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Fingerprint Verification Based on GA and SVM

Salma Bibi[1], Muhammad Ijaz Khan[1], Mudasir Mahmood[1], Faryal Gul[1], Saadat Ullah[1]

salmameerani@gmail.com
ijaz171@gmail.com
mudasir@gu.edu.pk
faryalgul62@gmail.com
ksaadat125@gmail.com

[1.] *Institute of Computing and Information Technology, Gomal University, Pakistan.*

***Abstract*—Fingerprints are the oldest and important biometric trait for personal identification. Much work is done in this field but still fingerprint verification systems are facing the challenges of accuracy and speed. Even there are many misinterpretations in the different fingerprints of same finger due to noise caused by sensing devices and bad skin conditions. In this study, a new method Hybrid and Intelligent Biometric Classification (HIBC) has been developed for fingerprint verification. This method extracts hybrid texture features from gray scale fingerprint images. To save resources, useful features are selected by Genetic Algorithms (GA) and Support Vectors Machine (SVM) classifier is used for verification. Moreover, anisotropic diffusion filter is applied to enhance the fingerprints by reducing noise. The experimental results showed 99.3% verification accuracy with 0.7% Error Rate (ER).**

***Keywords*— Anisotropic diffusion filter, hybrid features, GA, SVM, LBP, GLCM, HOG.**

I. INTRODUCTION

In this modern electronic age, authentic personal identification has become a vital task to access the secured data and resources. Precise personal verification is considered necessary in a broad variety of civilian applications which involve the exploit of automatic teller machines, passports, cellular telephones and driving licenses. It also has become a key area of study in the field of forensic, security systems, privacy policies and inspection systems. Persons may be legitimated on the basis of password, Personal Identification Number (PIN), smart card, ID card or passport, or by measuring some physical or behavioral traits like fingerprint, palm print, face image, iris, eye retina, gait or signature. Although the password, token and PIN-based (driving licenses, passport and ID card) identification approaches are easy and simple to use; but some major limitations have also been observed in these approaches. Hence, these general practices are not capable to assure the security requirements of modern information systems. In these situations, the need of accurate automatic personal identification is increasing for the operations of electronically inter-connected information systems. Therefore, the biological traits (fingerprints, iris, nose, gait, eyes, ears, jaws, voice patterns etc.) can be more reliably used for personal identification. Fingerprint is one of the most prominent methods among biometrics. Fingerprint-based verification is the reliable and established technique. Fingerprint is the oldest method of biometric verification and is successfully used in many applications. It is a reliable and stable method. Its accuracy rate is relatively high than other biometrics. It is easy to acquire and takes less space in memory. Its accuracy rate is relatively high than other biometrics. The important characteristics of fingerprints are: fingerprint details are permanent and unique for each person [1] and do not vary overtime. Even the identical twins have their own unique fingerprints. Keeping in view the importance of fingerprints, this research is objected to develop an algorithm for personal verification based on fingerprints. The proposed system is consisting of three important phases. These phases may include i. Enhancement, ii. features management and iii. verification. The enhancement phase may boost up the quality of fingerprint by reducing the effect of noise. Noise is reduced without degrading the fine details of fingerprints. The features management phase may consist of features extraction and selection. Hybrid texture features are obtained by applying LBP (Local Binary Patterns), HOG (Histogram Oriented Gradients), Moments of gray-level histogram and gray-level co-occurrence matrix. The dominant features have been selected by employing genetic algorithms (GA). The final stage is verification. SVM (Support Vector

Machines) classifier is used for verification task. The results showed significant improvement in accuracy and speed.

II. RELATED WORK

Fingerprint verification system identifies the persons with high confidence. Since 19th century, extensive work has been done on fingerprints. Fingerprints are widely used for attendance, entrance, authentication and polling etc. Some of the work done on fingerprints has been summarized as under:

A robust fingerprint verification system which is based on spectrum features of fingerprints has been employed by Kasban [2]. Gabor filter and Adaptive Histogram Equalization (AHE) has been used to improve the quality of fingerprint. Power density spectrum and autocorrelation functions have been used to extract the spectrum features. SVM [3, 4] has been trained on these features. Finally, SVM has been employed in features matching phase to perform the verification of person by fingerprint spectrum features. The efficiency of this approach has been evaluated by experiments on public domain fingerprint databases like FVC2000 [5], FVC 2002 [6] and FVC 2004 [7]. The performance evaluating metrics like Receiver Operating Curve (ROC), Equal Error Rate (EER) and execution time of matching have been calculated in this study. The EER of 3.09, 1.06 and 1.98 has been achieved for FVC2000, FVC2002 and FVC2004 respectively.

