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SPECIAL ISSUE ON RECENT RESEARCH CHALLENGES IN BIO-MEDICAL APPLICATIONS

Optimized Feature Selection for Multi Modal Biometrics Using Palmprint and Palmvein

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Biometrics-based security applications are used for accurate identification of person. It recognizes and determines an individual's identity based on their physical or behavioral characteristics like fingerprint, ear, face, hand geometry, retina, voice, gait or iris. Any human physiological or behavioral characteristic can be a considered as biometric characteristic when it satisfies requirements like universality, permanence, uniqueness, and collectability. Fusing many biometric sources for authentication of identity is a method to alleviate sensing and signal processing technology's imperfection. Fusion before matching considers raw data acquired from sensing devices and from processed data after feature extraction. This paper proposes a multimodal biometric system with palmprint and palmvein. Features are extracted using Wavelet based texture features and autoregressive model and fused. A novel feature selection based on Artificial Bee Colony (ABC) is proposed and the selected features are classified using k-Nearest Neighbor and Naïve Bayes. Experimental results demonstrates that the proposed technique improves the recognition rate.

Key words: Biometrics, Palmprint, Palmvein, Z Score Normalization, Artificial Bee Colony (ABC), k-Nearest Neighbor (kNN), Naïve Bayes.

Biometrics is a science to measure and analyze the human body's biological data. A biometric system is essentially a pattern recognition system to measure and analyze the body's physiological characteristics like eye retinas and irises, fingerprints, facial patterns, voice patterns, and hand measurements or behavioral characteristics like gait for authentication[1]. Unimodal biometric system uses one single biometric trait for authentication whereas multimodal systems use two or more traits for authentication. Multimodal biometric systems have ensured identification and used as a security measure for decades. Multi-biometric systems address non-universality. It is hard for an intruder to spoof a user's many biometric traits due to multi-biometric systems' anti-spoofing measures. Multi-biometric systems ensure challenge-response authentication. Various factors to be considered during design of a multimodal system are[2]:

1. Choice and number biometric traits to be used,
2. The biometric system level providing multiple traits for integration,
3. Techniques used to integrate information and
4. Cost against matching performance trade-off.

Biometric characteristics are split into two classes: Physiological refers to the body's shape and Behavioral refers to a person's behavior. Fingerprints, palmprints, and iris have critical properties like uniqueness, universality, collectability, and permanence for personal authentication, finger-knuckle prints are an emerging biometric traits[3, 4]. Compared to to other physical characteristics, palmprint authentication

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has many advantages: low intrusiveness, low-resolution imaging, high user acceptance and stable line features.

Multi-modal biometric fusion improves accuracy of biometrics-based verification (one-to-one comparison) and identification (one-to-many comparison)[5, 6] empirically. Biometric systems integrating information early during processing are more effective than systems which perform integration later. Feature set are rich information about biometric data input than matching score or matcher's output decision, feature level fusion ensures better recognition results. Individual classifiers collect and process biometric data. Every classifier outputs a match score for specific biometric modality. On receipt of match scores from participating individual biometric classifiers, an attribute vector is created by a fusion agent from individual scores.

Various biometric recognition systems developed can be divided into two groups: appearance based and feature based[7]. Appearance based algorithms use input images' grayscale values directly while feature based systems extract grayscale value features and use them for actual recognition. Grayscale variance in a sector quantifies underlying ridge structures for use as a feature which are unique descriptors of person's brain activity providing input for classification. Multi biometrics aims to reduce one or more of the following[1]:

• False accept rate (FAR)
• False reject rate (FRR)
• Failure to enroll rate (FTE)
• Susceptibility to artefacts/mimics

Palms are large with abundant features of varied levels like palm lines, creases, texture, delta points, ridges, and minutiae. Faking a palmprint is tougher than faking a fingerprint as palmprint texture is more complicated; one rarely leaves his/her complete palmprint anywhere without intention. Palmvein fused with palmprint increases system robustness. Palmvein patterns based biometric recognition systems are popular as they are universal, unique, stable, and permanent with strong immunity to forgery. As the veins are below the skin, mostly invisible to the eye, they ensure resistance against forgery[8]. The hand's complex vascular pattern allows computation of good features set for use in personal identification.

