclidean Distances (ED) (1: 1 Matching): CASIA Palmprint Database

The ED Values are calculated and recorded for 48 images of CASIA Palmprint Database are between 0 for 0.4 images for palmprint inputs from same palm and exceed 0.4 which is the threshold for no match for palmprint inputs from different palms.

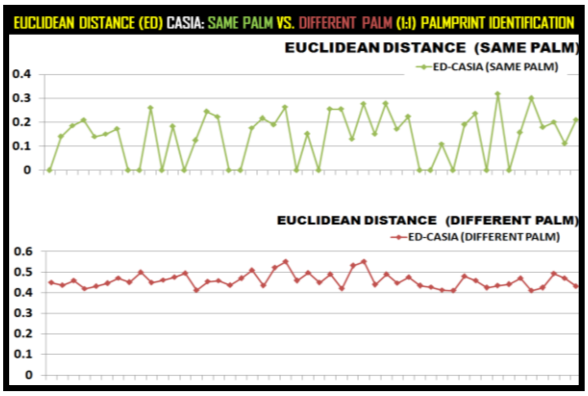

Fig 7_Euclidean Distance (ED) Comparison (1:1 Matching): CASIA Database(Dataset 1)

Analysis Graph 6: Comparison of Euclidean Distances (ED) (1: 1 Matching): IIT Delhi Palmprint Database

The ED Values are calculated and recorded for 48 images of IIT Delhi Palmprint Database are between 0 for 0.4 images for palmprint inputs from same palm and exceed 0.4 which is the threshold for no match for palmprint inputs from different palms. The comparison graphs of Euclidean Distance evaluated from testing of FFT- PCA Palmprint Recognition Application on the same palm and different palm inputs from IIT Delhi Palmprint Database are compared and depicted graphically in figure below. The graph shows from ED values that one-to-one palmprint verification application did not perform efficiently for IITD Palmprint database for both same and different palm inputs.

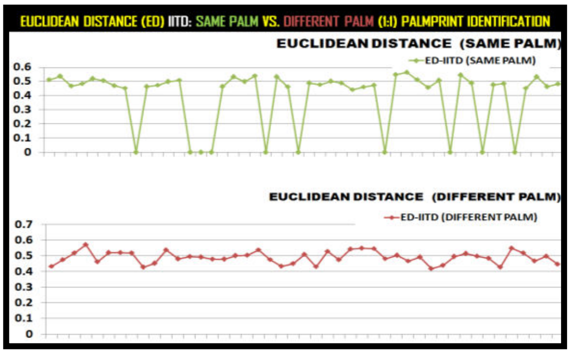

Fig 8_Euclidean Distance (ED) Comparison (1:1 Matching): IITD Database (Dataset2)

Analysis Graph 7: Comparison of Euclidean Distances (ED) (1: 1 Matching): Hong Kong PolyU Palmprint Database

The ED Values are calculated and recorded for 48 images of Hong Kong PolyU Palmprint Database are between 0 for 0.4 images for palmprint inputs from same palm and exceed 0.4 which is the threshold for no match for palmprint inputs from different palms. The comparison graphs of Euclidean Distance evaluated from testing of FFT- PCA Palmprint Recognition Application on the same palm and different palm inputs from Hong Kong PolyU Palmprint Database are compared and depicted graphically in figure below.

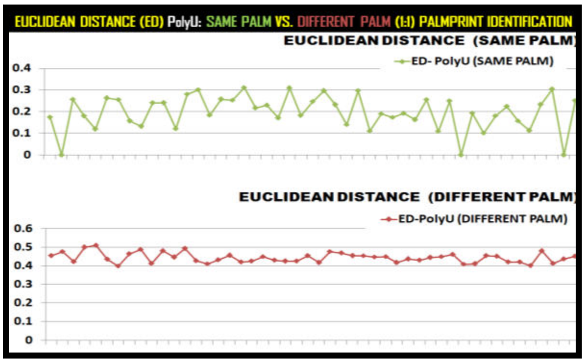

Fig9_Euclidean Distance (ED) Comparison (1:1 Matching): PolyU Database (Dataset3)

Analysis Graph 8: Application Performance Evaluation Accurate Matches Vs. Inaccurate Matches (1: 1 Matching)

The CASIA Palmprint Database Dataset1 has 48 accurate image class matches out of 48 and zero inaccurate matches. The IIT Delhi Database has only 22 accurate image class matches out of 48 and 26 inaccurate matches. The Hong Kong PolyU Database has 48 accurate image class matches out of 48 and zero inaccurate matches.