Fingerprint recognition and reconstruction technique based on minutiae has been proposed by Cao and Jain [8]. The reconstruction accuracy of 11.65% Missing Minutiae Rate MMR and Spurious Minutiae Rate SMR of 5.67% has been achieved by Cao and Jain. Minutiae based fingerprint matching scheme has been proposed by Shaveta and Walia [9]. The feature vector of this approach is comprised of minutiae position, orientation and their weights. The matching algorithm utilized the SVM and Recursive Neural Network. SIFT algorithm with Gaussian blurring and sliding window contrast adjustment technique has been proposed by Sing *et al.* [10] for fingerprint matching based on sweat pores. Artificial Neural Network based technique has been employed to recognize the classes of fingerprints. Minutiae points have been extracted and used as input of classifier.

Another minutiae matching technique is proposed by Gopi and Pramod [11]. They have enhanced the fingerprint image quality by employing Gabor filter and Fast Fourier Transform. Features of the fingerprint have been extracted at four different orientations of Gabor filter. Then the results of these orientations have been combined. For Fourier transform, the image has been sub-divided into 32 x 32 frames and frequency domain filtering has been applied on these frames. Finally, an enhanced image has been obtained by adding the results of both enhancements. Binarization and thinning has been performed to extract minutia points. The minutiae set consisting of ridge bifurcations and ridge endings have been considered in this study. The recognition rate of 95% has been recorded by this approach.

A Gaussian weighted method based fingerprint reconstruction and verification technique is proposed by Liu *et al.* [12]. By this method, the orientation field of the fingerprint is reconstructed from the minutiae templates. The proposed approach accurately models the ridge orientation by considering the former information about ridge flow patterns. The proposed method has assigned different weights to different ridge directions. As it has been observed that the perpendicular ridge direction has smaller variations as compared to the parallel ridge direction. Minutiae density indicator has been used to avoid the weight accumulated from the dense minutiae region. Experimental results revealed that proposed technique has produced accurate orientation field. The accuracy is measured by the fingerprint classification based on orientation field. Secondly, the fingerprint matching is performed which is based on the orientation descriptor of ridges. The classification accuracy has been recorded as 88.07%.

Spatial grey level dependence matrix method (SGLDM) has been implemented by Jhat, Mir and Rubab [13] for unique personal verification. Texture features have been extracted based on SGLDM. About 24 texture features have been obtained using this method, but only four representations namely; local homogeneity, inertia, energy and entropy; have been considered for pattern recognition. The accuracy of the proposed method has been computed in terms of the False Rejection Rate (FRR) and False Acceptance Rate (FAR). The experimental results obtained by FVC 2002 DB1 and DB2 showed FAR of 4.99 % and 5.01 % with FRR of 8.95 % and 8.75 % respectively.

In some studies, fingerprints are classified into one of five fingerprint classes like arch, tented arch, right loop, left loop and whorl (see fig. 1). Fingerprint classification leads to fingerprint matching. It is claimed that fingerprint classification speeds up to fingerprint verification. But this claim is not always true.

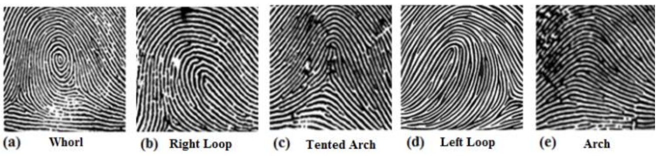

Fig. 1 Classes of Fingerprints

Fingerprint classification based on partitioning cluster approach is proposed by Bhuyan, Saharia and Bhattacharyya [15] and found better to significantly reduce the mis-classification errors. This approach showed the classification accuracy of 98.3%. Fingerprint verification on the basis of Invariant Moments is studied by Leon *et al* [1]. Gabor Filters and Fast Fourier Transform (FFT) have been employed for image enhancement. Feature vector comprised of distance and angle between minutiae has been used for matching purpose. The invariant moments have been used for verification. This work showed acceptance percentage of 84.61.

Ridge orientation information has also been considered by Lu *et al.* [16] for fingerprint classification. They have employed support vector machines (SVM) classifier. The pre-processing steps such as reference point acquisition and ridge flow direction have been acquired. The reference point has been detected based on orientation fields. This technique has the ability to find the reference point for each class of fingerprints. Gabor filter has been employed to extract the orientation features of fingerprints. Finally, the extracted features have been input to SVM classifier for classification. This work proposed a three stage classification approach by using SVM. Fingerprints are classified according to their local features. One VS All and Pair-wise SVMs have been used to evaluate their performance. 93.5% accuracy ratio has been achieved.

