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Face Recognition Using Fused Spatial Patterns

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ABSTRACT

Biometric recognition or biometrics is an automatic recognition system, based on physiological and/or behavioral characteristics of an individual. Biometrics makes it possible to confirm, establish an individual's identity based on "who he/she is", instead of "what he/she possesses" (ID card) or "what he/she remembers" (password). A person's biometric characteristics are unique. Such keys are impossible to copy and reproduce exactly. These are ideal keys theoretically. But using biometric identification creates many specific problems. This study proposes face recognition system where features are extracted using Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) and fused. Classifiers like k nearest neighbor (kNN) and Support Vector Machine (SVM) classify the features extracted. Binary Particle Swarm Optimization is used for the optimization process.

Keywords: Biometrics, Gray Level Co-occurrence Matrix (GLCM), Face recognition, Local Binary Pattern (LBP), k nearest neighbor (kNN) and Support Vector Machine (SVM), Binary PSO

1. INTRODUCTION

A biometric system is a pattern recognition system operating by acquiring biometric data from an individual, extracting feature set from data, and comparing it with material in a database template.

Based on application context, a biometric system operates either in verification or identification modes [1]: In **verification mode**, it validates a person's identity by comparing captured biometric data with her own biometric template(s) in a system database. In **identification mode**, it recognizes an individual by searching all users' templates in database for a match. Biometric identifiers are divided into 2 groups:

1. Physiological
2. Behavior

Physiological biometrics include fingerprint, iris, palmprint, face are most commonly used biometrics. Matching salient points distance on pinna from a landmark ear location is a suggested recognition method. The technique is simple, economical, and easy to use. Dry weather or anomalies like dry skin do not have negative effects on verification accuracy. As hand geometry is not very distinctive it is unsuitable for individual identification in a large population, but not in verification mode [2]. Gait is the peculiar way of one's walk and it is complex spatio-temporal biometrics. Though not meant to be distinctive it is used in low-security applications. Gait is a behavioral biometric and may change over a time, due to body weight changes or brain damage.

A fingerprint has a pattern of ridges and furrows on each finger's tip. Fingerprints are used for identification over centuries as matching accuracy is high. Facial images are common biometric characteristic used to ensure personal recognition, so this idea is used in technology. Retinal recognition forms an "eye signature" from the retina's vascular configuration which is characteristic for each individual and each eye, respectively.

The iris forms in the third month of gestation and patterns are complete by the eight month. Palms of the human hands like fingerprints contain unique ridge and valley patterns. As palm is larger than finger, palmprint is more reliable than fingerprint. An individual's voice features are based on physical characteristics like vocal tracts, nasal cavities, mouth and lips to create a sound. Signature is a simple and concrete expression of human hand geometry's unique variations. How a person signs their name is a characteristic of that individual. Deoxyribonucleic acid (DNA) is a most reliable biometric, a one-dimensional code unique for every person. Identical twins are exceptions [3].

User identity authentication is done in 3 ways: 1) something a person knows (password), 2) something a person has (key, special card), 3) something a person is (fingerprints, footprint). Finger print scans are used for years by law enforcement and government agencies and are a reliable, identifier. Retina/iris scans, confirmed a person's identity by analyzing blood vessels arrangement in the retina or color patterns in the iris Voice recognition, uses a voice print which analyses how a person speaks a specific word or word sequence unique to that individual. Facial recognition uses unique facial features for identification. Authentication using biometrics has the following characteristics [4]:

Universality: a person should have a characteristic; *Distinctiveness*: two persons should be sufficiently different regarding characteristic; *Permanence*: characteristic should be invariant (regarding matching criterion) over time; *Collectability*: characteristic should be measured quantitatively.

A biometric system framework is divided into 5 subsystems: transmission, data collection, decision, signal processing, and data storage.