Feature selection, important pre-requisite in classification[9], extracts relevant and useful features from feature set by eliminating irrelevant, redundant and noisy features. This process helps to improve the efficacy of the classifier and reduce the computational complexity. The process consists of two modules: Evaluation and Generation. In evaluation step, a candidate's feature subset is evaluated and in generation step, candidate feature subsets are generated. When evaluation uses a classifier to evaluate generated feature subsets, it is called wrapper approach. When a classifier is not involved, and feature subsets are evaluated based on data's intrinsic properties, it is called filter approach. This work presents a multimodal biometric system using palmprint and palmvein and a novel feature selection based on Artificial Bee Colony (ABC) is proposed. The reminder of the paper is organized as follows: Section 2 discusses related work. Section 3 explains methodology. Section 4 discusses results of experiments in this work and Section 5 concludes the paper.

Related work

A multimodal biometrics system merging fingerprint and palmprint features to overcome unimodal biometrics limitations was proposed by Mhaske and Patankar[10]. Modified Gabor filter independently obtained a fingerprint and palmprint feature ensuring more accuracy when compared to traditional Gabor filter. The authors felt the new methodology performed better compared to unimodal approaches using only one fingerprint or palmprint. Multiple biometrics lowered system error rate.

A multimodal biometric prototype that captured a palmvein and three fingerprints simultaneously and evaluated whether their combination was statistically independent was proposed by Yamada and Endoh[11]. Evaluating false acceptance using palmvein images and collected fingerprint images with the new prototype confirmed that this combination was almost independent.

Hand vein biometric in unimodal status and in combination with palmprint in multimodal situations was analyzed by Raghavendra *et al.*,[12]. Non-standard edge mask was used in schemes to extract hand vein pattern accurately and classified with Kernel Direct Discriminant Analysis (KDDA) to make accept/reject decisions. The new non-standard edge masks performance was compared to traditional edge detection masks, and statistical validation of results was presented with 90% confidence interval. The scheme's robustness was analyzed by evaluating the algorithms and those on data corrupted by noise. Final results showed that the new methods performed efficiently.

Multimodal biometrics for face/palmprint images using fusion at feature level was introduced by Ahmad *et al*.,[13]. Gabor based image processing extracted discriminant features while Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) reduced each modality's dimension. LDA output features were serially combined/classified by Euclidean distance classifier. Experiment results based on ORL face and Poly-U palmprint databases proved this fusion technique increased biometric recognition rates compared to those of single modal biometrics.

A multimodal recognition algorithm using palmprint and palmvein images was proposed by Gaikwad and Narote[14]. A multimodal identification system using Contourlet transform to analyze features in palmprint/palmvein images was proposed. The new algorithm captured local minutae and a global feature from a palmprint/palmvein images storing them as a compact code. After ROI extraction from source images, the (2-D) image spectrum was divided into sub-components (called subbands) with iterated directional filter bank structure. Feature matching technique was performed with Euclidean Distance algorithm using CASIA Palmprint Database V1.0.

An innovative contactless palmprint/palmvein recognition system was presented byMichael *et al*.,[15]. A hand sensor that captured palmprint/palmvein image using low-resolution web camera was designed. To obtain a clear image of the palm's vascular pattern, a new image enhancement technique called Local-Ridge-Enhancement (LRE) was suggested which removed illumination error while ensuring contrast between print/vein pattern and background image. Also, a simple and robust directional coding technique encoded palmprint/palmvein features in bit string representation. Palmprint/palmvein experts scores output were fused using SVM. This feature fusion yielded promising implementation result.

A Conjugate 2DPalmHash Code (CTDPHC), constructed by 2DPalmHash Codes (2DPHCs) of palmprint/palmvein as a cancelable multi-modal biometric was proposed by Leng *et al*.,[16]. To determine 2DPHCs, proper fusion strategy of palmprint/palmvein various fusion rules were compared and discussed at score level. 2DPHCs transposition orientation ranges were also fine-tuned to improve performance accuracy. Compared to 2DPHC, CTDPHC had higher verification accuracy and stronger anti-counterfeit ability, without computational complexity or storage cost.

Three 3-D palmprints global features describing shape information and used for coarse matching and indexing to improve palmprint recognition efficiency specially in large databases was proposed by Zhang *et al*.,[17]. Then two schemes 1) coarse-level matching and 2) ranking support vector machine were adopted to improve palmprint recognition efficiency. A series of 3-D palmprint recognition experiments were conducted with an established 3-D palmprint database, and results proved that the new method greatly lowered penetration rates.