Bimodal biometric systems consisting of two biometric traits like fingerprints and iris is studied by Altun *et al*. [17]. The feature vector of iris templates has been obtained by encoding gray level iris image. The feature vectors of fingerprints may consist of Finger Code. Filter-bank based method has been used to extract the Finger Code from the fingerprint images. The extracted features of fingerprint and iris have been integrated at the feature extraction level. Features of both traits have been extracted and given input to feed-forward artificial neural networks (ANNs) model for personal verification. In order to reduce the dimension of data and training time of classifier, features selection step has also been performed by utilizing GA approach. 99.3% success rate has been achieved by this approach.

SVM and weighting method has been proposed by Jia *et al*. [18] for fingerprint matching. Weight has been assigned on the basis of distance between minutiae. The conventional minutiae-based matching has been performed by using SVM. This approach not only used minutiae location but also a weight feature (distance between a minutia and its nearest neighbor minutia). Here two class classification problem has been considered i.e. two images either matched or not. Feature vector consisted of minutiae position, orientations and weights. Minutiae of two fingerprints have been matched and compared with a threshold to decide either match is successful or not. The performance of algorithm has been measured on the basis of FMR (false match rate) and FNMR (false non-match rate). The FNMR of 4.08% and FMR of 0.1% has been recorded by using weighted approach.

Global comprehensive similarity based scheme has been introduced by He *et al.* [19] for fingerprint matching. They have represented fingerprints as the collection of local regions which are composed of minutia-simplexes. In this scheme, the ridge-based nearest neighbor of minutiae are combined with the minutiae simplex to represent the features among minutiae. The preprocessing steps consist of orientation field estimation, binarization and finally thinning. Then thinned fingerprint image has been used to extract the minutiae. The experimental results are evaluated on three fingerprint databases like FVC2000, FVC2002, FVC2004. The EER of 1.64%, 2.772% and 2.719% has been achieved respectively. This method has produced better results but it is very sensitive to fingerprint quality.

III. PROPOSED TECHNIQUE

The proposed method is named as HIBC (Hybrid and Intelligent Biometric Classification). This method is based on GA and SVM classifier. The proposed methodology comprises of three phases of Image enhancement phase, features management phase and verification phase. It takes the scanned fingerprint images as input, image enhancement is performed and then hybrid texture features are extracted. The useful features selected by GA and SVM are employed for personal verification. The computational process is carried out in MATLAB 2017b for image enhancement and features extraction process. A dimension reduction and selection technique GA was used.

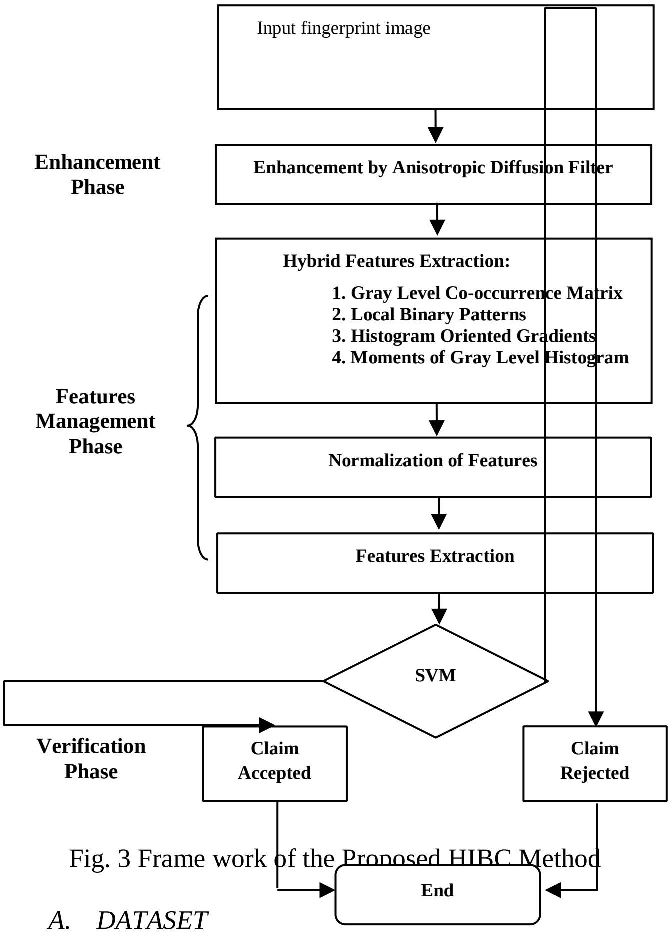

Fig. 3 Frame work of the Proposed HIBC Method

A. DATASET

A standard data set Sokoto Coventry Finger Print data set (SOCOFing) is considered to test the proposed biometric verification algorithm. The causes to choose this data set is that Sokoto Coventry Fingerprint Dataset is a database of finger prints, specially designed for research purposes. SOCOFing is consist of 6,000 images of fingerprints. Fingerprint images are collected from 600 African peoples. Finger print image file size was 39.69 KB. Dataset was consisting of Genuine, simple and hard altered real fingerprint images. The datasets are divided into two subsets where 70% of the database is used for training subset while 30% of the database is used for testing subset. In the proposed method, 6000 fingerprint images were divided into 4200 images for the training and 1800 fingerprint images for the verification. The hybrid features extraction of training data set images were made.