Presentation of a biometric characteristic to a sensor introduces a behavioral (and, so psychological) component in biometric methods. This component varies between users, between applications, and between test laboratory and operating environment. Sensor output is input data on which system is built and is convolution of: (1) biometric measure; (2) how it is presented; and (3) the sensor's technical characteristics. The measurement's repeatability and distinctiveness are negatively impacted by factor changes. When a system is open, presentation and sensor characteristics should be standardized to ensure that biometric characteristics collected in one system match those collected of same individual in another system.

A user must not willfully change biometric or its presentation to avoid being matched to earlier records when a system is used in an overt, non-cooperative application. Most, biometric systems collect data at one location and store/process it in another requiring data transmission. When huge amount of data is involved, compression is necessary prior to transmission or storage to conserve both bandwidth and storage space. Depending on the biometric system there are one or more types of storage used. Enrolled users templates or models are stored in a database for comparison by pattern matcher with incoming feature samples. A decision subsystem implements system policy by directing database search, and determines "matches" or "non-matches" based on distance or similarity measures from pattern matcher and finally makes an "accept/reject" system policy based decision. Figure 1 reveals a general framework for biometric system.

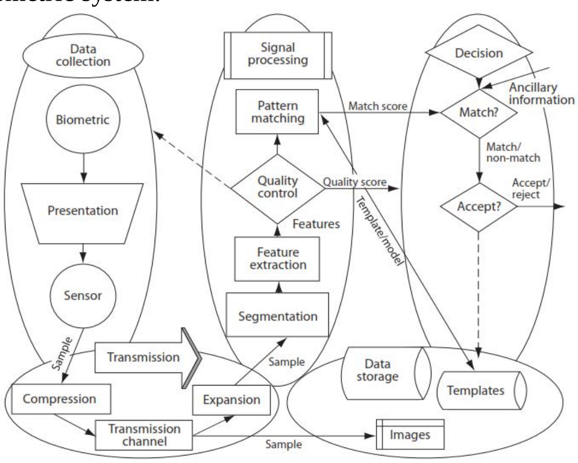

Figure 1: General framework for biometric system

Biometric system design is based on four modules:

Sensor module: It captures individual's biometric data.

Feature extraction module: where acquired biometric data is processed to extract a set of salient/discriminatory features.

Matcher module: where features during recognition are compared with stored templates to generate matching scores.

System database module: used by biometric system to store enrolled users biometric templates. Enrollment module is responsible for enrolling individuals in a biometric system database.

Face recognition can be done passively without explicit action or participation by the user as face images are acquired by a camera from a distance. This is specifically useful for security and surveillances. The following methods are used for face recognition.

1. Holistic Matching Methods

Here a complete face region is considered as input data in a face catching system. Good examples of this method are Eigen faces

2. Feature-based (structural) Methods

In this method, local features like mouth, eyes, and nose are initially extracted and the locations and local statistics (geometric/appearance) fed into a structural classifier.

3. Hybrid Methods

These combine both holistic and feature extraction methods. Usually 3D Images are used in hybrid methods. A face in profile is enough as the system uses depth and a measurement axis which provides enough information for full face construction.

In this paper features are extracted using Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) and fused. Classifiers like k nearest neighbor (kNN) and Support Vector Machine (SVM) classify the features extracted.

2. LITERATURE REVIEW

An algorithm for (image-based) object recognition proposed by Wright et al., [5] provided new insights into two crucial face recognition issues: feature extraction and robustness to occlusion. Experiments were conducted on public available databases to verify the new algorithm's efficacy. An ''ex cursus'' of face recognition trends in3D model and 2D imagery based algorithms was provided by Abate et al., [6]. A comprehensive scheme is represented by systems integrating many types of biometrics. Computational tools and a hardware prototype for 3D face recognition were presented by Kakadiaris et al., [7]. The study resulted in a Face Recognition Grand Challenge 3D facial database with thousands of scans. This is the highest performance reported on FRGC v2 database for 3D modality.