A new method for palmprint preliminary classification was proposed by Dhananjay *et al*.,[18]. An algorithm to implement proposed classification scheme was proposed. Results demonstrated classifying palmprints was efficient with the proposed method.

Ramsoful and Heenaye-Mamode Khan[19] implemented three feature extraction techniques called Hough lines transform, Pixel by Pixel Method and Directional Coding Method. These were applied to 500 images from 100 individuals of various ages. Mahalanobis Distance and Correlation Percentage were used for matching. The results revealed that Pixel by Pixel Method provided best feature extraction with a 0.03% False Rejection Rate (FRR).

A palm print recognition method based on adaptively fusing 2D and 3D palmprint images was proposed by Zhang[20]. Automatic weighted combination strategy was used, and results proved that the new method ensured higher accuracy.

Travieso*et al*.,[21] proposed a new, simple and robust biometric verification system using hand palm texture. Then, a "derivative method" extracted texture features from gray-scale images with a differentiation/binarization process. 1090 hand images from 109 people with 10 samples each were acquired by a commercial scanner of 150 dpi resolution. SVM, the main classifier used as verifier in closed/open modes. Results revealed an EER=0.30% and EER=0.032% proving that it worked in both open and closed modes.

Rotinwa-Akinbile *et al.*,[22] proposed a new, contactless palmprint recognition system using palm printprincipal line-based feature extraction techniques. Discriminative palmprint features were extracted from pre-processed acquired images with a low cost camera. The new technique was a rotation, scale and translation invariant and 100% accuracy was achieved in a 1-to-4 recognition/classification verification.

An identification-verification biometric system based on combined geometrical and palmprint hand features was presented by Fuertes *et al.*, [23]. Wavelet transform, 2D Gabor filter, and derivative method extracted texture features from gray-scale images. SVM was the main classifier used as identifier/verifier. Feature, score and decision level fusion was implemented. A 99.97% accuracy and EER=0.0032% was revealed in the final results.

A new palm print verification using Local Binary Pattern (LBP) method and its related analysis to capture palmprint texture was discussed by Promila and Laxmi[24]. Experiments proved that the new technique was simple, highly accurate and took less time to process palmprint images.

A new, multispectral recognition method was introduced by Amel *et al.*,[25]. Palmprint and palmvein features fusion was suggested to increase biometric person recognition accuracy. Performance of 3 classifiers: k-NN, SVM and 'One-Against-One' multi-class SVM (OAO-SVM) was tested with RBF kernel to assess the new biometric system generalization capability for multispectral palmprint image recognition. Result validation was performed on multispectral palmprint images of CASIA database.

METHODOLOGY

In this work, Wavelet based texture features extract features from palmprint while autoregressive model based texture feature is extracted for palmvein. The z score normalization normalizes obtained features which are fused through concatenation. Feature selection is through ABC and classification is achieved with kNN and Naive Bayes for 50, 75 and 100 features.

Dataset

PolyU database has palmprint images from 386 palms, captured with a specialized device via a camera. PUT Vein pattern database has 2400 images of vein patterns, half of which have a palm or vein pattern (1200 images) with the other half having a wrist vein pattern (1200 images). Data was from both hands of 50 students; ensuring 100 different patterns for palm/wrist region. Pictures were taken in 3 series of 4 pictures each, with a week's interval between every series. In palm region, volunteers were requested to place his/her hand on device to cover acquisition window so that line below their fingers coincided with the edge. There were no additional positioning systems[26]. In wrist region, palm and wrist were placed comfortably to position a hand.

Table 1. Recognition Rate (Palmprint)

Number of features	Naïve Bayes	K Nearest Neighbor
50	87.75	87.125
75	88.875	87.375
100	89.125	87.75
Proposed Feature selection	92.125	91.5

Table 2. Recognition Rate (Palmvein)

Number of features	Naïve Bayes	K Nearest Neighbor
50	86.5	85.875
75	87	86.25
100	87.375	86.625
Proposed Feature selection	90.125	89.75

Table 3. Recognition Rate (Fusion)

Number of features	Naïve Bayes	K Nearest Neighbor
50	89.25	90.25
75	92.75	92.5
100	93.625	93.25
Proposed Feature selection	95.875	95.25

Wavelet based texture features and autoregressive model

Textures provide characteristics for surface/object identification from aerial/satellite photographs, biomedical images and other images[27]. Texture analysis is fundamental for applications like biomedical image processing, automated visual inspection, Content Based Image Retrieval (CBIR) and remote sensing. Texture analysis method selected for feature extraction is critical for texture classification success. Waveletsare a recent tool to analyze texture information[28] assuming that energy distribution in frequency domain identifiestexture; conventional approaches computed wavelet subband energies as texture features.