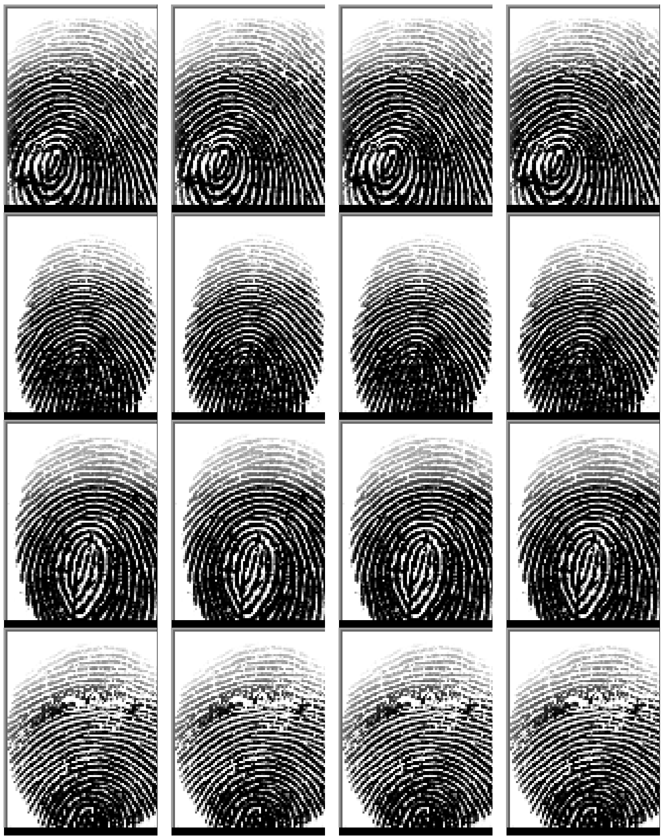

Fig. 2 Images Samples

After testing the proposed methodology on SOCOFing Dataset, A Local dataset of 520 images was also used for this work to check the competency and validity of the proposed technique. This Dataset was acquired by 65 volunteer participants and 8 prints per person were obtained. Fingerprints were acquired from both genders (male and female) of age group 15-45 years. The dimension of each fingerprint was 326 x 357 pixels, while the resolution of each image was 500x500 PPI. The acquired images were in .tiff format.

B. FINGERPRINTS ENHANCEMENT

Fingerprint images are seldom of good quality. They may be corrupted and tainted due to varying skin and impression conditions. The degradation of fingerprints obstructs the fingerprint verification process. Therefore, before analysis, it is acute necessary to make use of enhancement techniques to make the images suitable for analysis. In this study, anisotropic diffusion filter is used for fingerprint enhancement. Anisotropic diffusion filter is used to reduce the image noise without eliminating the key image contents like edges, lines and other details which are important for analysis of image. Anisotropic diffusion is implemented by means of a generalized diffusion equation. It is an iterative process where each successive image is obtained by applying diffusion equation on previous image. This process continues until sufficient level of smoothing is achieved. The following equation has been used for anisotropic diffusion filtering:

$$I_t = div(c(x, y, t)\nabla I) = c(x, y, t)\Delta I \nabla c . \nabla I \quad (1)$$

Where div is a divergence operator, ∇ and Δ respectively represent the gradient and Laplacian operators with respect to space variables and *t* represents the time scale.

Fig 4: Fingerprint enhancement (a) original image (b) Enhanced image with integration constant= 0.1, gradient modulus threshold=5

C. HYBRID FEATURES EXTRACTION

The fingerprints are represented by features vector and features play a vital role during the design of a fingerprint verification system. The representation mainly concludes the accuracy and scalability of the system. Mostly AFIS are based on minutiae features but there are many drawbacks which make the minutiae features unsuccessful for fingerprint verification system. The proposed system has extracted hybrid texture features from the fingerprints to maximize the efficiency and accuracy of the verification system. Texture represents the surface and structure of an image. The texture features have been calculated in the spatial domain. The features vector may comprise of Local Binary Pattern (LBP), Grey Level Co-occurrence Matrix (GLCM), Moments of Grey Level Histogram and Histogram Oriented Gradients (HOG).