A robust face recognition, Histogram of Gabor Phase Pattern (HGPP) was proposed by Zhang et al., [8]. In HGPP, quadrant-bit codes are extracted from faces based on Gabor transformation. Global Gabor Phase Pattern (GGPP) and Local Gabor Phase Pattern (LGPP) encoded phase variations. GGPP captures variations from orientation changing of Gabor wavelet at given scale (frequency), while LGPP encodes local neighborhood variations using a new local XOR pattern (LXP) operator. The new methods were successfully applied to face recognition, and results on large-scale FERET and CAS-PEAL databases revealed that the new algorithms greatly outperformed other systems regarding recognition rate.

Techniques that identified parameterized and analyzed linear/nonlinear subspaces from original Eigen faces technique to recently introduced Bayesian method for probabilistic similarity analysis was described by Shakhnarovich and Moghaddam [9] in a chronological order. Comparative experimental evaluation of some techniques was also discussed. Practical issues related to subspace methods application were discussed for varying illumination, pose and expression.

A new representation called Multiscale Block Local Binary Pattern (MB-LBP) proposed by Liao et al., [10] was applied to face recognition. Local Binary Pattern (LBP) was effective for image representation, but was too local to be robust. Experiments on Face Recognition Grand Challenge (FRGC) ver2.0 database proved that the new MB-LBP method greatly outperformed other LBP based face recognition algorithms.

A new face identification approach by formulating pattern recognition problem regarding linear regression was presented by Naseem et al., [11]. The new Linear Regression Classification (LRC) algorithm comes under the category of nearest subspace classification. Comparison with state-of-the-art algorithms clearly revealed the new method's efficacy. The new methodology achieved best results ever for scarf occlusion.

A new approach to solve supervised dimensionality reduction problem by encoding image object as general tensor of second or higher order was presented by Yan et al., [12]. A discriminant tensor criterion where multiple interrelated lower dimensional discriminative subspaces were derived for feature extraction was proposed. Then, a new approach called mode optimization was presented and called Multilinear Discriminant Analysis (MDA). Experiments on ORL, FERET and CMU PIE, databases by encoding face images as second or third-order tensors demonstrated that the new MDA algorithm based on higher order tensors outperformed conventional vector-based subspace learning algorithms, specially with small sample sizes.

Two face recognition systems were proposed by Eleyan and Demirel [13]. The first was based on PCA preprocessing followed by a FFNN based classifier (PCA-NN) and the second was based on LDA preprocessing followed by FFNN (LDA-NN) based classifier. Feature projection vectors got from PCA and LDA methods were input vectors for training/testing of FFNN architectures. The new systems showed improved recognition rates over conventional LDA and PCA face recognition systems using Euclidean Distance based classifier. Also, recognition performance of LDA-NN was higher than PCA-NN among the new systems.

Two algorithms for face recognition to deal with pose variations and misalignment was proposed by Maturana et al., [14]. The proposed algorithm's accuracy was compared with Ahonen's LBP-based face recognition system and on another two baseline holistic classifiers on 4 standard datasets. Results showed that the new NBNN based algorithm outperformed other solutions, and were markedly more in pose variations.

A new and efficient Local Binary Pattern (LBP) texture features based facial image representation was presented by Ahonen et al., [15]. The new method's performance was assessed in face recognition issues under various challenges. The authors approach is not limited to these examples as it is generalized to other object detection and recognition task types.

A new approach to face recognition considering shape and texture information to represent face images was presented by Ahonen et al., [16]. Experiments revealed the new technique's superiority over other methods that were PCA, Bayesian Intra/extrapersonal Classifier and Elastic Bunch Graph Matching on FERET including testing the method's robustness against various facial expressions, lighting and subjects aging. The new method's simplicity ensured very fast feature extraction.

3. METHODOLOGY

Binary Particle Swarm Optimization is used for the optimization. The flowchart of the proposed methodology is shown in figure 2.