Energy distribution's mean and variance of transform coefficients for each subband at each decomposition level construct feature vectors. Let image subband be $W_n(x, y)$, with n denoting specific subband. In Gabor Wavelet Transform (GWT) the index n is regarded as mn with m indicating a certain scale and n a certain orientation. The resulting feature vector $f = \{\mu_n, \sigma_n\}$ with[29],

$$\mu_n = \iint |W_n(x, y)|\, dx\, dy$$

$$\sigma_n = \sqrt{\iint \left(|W_n(x, y)| - \mu_n\right)^2 dx\, dy}$$

Wavelet transform represents an arbitrary function as a wavelets superposition. Any superposition decomposes a function into various levels, where every level is further decomposed with that level's resolution[30].

A one dimensional signal is provided a combination of current output value and past output values of a system that input signal is white noise having Gaussianity for autoregressive modeling. Previous outputs weights minimize average square errors of anticipated autoregressive parameters. If *x(n)* indicates input which is zero mean white noise and *y(n)* indicates output, then the system's autoregressive model is expressed as[31],

$$\sum_{k=0}^{p} a(k)y(n-k) = x(n)$$

Where *a(k)* demonstrate autoregressive parameters which model a signal or system producing a signal.

Z score normalization

Normalization (scaling) in pattern recognition ensures that certain features (with larger range/variance) don't dominate distance

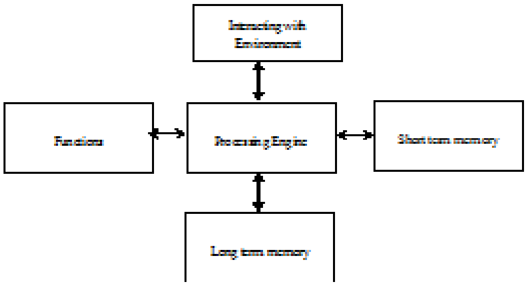

Fig. 1. Architecture of Artificial Bees' Colony System

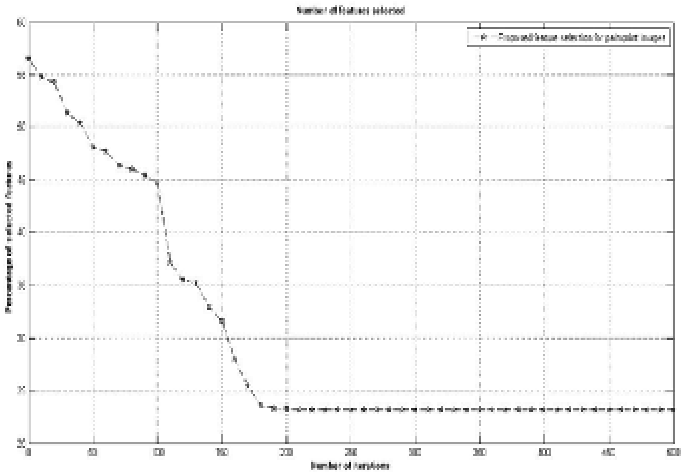

Fig. 2. Proposed feature selection for Palmprint

calculations during classification. Normalization should allow a feature component to equal regarding its contribution to distance[32]. Z score transformation methods were incorporated through use of a statistical test like two-sample-for-means Z test[33].

Zscore: s' = (s - mean)/(standard deviation)

Concatenation is performed after feature extraction. Fused images with nonlinear information are processed to extract information and to reduce feature dimensions by linear and non-linear dimensional reduction methods[34]. Using a concatenation process that does not consider data distribution in both modalities, some data may be redundant and overlap others. In reality, some modalities have nonlinear features distributions like face images with different poses/expressions or palmprint images with various aging levels. This uses linear subspace reduction techniques which cannot exploit information in these modalities fully.