C. FEATURES NORMALIZATION

After feature extraction, features have been normalized so that all the features lie on the same scale. Feature normalization prohibits features to dominate each other. There are different approaches to normalize the features but in this work features have been linearly scaled to bring them in range (0, 1) by using the following equation:

$$f_{norm} = \frac{f_{old} - f_{old}^{min}}{f_{old}^{max} - f_{old}^{min}} \quad (2)$$

D. FEATURES SELECTION

Feature selection is an important factor which impacts the classification accuracy. This process optimizes the feature subset which results in optimized use of resources. Genetic Algorithm (GA) has been used in this study for features selection.

1) Genetic Algorithm (GA): GA has the power to optimally select best suitable features subset. GA is an adaptive optimization search methodology based on Darwinian natural selection and genetics in biological systems. Based on the Darwinian principle of 'survival of the fittest', the GA acquires the optimal solution after a series of repetitive computations. GA has the ability to efficiently deal with large search spaces.

In GA, the candidate solutions are described as bit strings which are called chromosomes. The process of searching an optimal solution starts with a random population of initial solutions. The chromosomes of the current population are assessed relative to a given measure of fitness. The fit chromosomes are selected probabilistically as seeds for the next population by means of genetic operations such as random mutation and crossover.

E. FINGERPRINT VERIFICATION

Verification is the core activity of this system. It is the process of accepting or rejecting the identity claim of an individual based on fingerprint. After feature extraction and selection process, a suitable classifier is employed to accomplish the verification task. Support Vector Machine (SVM) is selected as a classifier for this work.

1) Support Vector Machines (SVM): Support vector machines (SVMs) [4] solve the two-class problems of pattern recognition by defining the separating hyper-plane with maximum distance to the closest points of the training set. These points are called support vectors (Fig. 3). In case of non-linearly separable data, a non-linear transformation $\Phi(\cdot)$ can be applied which maps the data points $x \in R^n$ into a high dimensional space H which is called feature space. The data in the feature space is separated by the optimal hyper-plane.

The mapping $\Phi(\cdot)$ is represented in the SVM classifier by a kernel function $K(\cdot,\cdot)$ which defines an inner product $K(x,t) = \Phi(x).\Phi(t)$ in H. The decision function of the SVM is given as under:

$$f(x) = \sum_{i=1}^{l} \alpha_i y_i K(x_i, x) \quad (3)$$

Where l denotes the number of data points, and y_i is the class label of training point x_i. Coefficients α_i can be obtained by solving a quadratic programming problem with linear constraints [4]. The support vectors are the closest points to the separating boundary and the value of α_i can be non-zero for these points. The Kernel functions used in SVM are defined as follows:

Polynomial of power p: $K(x_i, x_j) = (1 + x_i T x_j)^p$ (4)

Gaussian (radial basis function network):

$$K(x_i, x_j) = exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad (5)$$

where σ is the variance of the Gaussian.

Sigmoid: $K(x_i, x_j) = tanh\ tanh\ (\beta_0 x_i T x_j + \beta_1)$
(6)

The distance of the support vectors to the hyper-plane is called margin. The margin is defined as follows:

$$M = \left(\sum_{i=1}^{l} \alpha_i\right)^{\frac{1}{2}} \quad (7)$$

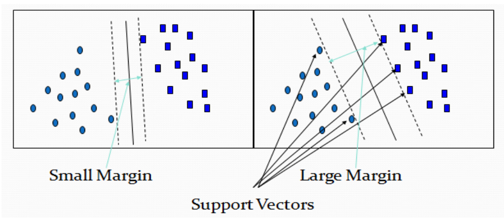

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fig. 5 Support Vectors and Margins for Linearly Separable Data

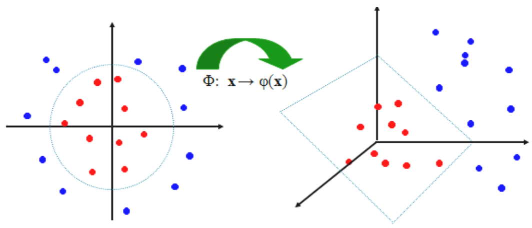

Fig. 6 Hyper-plane for non-linearly separable data

IV. IMPLEMENTATION DETAILS AND RESULTS

The standard dataset was essential issue in this experimental based study because the performance of image verifications highly depends on training dataset. Considering these factors, this investigation used approximately 6000 fingerprint images to attain satisfactory results.

A dataset consisting of 6000 Genuine, simple, hard altered real fingerprint images of 600 participants and a local dataset of 520 scanned fingerprint images acquired by 65 participants were used for this work. The results of each phase are discussed in this section.

A. Enhancement

The quality of enhanced image is measured by peak signal to noise ratio (PSNR). Easy calculation and analytical tractability are the dominant traits of PSNR. The PSNR of 35.67 dB was achieved by the applied enhancement technique. This PSNR value depicts that the image is sufficiently enhanced by using anisotropic diffusion filter.