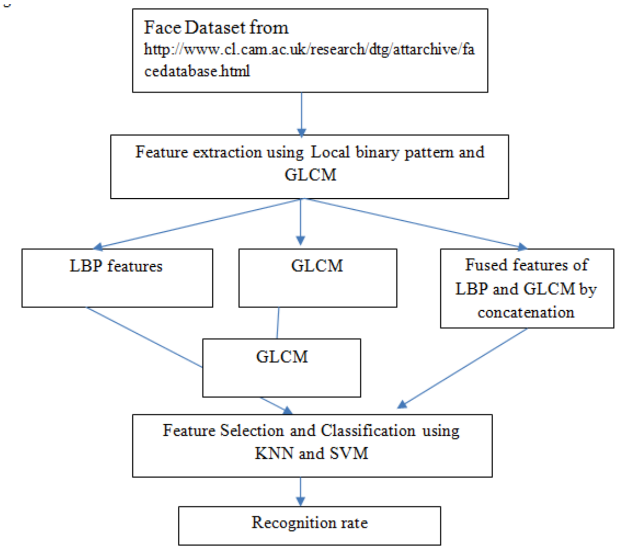

Figure 2: Flowchart of the proposed Framework

3.1 Database

The ORL Database of Faces' comprises of set of face images taken at the lab during April 1992 to April 1994. There are ten different images of 40 distinct subjects [17]. In some subjects, images were taken at different times, changing the lighting, smiling / not smiling), facial details (glasses / no glasses), and facial expressions (open / closed eyes). The image size in this database is 92x112 pixels, with 256 grey levels per pixel. One for each subject, the images are organised in 40 directories, which are named as sX, where X indicates the subject number (which is between 1 and 40). In all these directories, there are ten different images of that subject, which are named as Y.pgm, where Y is the image number for that subject (which is between 1 and 10).

3.2 Feature Extraction

3.2.1 Local Binary Pattern (LBP)

A texture descriptor, Local Binary Pattern (LBP) operator is used in object recognition to ensure in face recognition good performance [18]. LBP is a fine scale descriptor to capture small texture details. Local spatial invariance is through locally pooling (histogram) resulting texture codes. As it is very resistant to lighting changes, LBP codes fine facial appearance and texture [19] details.

It is a unifying approach to conventional divergent statistical and structural texture analysis models. An important LBP operator property in real-world applications is robustness to monotonic gray-scale changes caused by illumination variations. Another property is computational simplicity, which analyzes images in real-time settings. The system's drawbacks are being highly sensitive to glasses and being time consuming [20].

Original LBP operator labels image pixels by thresholding each pixel's 3-by-3 neighborhood with center pixel value and considering results a binary number. Labels 256-bin histogram computed over an image is used as texture descriptor. Each histogram (LBP code) bin is regarded as a micro-texton. Local primitives codified by such bins include different curved edges, spots and flat areas [21].

3.2.2 Gray Level Co-occurrence Matrix (GLCM)

Gray Level Co-occurrence Matrix (GLCM) extracts second order statistical texture features. GLCM functions characterize image texture by calculating how often pixel pairs with specific values and in specified spatial relationship occur in an image, creating a GLCM, and leading to extracting statistical measures from the matrix. MATLAB's gray co matrix function creates a GLCM by calculating how often a pixel with intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with value j. By default, spatial relationship is a pixel of interest and a pixel to its immediate right (horizontally adjacent) [22, 23].

GLCM is a matrix where number of rows and columns are equal to number of gray levels, G, in image. Matrix element $P(i, j \mid \Delta x, \Delta y)$ is relative frequency with which 2 pixels, separated by pixel distance (Δx, Δy), occur in a neighborhood, one with intensity i and other with intensity j. One may say that matrix element $P(i, j \mid d, \theta)$ contains second order statistical probability values for changes between gray levels i and j at a specific displacement distance d and at particular angle (θ) [24]. Due to large dimensionality, GLCM's are sensitive to texture samples size on which they are estimated. Thus, number of gray levels is reduced. GLCM is a popular statistical method to extract texture features from images.