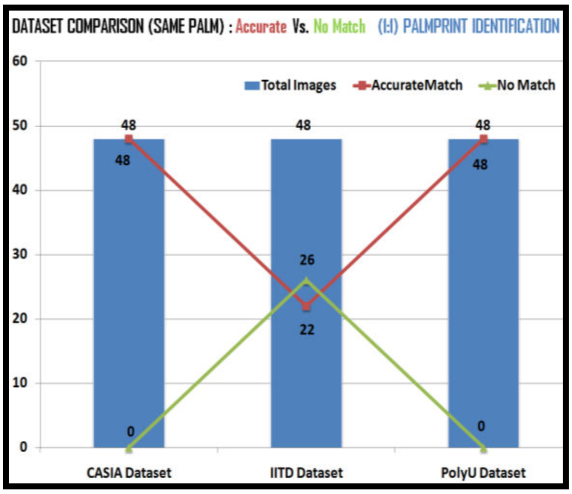

Fig10_Performance Evaluation (Accurate Vs. Inaccurate Matches)

Analysis Graph 9: Application Performance Evaluation %Accuracy and %Error (1: 1 Matching

The CASIA Palmprint Database Dataset1 has 48 accurate image class matches out of 48 and zero inaccurate matches with 100% accuracy and zero error. The IIT Delhi Database has only 10 accurate image class matches out of 48 and 38 inaccurate matches with %accuracy of 45.8% and %error of 54.2%. The Hong Kong PolyU Database has 48 accurate image class matches out of 48 and zero inaccurate matches with 100% accuracy and zero error.

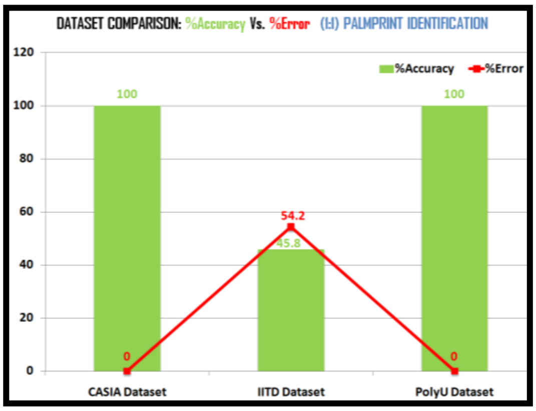

Fig11_Performance Evaluation (%Accuracy & %Error)

Analysis Graph 10: Comparison of ANN System Recognition Time (CASIA Vs IITD Vs PolyU)

The graph shows comparison of ANN System Recognition Time in seconds for each of the three datasets for all individual inputs from all dataset classes. The comparison show there is a minimal increase in recognition time as the type of the dataset changes still the recognition time performance of ANN remains very high with recognition time ranging from 0.07 seconds to 0.16 seconds which is considerably low and highly rapid for 1: N Matching. Also, the trends for 1:1 Matching show that ANN system recognition time further reduces and falls in the range between 0.05 seconds to 0.14 seconds which is shown by overlaps in the graph below.

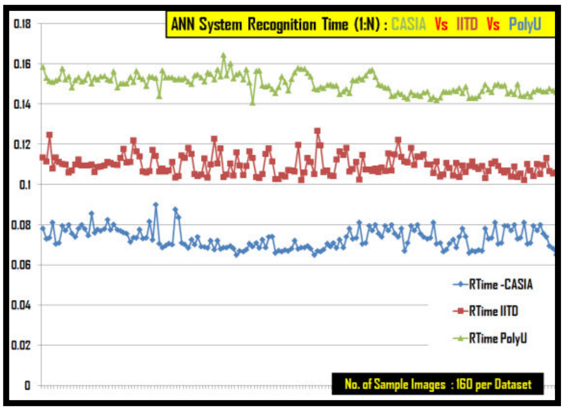

Fig12_Performance Evaluation (ANN Recognition Time) (1: N Matching)

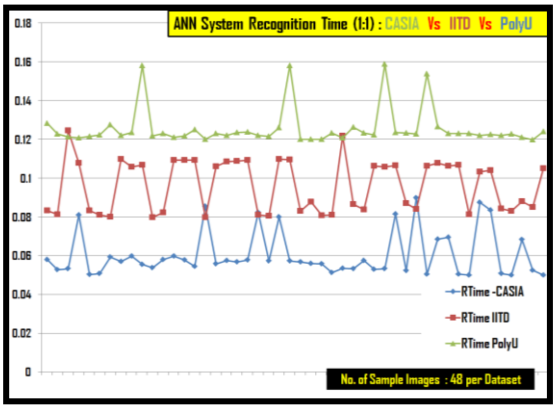

Fig13_Performance Evaluation (ANN Recognition Time) (1:1 Matching)

Analysis Graph 11: Application Performance Evaluation (Overall Analysis)

The comparison graph is shown for overall analysis for combined values of all the three datasets for 1:N Matching, 1:1 Matching and Total combined test results for both types. Thus the overall % accuracy is calculated to be 88.5% and the overall % error is 11.5%.