B. Hybrid features extraction and selection

Features extraction is very important step to uniquely represent an image. In this study, gray scale images were used for feature extraction. Hence, Segmentation, binarization and thinning steps were omitted in this study. Different texture features of fingerprints were extracted by implementing LBP, GLCM, HOG and moments of gray-level histogram algorithms in MATLAB 2017Ra.

An aggregate of 190 integrated texture features was extracted from each image. In order to minimize the classification time and to maximize the use of resources, the dimensionality of features was reduced by GA. It uses the computational intelligence to search the most suitable set of features for the problem in hand. Features were reduced to make the efficient use of resources. In this study, GA was implemented in WEKA 3.6. GA parameters were set in WEKA as follows:

TABLE I
GA PARAMETERS AND VALUES

GA Parameters	**Parameter Value**
Crossover Probability	0.8
Maximum Generations	20
Mutation Probability	0.033
Population Size	20
Report Frequency	20

It was found that some values of features are dominating the other features. To minimize the effect of dominancy, features were scaled in the range of 0-1, which is called features normalization. GA was applied to both scaled and un-scaled features set. GA has selected 68 features out of 190 un-scaled features. While, the dimensionality of feature set was reduced to 54 out of 190 scaled features. This reduced feature set was given to SVM classifier for verification purpose. The metrics, like accuracy, error rate and CPU time (training and testing time) were evaluated in this study to check the performance of proposed model. As the dataset was non-linear in nature, therefore, SVM with kernel trick has was employed for classification. The classification results with 10-fold cross validation achieved are as under:

TABLE II
CLASSIFICATION METRICS BASED ON SVM – POLYNOMIAL KERNEL

Features	**Accuracy %**	**Error Rate %**	**CPU Time (Sec)**
190 Hybrid Features	98.8	1.2	44
190 Scaled Hybrid Features	99.4	0.6	41
68 GA Selected Features	98.3	1.7	39
54 Scaled & GA Selected Features	99.2	0.7	27

The results depicted by polynomial kernel clearly illustrate the significant improvement in accuracy due to scaled data and reduced features. Scaling highly impact on classification accuracy and reduced features significantly affected CPU time. After applying GA, 38% reduction in CPU time was observed but accuracy was decreased to 0.2%. This reduction in accuracy was required to improve.

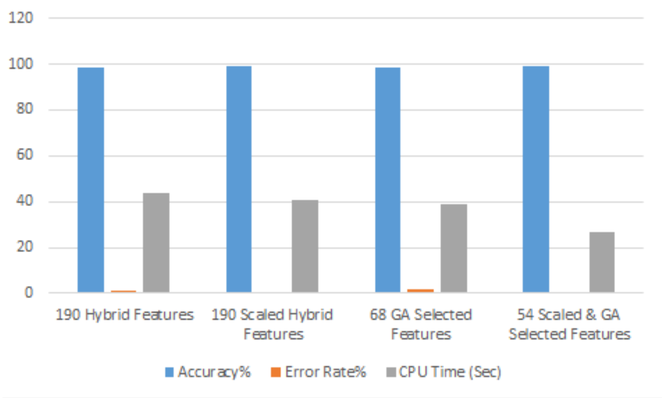

Fig. 7 Classification metrics based on SVM – Polynomial Kernel

Then RBF Kernel was employed to train the SVM classifier. It was considered that RBF is a popular SVM kernel for non-linear dataset. It is a combination of linear and polynomial kernel. But, RBF kernel delineates a function space which is much larger than polynomial kernel. It is particularly useful kernel in case of lack of expert knowledge about data and domain. RBF is a non-parametric model. So, it produced infinite dimensional feature space. It was proved more flexible kernel than polynomial kernel in the sense that it has the ability to model many functions with its function space.

TABLE III
CLASSIFICATION METRICS BASED ON SVM – RBF KERNEL

Features	**Accuracy %**	**Error Rate %**	**CPU Time (Sec)**
190 Hybrid Features	96.9	3.1	60
190 Scaled Hybrid Features	99.3	0.7	51
68 GA Selected Features	96.9	3.1	38
54 Scaled & GA Selected Features	99.3	0.7	27

RBF kernel showed significant improvement in accuracy due to scaling of feature set. Reduced features not showed any improvement in accuracy but CPU time was reduced by 46%.