3.2.3 Fused Features

Obtained features are fused through concatenation to derive final feature vector set [25]. Feature level fusion is by concatenating two feature point sets resulting in a fused feature point set $concat=(s_{1norm}, s_{2norm}, \ldots s_{mnorm}, \ldots, m_{1norm}, m_{2norm}, m_{mnorm})$. Feature normalization aim is modifying features values location (mean) and scale (variance) to ensure that each component's contribution to final match score is comparable. Adopting an appropriate normalization scheme addresses outliers' issues in feature values [26]. In this study, Min-max technique is used for normalization

Min-max technique computes x' as,

$$x' = \frac{x - \min(F_x)}{\max(F_x) - \min(F_x)},$$

where F_x is function generating x. min-max technique is effective when component feature values minimum and maximum values are known earlier.

3.3 Feature Selection

3.3.1 Mutual Information

"Mutual information" used in word associations and applications statistical language modeling measures interdependence between random variables. It should be called "point-wise mutual information" as it is not applicable to 2 random variables. In information theory, this term refers to 2 random variables. Information theory measure compares total agreement degree between classifications and clustering preferring the latter with high purity (homogeneous based on classification).

$$MI = \sum_{i=1}^{k}\sum_{j=1}^{k} \frac{|C_i \cap P_j| \log(n|C_i \cap P_j|)}{nk^2 |C_i||P_j|}$$

3.3.2 Binary Particle Swarm Optimization

A binary optimization issue is a (normal) optimization problem, where search space S is a set of strings of 0s and 1s of fixed length, n. A binary optimization algorithm solves binary optimization problems, solving many discrete problems. PSO algorithm is a fairly new collaborative computation technique first proposed by Kennedy and Eberhart [32, 33] and derived from the social psychological theory. It was robust in solving problems with linearity and non-differentiability, multiple optima and high dimensionality through adaptation. PSO like other evolutionary computation techniques is a population based search algorithm initialized with a random solutions population called particles.

Unlike other evolutionary computation techniques, every PSO particle is associated with a velocity. Particles fly through search space with velocities, that are dynamically adjusted based on their and swarm's historical behaviors. Hence particles have a tendency to fly to better and better solutions in a search process. Kennedy and Eberhart presented the binary PSO model based on a modification of real-valued PSO. As with original PSO, fitness function f must be defined. Here, it maps from n-dimensional binary space B^n (bit strings of length n) to real numbers: $f: B^n \rightarrow \Re^n$.

In binary PSO, particle's personal best and global best are updated as in a real valued version. The difference between binary PSO and the real-valued version is that particles velocities are defined regarding probabilities that a bit changes to one [34]. Using this definition a velocity is restricted within range [0, 1]. A map to map all real valued velocity numbers is introduced to the range [0, 1]. Normalization function used here is sigmoid function as:

$$V_{ij}'(t) = sig(V_{ij}(t)) = \frac{1}{1+e^{-V_{ij}(t)}}$$

And the new position of particle is obtained using the equation below:

$$x_{ij}(t+1) = \begin{cases} 1 & if \quad r_{ij} < sig(v_{ij}(t+1)) \\ 0 & \quad\quad otherwise \end{cases}$$

where r_{ij} is a uniform random number in range [0, 1].

3.3 Classifiers

3.3.1 k-nearest neighbors (kNN)

k-nearest neighbors (kNN) is a non-parameter pattern recognition algorithm in the field. It is also a supervised learning predictable classification algorithm [27]. kNN classification rules are generated by training samples without additional data. kNN classification algorithm predicts test sample category according to k training samples which are nearest neighbors to test sample, and judge it to a category with largest category probability [28].

3.3.2 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a machine learning algorithm used for pattern recognition. Pattern recognition classifies data based on a priori knowledge or statistical information from raw data, a powerful tool in data separation in various disciplines. There are different pattern types i.e. linear and non-linear. Linear patterns are easily distinguishable and are separated in low dimension while non-linear patterns are not easily distinguishable and cannot be easily separated. So, these patterns need further manipulation to ensure easy separation [29].

Original input space is mapped into a high dimensional dot product space called feature space in SVMs. In feature space optimal hyperplane is determined to maximize generalization ability [30]. SVMs aim to minimize generalization error upper bound through maximizing margin between separating hyper plane and data. As SVMs generalize well in high dimensional spaces under small training sample conditions and are superior to conventional empirical risk minimization principle used by most neural networks, SVMs are successfully applied many applications including face detection, verification and recognition [31].