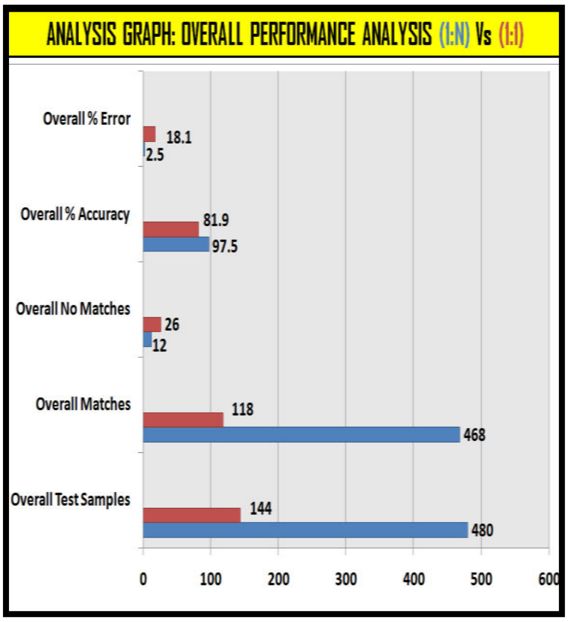

Fig14_Overall Result Analysis and Performance Evaluation

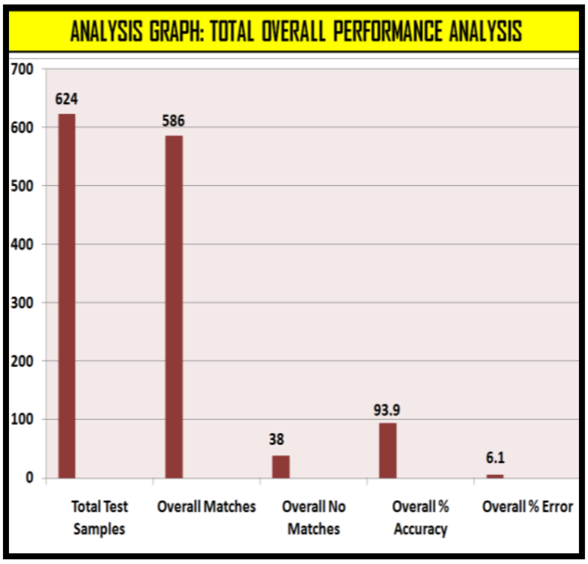

Fig15_Total Overall Result Analysis and Performance Evaluation

Conclusion:

The results for individual datasets are logged and evaluated as follows. The CASIA Palmprint Database Dataset1 has 159 correct image class matches out of 160 leading to a high % accuracy performance of 99.375%. The IIT Delhi Database has 153 correct image class matches out of 160 leading to a slightly lower % accuracy performance of 95.625%. The Hong Kong PolyU Database has 156 correct image class matches out of 160 leading to a slightly higher % accuracy performance of 97.50% than IITD Palmprint Database and slightly lower % accuracy than CASIA Palmprint Database. CASIA Palmprint Database Dataset1 has 01 incorrect image class matches out of 160 leading to a low % error performance of 0.625%. The IIT Delhi Database has 07 incorrect image class matches out of 160 leading to a slightly higher %error performance of 4.375%. The Hong Kong PolyU Database has 04 incorrect image class matches out of 160 leading to a slightly lower % error performance of 2.5% than IITD Palmprint Database and slightly higher % accuracy than CASIA Palmprint Database. Human identification has drawn considerable attention over the last 25 years. However, some people do not have clear biometric markers because of their physical work or problematic skin. Iris and retina recognition provide very high accuracy but suffer from high costs of input devices or intrusion into users. Recently, many researchers have focused on face, voice verification systems; nevertheless, their performance is still far from satisfactory. The future of biometric security lies in multimodal systems, with eyes, hands and face with maximum use today still there is a need to strengthen the human based security and identification as many times some of these existing systems even when used with multi-level and modals of security still fail to perform or give required results.

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