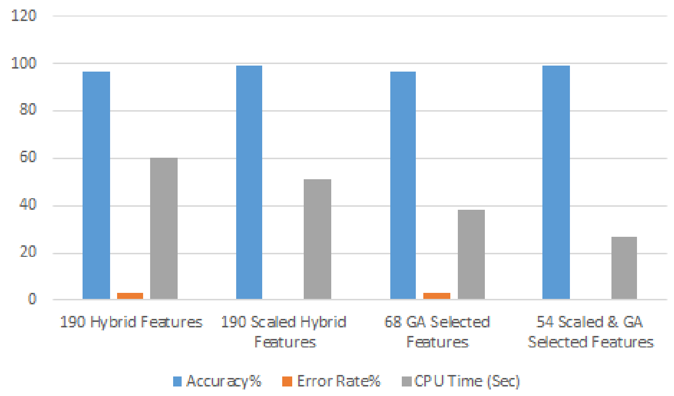

Fig. 8 Classification metrics based on SVM – RBF Kernel

Finally, the SVM was trained by using sigmoid kernel. This kernel function was originated from neural network theory. The sigmoid kernel worked like a multilayer perceptron neural network. Sigmoid kernel geometrically interpreted the higher-dimensional feature spaces by utilizing hyperbolic tangent as the activation kernel for the non-linear feature space.

TABLE IV
CLASSIFICATION METRICS BASED ON SVM – SIGMOID KERNEL

Features	**Accuracy %**	**Error Rate %**	**CPU Time (Sec)**
190 Hybrid Features	96.9	3.1	47
190 Scaled Hybrid Features	98.8	1.2	40
68 GA Selected Features	96.9	3.1	33
54 Scaled & GA Selected Features	99.3	0.6	28

Sigmoid kernel showed positive impact in accuracy and CPU time due to reduced features. In case of scaling, there was 1.9% increase in accuracy and 15% decrease in CPU time. While, the proposed model showed 2.5% increase in accuracy and 41% reduction in CPU time.

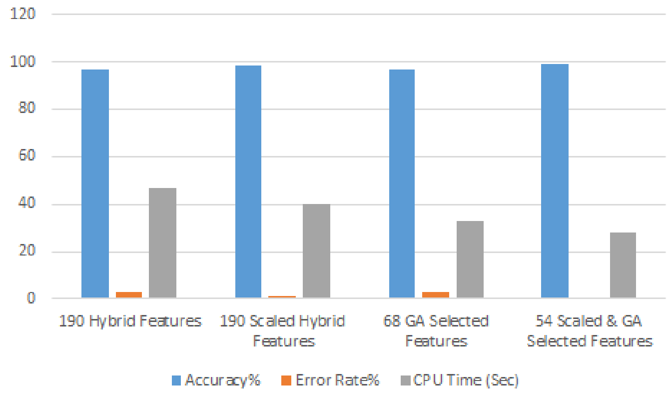

Fig. 9 Classification metrics based on SVM – Sigmoid Kernel

The results obtained by different kernel functions were evaluated and found that RBF and Sigmoid kernels showed better accuracy rate than other kernels, but Sigmoid kernel consumed more training and testing time than other kernels.

TABLE V
PERFORMANCE COMPARISON OF SVM AND DIFFERENT KERNELS ON 54 SCALED & GA SELECTED FEATURES

	Accuracy %	**Error Rate %**	**CPU Time (Sec)**
SVM-Polynomial Kernel	99.2	0.7	27
SVM-RBF Kernel	99.3	0.7	27
SVM-Sigmoid Kernel	99.3	0.6	26

V. COMPARISONS WITH KNN and PNN

Finally, the metrics achieved by SVM were compared with other classifiers like KNN and PNN. KNN is a very straightforward and simple algorithm. KNN uses the majority vote of neighbors to classify a data instance. The accuracy rate of KNN with K=1 was computed and recorded as under:

TABLE VI
CLASSIFICATION METRICS BASED ON KNN WITH K=1

Features	Accuracy %	Error Rate %	CPU Time (Sec)
190 Hybrid Features	98.3	1.7	03
190 Scaled Hybrid Features	99	0.9	02
68 GA Selected Features	97.9	2.1	02
54 Scaled & GA Selected Features	98.8	1.1	1.5

PNN is feed-forward neural network. It computes non-linear decision boundaries by using exponential function instead of sigmoid function which is used in neural network. It is a four layered neural network and has the ability to map input instances to any number of classes.

The accuracy rate of PNN was computed and recorded as under:

TABLE VII

CLASSIFICATION METRICS BASED ON PNN WITH SPREAD = 0.1

Features	Accuracy %	Error Rate %	CPU Time (Sec)
190 Hybrid Features	96.9	3.1	28
190 Scaled Hybrid Features	98.9	1.1	34
68 GA Selected Features	96.9	3.1	21
54 Scaled & GA Selected Features	98.2	1.7	18

The results depicted that KNN and PNN utilized less CPU time than SVM but their accuracy rate was recorded lower than SVM. The performance of KNN was highly affected with noisy data. It didn't perform well for highly distorted data.