Feature Selection using Artificial Bee Colony (ABC)

Feature selection ensures a smaller, more distinguishing subset compared to starting data, selecting distinguishing features from a features set, and eliminating the irrelevant. Reducing data dimension is by locating small important features set resulting in lowered processing time and

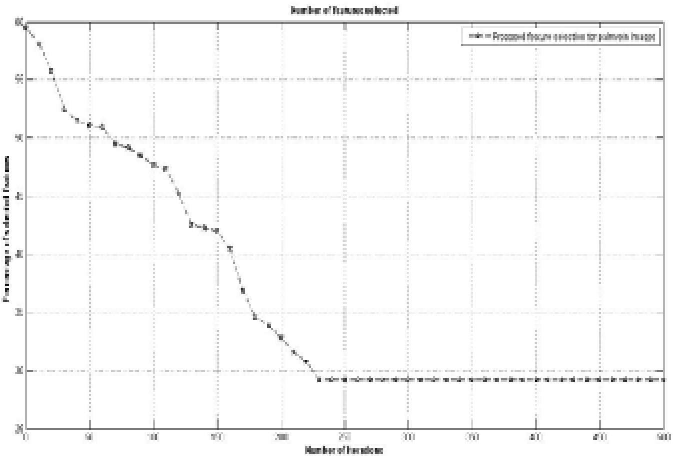

Fig. 3. Feature selection for palmvein

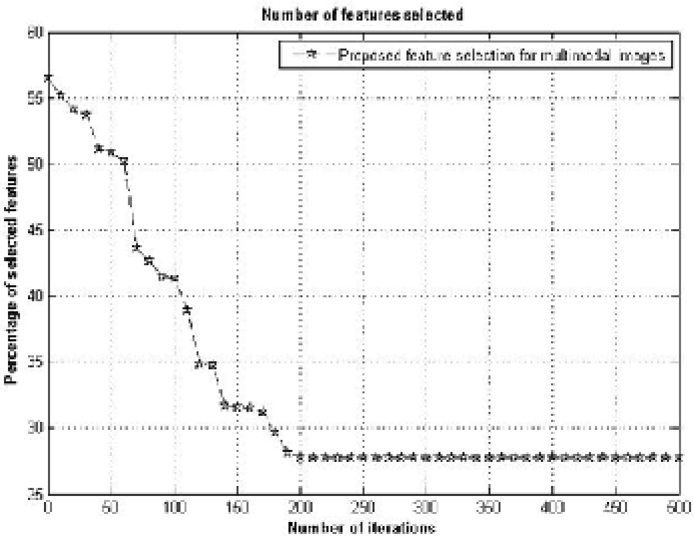

Fig. 4. Feature selection for fusion

increased classification accuracy[35].

ABC algorithm is a population-based stochastic optimization inspired by honey bee swarms intelligent foraging behavior used for clustering, classification and optimization studies. Artificial bees in the ABC algorithm are employed bees, onlooker bees, and scout bees. Each Food Source (FS) has only one employed bee.

A fitness function assigns a quality or ‘nectar’ value to food sources. Every employed bee searches for a new food source in its neighborhood, moving closer to it if it has high nectar value[36]. Employed bees share food source information with onlooker bees in the hive. Every onlooker bee selects an employed bee food source probabilistically in a procedure similar to roulette wheel selection.

ABC optimization approach’s general algorithmic structure is given by[37]:

Initialization Phase
REPEAT
Employed Bees Phase
Onlooker Bees Phase
Scout Bees Phase
Memorize the best solution achieved so far
UNTIL (Cycle = Maximum Cycle Number or a Maximum CPU time)

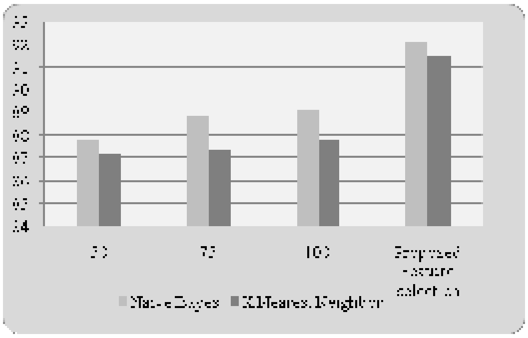

Fig. 5. Recognition Rate (Palmprint)