4. EXPERIMENTAL RESULTS

In this study, ORL face database was used. 35 person images were taken. For each person, 10 images were taken. Three 5x5 size images used for training and equal amount were used for testing. The recognition rate for various techniques is evaluated. The experiments are conducted in two sets. In the initial set of experiments, LBP, GLCM and Fused features are classified using KNN and SVM. In the second set of experiments, feature selection is incorporated.

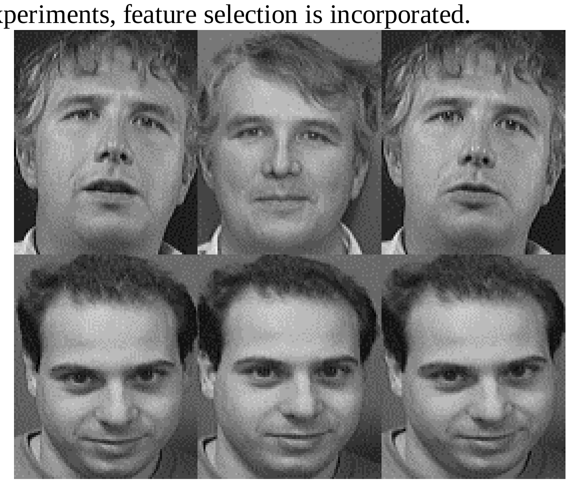

Figure 3: Sample images

The recognition rate achieved for different type of features and classifiers is tabulated in Table 1.

Table 1: Recognition Rate for Different Features

Techniques	Recognition rate
LBP features - KNN	0.8114
GLCM features - KNN	0.8057
LBP features - SVM (poly kernel)	0.8457
LBP features - SVM (RBF kernel)	0.8629
GLCM features - SVM (poly kernel)	0.84
GLCM features - SVM (RBF kernel)	0.8343
Fused features - KNN	0.8743
Fused features - SVM (poly kernel)	0.8857
fused features- SVM(RBF kernel)	0.8971

Figure 4 depicts the recognition rate achieved for LBP and GLCM features and figure 5 depicts the recognition rate achieved for fused features.

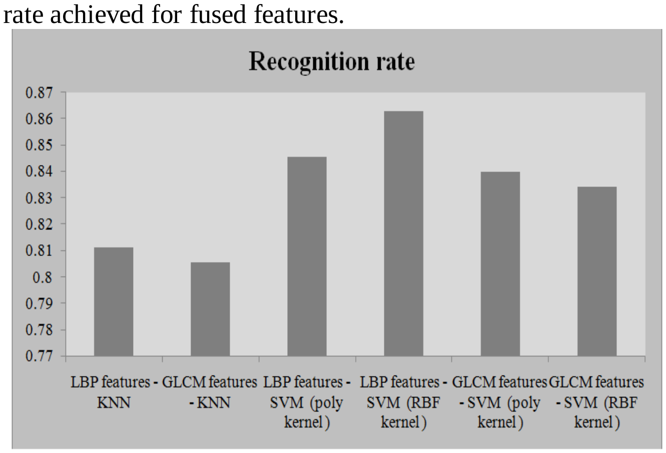

Figure 4: Recognition rate for different features

It can be observed from the graph that LBP features achieve better recognition rate than GLCM features. Similarly, SVM with RBF kernel is most efficient in classifying the features. LBP features with SVM-RBF kernel achieved the best recognition rate of 86.29%.