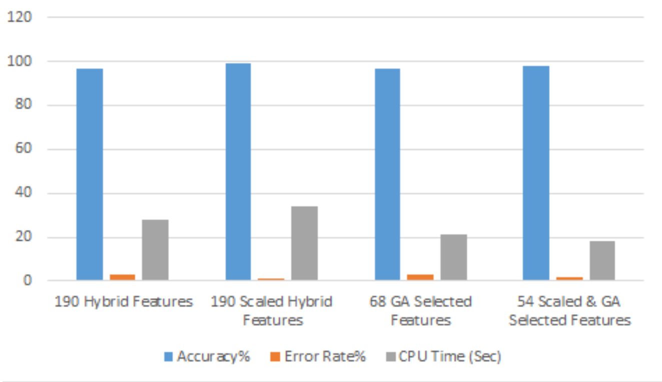

Fig. 11 Classification metrics based on PNN with spread = 0.1

Although the training time of SVM was high as compared to KNN and PNN, but its classification accuracy was recorded high enough. So, it was concluded that SVM can be successfully used for biometric personal verification.

GA significantly affected on efficient use of resources. After employing GA, there was 73% reduction in the dimensionality of feature set. Hence, the storage space and training/testing time was also decreased. GA sufficiently reduced the usage of resources. It was concluded that the proposed model is not only improved the accuracy but also enable the system to efficiently utilize the resources.

In case of accuracy rate, RBF kernel performed better than other kernels. Because, it has the ability to define a larger feature space than Sigmoid and polynomial kernels. The CPU time of polynomial kernel is less than RBF and sigmoid, but employing polynomial kernel generates a parametric model. The size of parametric model is always fixed and adding more data causes saturation to model. Hence, RBF kernel is a best choice for an abundant amount of data.

V. CONCLUSION

A novel biometric verification scheme based on SVM and GA was proposed. Fingerprints were selected as a unique biometric trait for personal verification. The fingerprints are degraded due to abnormal skin conditions and sensing devices. Hence, anisotropic diffusion filter was employed to enhance the quality of fingerprint. Anisotropic diffusion filter performed diffusion within image region while preserved image fine details like edges and lines. PSNR measure was employed to evaluate the quality of enhanced fingerprints. A PSNR measure of 35.67dB was achieved, which depicted that image quality was significantly enhanced.

The task of verification was accomplished by extracting texture features, like LBP, GLCM, HOG and moments of grey levels, of the fingerprints. All of these techniques extracted texture features from grey scale image; hence segmentation, binarization and thinning steps were avoided in this study. A standard data set SOCOFing as well as a local dataset was used to implement the technique. A feature set of 190 features for each image was acquired. The features were scaled to avoid numerical complexities and dominancy of high ranged features over low ranged features. Scaling process sufficiently increased the performance of GA and SVM. GA was employed to reduce the dimensionality of feature set. GA resulted in 73% reduction in dimensionality of features. The reduced features caused reduction in CPU time. The CPU time was reduced by 39%, 55% and 41% for polynomial kernel, RBF kernel and sigmoid kernel respectively. The verification performance of proposed model was evaluated by the accuracy and error rate. Different kernel function of SVM were employed to check the verification accuracy. The proposed model depicted accuracy rate of 99.2%, 99.3% and 99.3% for polynomial kernel, RBF kernel and sigmoid kernel respectively. While the error rate of 0.8%, 0.7% and 0.7% was computed for polynomial kernel, RBF kernel and sigmoid kernel respectively. The performance of SVM was compared with PNN and KNN. The accuracy rate of 98.8% and 98.2% has been calculated for KNN and PNN respectively.

Hence, it was concluded that a combination of GA and SVM with kernel functions was successfully employed to achieve the objective of this study. The proposed model not only improved the verification accuracy but also enabled the system to efficiently utilize the resources.

VI. RECOMMENDATIONS

On the whole, a set of reliable techniques was applied for fingerprints enhancement, feature extraction and verification. These techniques can be applied to facilitate the further study of the statistics of fingerprints. But the quest of the best never ends. Therefore, it is recommended that some better optimization techniques should be explored to optimize the SVM parameters. Furthermore, bimodal biometric system can be implemented by using the proposed model. Clustering techniques can also be incorporated to enhance the accuracy of biometric verification system.

In addition, this study showed that scaling has great impact on classification accuracy. The scaling avoids the dominancy of attributes having greater numeric ranges over those having smaller numeric values. Scaling makes the data symmetric on same scale. Furthermore, scaling avoids numerical complications during the calculation. In SVM, kernel functions rely on inner product of feature vectors, hence large values lead to numerical problems. Therefore, scaling is very importance for SVM classifier. More Improvement in image scaling can surely enhance the accuracy and reduce the response time of algorithm. The quality of fingerprints can be further enhanced by applying hybrid filters

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