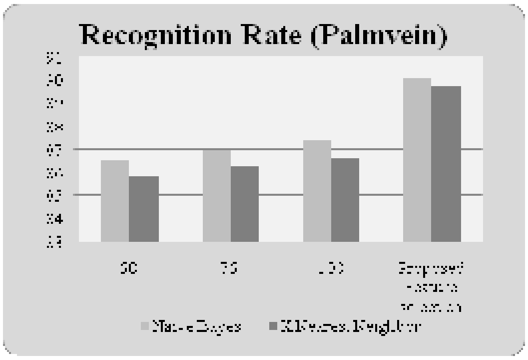

Fig. 6. Recognition Rate (Palmvein)

Classifiers

The nearest neighbor classifier compares prototype image feature vector and database feature vectors. It is got by finding distance between prototype image and database. Let C_{11}, C_{21}, C_{31}… C_{k1} be k database clusters.Class is located by measuring distance $H(x(q),C_k)$ between x(q) and k[th]cluster C^{k1}. Feature vector with minimum difference is the closest matching vector given by[38]

$$T\left(x(q), C_k\right) = \min\left\{\left\|x(q) - x\right\| : x \in C_k \right. \quad ...(4)$$

Naive Bayes algorithm is an effective and inductive learning algorithm for data mining as machine learning. This algorithm is of the wrapper approach. Naive Bayes classifier works as stated: let 5ØKÜ be a of random variables vector denoting observed attribute values in training set to certain class label 5ØPÜ in training set. Probability of every class given observed values vector for predictive attributes is computed using the formula [39]:

$$P\left(Y_j \mid X\right) \frac{P\left(Y_j\right) P\left(X \mid Y_j\right)}{\sum_{i=1}^{c} P\left(Y_i\right) P\left(X \mid Y_i\right)}, \qquad j = 1, \ldots, c$$

$$X = \left[x_1, x_2, \ldots, x_n\right] \quad ...(5)$$

where (Yi) is prior probability of class Yt and $P(Yj/X)$ is class conditional probability density functions.

RESULTS AND DISCUSSION

From 200 subjects, 6 palmprint and palmvein images are used. From each subject, two images were used for training and the rest used for testing..Figure 2,3& 4 shows the number of feature selected for palmprint only feature selection,

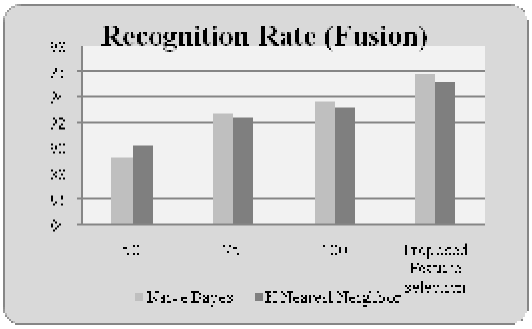

Fig. 7. Recognition Rate (Fusion)

palmvein only feature selection and the fused technique.

Palmprint provides the lowest number of features compared to all other techniques without compromising on recognition rate. For the fused technique 16% more features are selected compared to palmprint but the recognition rate increases substantially.

Higher features are required for palmvein due to its high feature dimension.

For various classifiers, the recognition rate achieved is given in Table 1

When only palmprint based feature extraction and proposed feature selection is used the recognition rate increased by 4.8645% when Naïve Bayes classifier is used and by 4.8985% whenkNNis used with 50 as seen in figure 5. Table 2 shows the recognition rate when palmvein alone is used.

The proposed feature selection increased recognition rate by 4.1047% wehn Naïve Bayes classifier is used and by 4.4128% when kNN with 50 number of features for the palmvein is used. Even when the number of features is increased to 100 the improvement is recognition rate is not significant as seen in figure 6. Table 3 shows the obtained recognition rate when both the features are fused.

The proposed feature selection increased recognition rate by 7.1573% using Naïve Bayes classifier and by 5.3908% when kNNis used with 50 number of fused features.

CONCLUSION

This work proposed a palmprint and palmvein based multimodal biometric system. Wavelet based texture features extract features from palmprint with autoregressive model based texture feature being extracted for palmvein. z score normalization normalized features which were also fused through concatenation. Feature selection is achieved by using ABC optimization algorithm. Classification is achieved through kNN and Naive Bayes for 50, 75, 100 features and for the new feature selection. Results proved that the new feature selection improved recognition rate by 7.1573% in fusion with Naïve Bayes classifier.

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