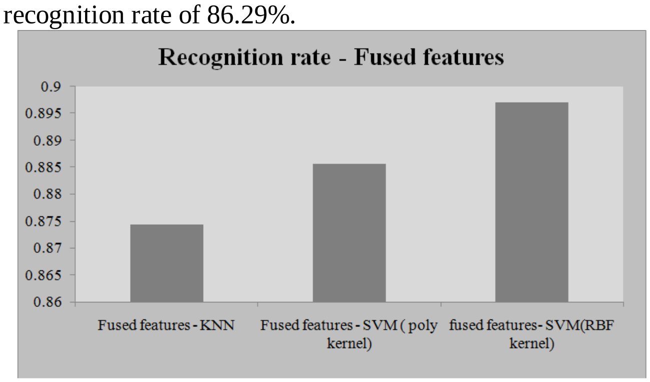

Figure 5: Recognition rate- Fused features for different features

Figure 5 shows the recognition rate achieved for fused features. It is seen that the SVM-RBF kernel achieves the best accuracy of 89.71%. It is seen from the experimental results that the fused features achieve 3.89% to 7.46% better recognition rate than LBP features and 5.3% to 8.17% when compared with GLCM features.

In the second set of experiments, the proposed feature selection method BPSO is evaluated and compared with MI. Figure 6 shows convergence achieved for the proposed BPSO feature selection method. It is seen that around 300 iterations, convergence is achieved.

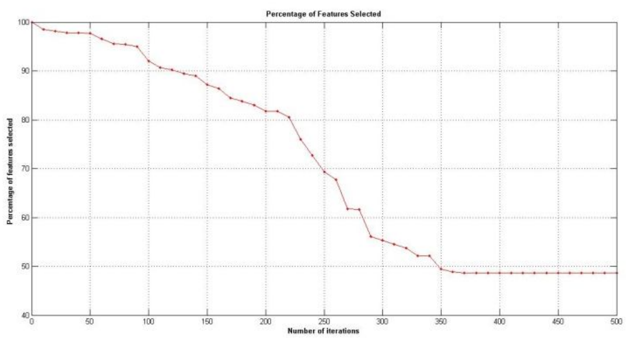

Figure 6: Best Fitness Achieved

Table 2: Recognition Rate for different feature selection methods

Techniques	Recognition rate
MI and KNN of fused features	0.8971
Binary PSO and KNN of fused features	0.9143
MI and SVM poly kernel of fused features	0.9143
BPSO and SVM poly kernel of fused features	0.9257
MI and SVM RBF kernel of fused features	0.9428
BPSO and SVM RBF kernel of fused features	0.9542

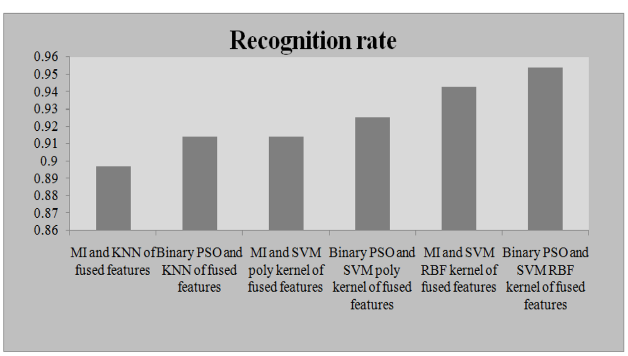

Figure 7: Recognition Rate - MI & Binary PSO for different feature selection methods

It is seen from the above figure that the Binary PSO and SVM-RBF kernel achieves the best accuracy of 95.42%. It is seen from the experimental results that the fused features achieve 4.2708% to 6.1686% better recognition rate than KNN fused features and 3.0231% to 4.2708% when compared with SVM poly kernel fused features.

5. CONCLUSION

A biometric system is a pattern recognition system operating by acquiring biometric data from individuals, extracting feature sets from acquired data, and comparing it with a database template set. Biometric systems begin with measuring behavioral/physiological characteristic. The key to systems is the assumption that measured biometric characteristic is distinctive between individuals and repeatable over time for same individual. In this study, face recognition is achieved using fused features and a proposed binary PSO based feature selection. GLCM and LBP are used for feature extraction. kNN and SVM are classifiers used for classifying the extracted features. Experiments showed that the fused features achieved better recognition rate and Binary PSO achieved better accuracy than other methods. Further investigation is required to improve the recognition rate using feature selection methods and soft computing techniques.

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