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# Supervised Feature Reduction Technique for Biometric Recognition Using Palm print Modalities

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## ABSTRACT

Technological resource assessments security is a major concerned and Biometric is one of the most robust identification techniques. The common approach for the biometric identification process is to compare the extracted feature vectors of query imposter with feature vectors of rest imposters. In biometric recognition, the datasets have very large number of imposters and this imposes the condition on the identification process. To make the identification process fast, dimensionality reduction is required at either dataset or in feature vectors. This paper proposes the palmprint identification algorithm with dimensionality reduction at datasets as it reduces feature vector size too. One Dimensional Principle component analysis (1DPCA) cannot correlate the neighbor pixels and transformation from 2-dimension-to-1-dimension increases the computation cost. Therefore, two Dimensional PCA (2DPCA) is employed to process the dataset fast in comparison with 1DPCA. For classification, Supervised learning-based classifier provides higher accuracy and hence Support Vector Machine (SVM) classifier is used for recognition. The success of the classifier depends on the extracted features to be matched. The proposed algorithm uses Histogram of Gradient (HOG) features which is the best combination with SVM. Accuracy of the proposed algorithm is compared with the accuracy of other models. The experiment results and comparative analysis on PolyU datasets reveal that the proposed algorithm achieves 96.36% accuracy which is best amongst all.
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**KEY WORDS:** 2D-PRINICIPAL COMPONENT ANALYSIS, HISTOGRAM OF GRADIENT, PALMPRINT RECOGNITION.

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## INTRODUCTION

Biometrics is now a day's widely used for person identification and authentication. It is a pattern recognition process based on his/ her physiological or behavioral characteristics (Zhang, 2013). The unique physiological characteristics like iris, face, fingerprint, hand geometry and voice are known as Biometrics, various researchers have explained using these biometric modalities for identification (Chen et al, 2013; Ahmad et al, 2016). Both spatial and spectral features are used for finger knuckle recognition (Kumar, 2019). Abdulbaqi et al detected fingerprint edges using active contour model of Euclidean distance transformation (Abdulbaqi et al, 2018). Fusion of face and iris at feature level and score level gives accuracy of 99.22% and 100% respectively(Alay et al, 2019). Nguyen et al explained convolutional neural network extractor of fingerprint minutiae (Nguyen et al, 2020).

The major application areas of the biometrics are ATMs, smart card, personal computers, network access, keyless entry for automobiles etc. Even though many state-of-the-art security systems are developed, the cyber-attack has exposed weaknesses of the security systems. Out of these, palm based identification have been intensively developed because of its crucial advantage over other features. The classical feature of palm region ridge ending and ridge bifurcation (minutia) are used for palmprint matching. The palm region can be easily recognized in low resolution images also. High resolution image also contains ridges and wrinkles which can be utilized as classification and matching features. The palmprint matching process consists of four steps. First is to crop region of interests. Features are extracted in the second step. The extracted features are reduced in third step and the last step is classification for individuals' identification.

The algorithms used for palmprint feature extraction are classified as: 1) structure-based approaches, 2) Statistics-based approaches, 3) Subspace-based approaches and 4) texture & transform domain frequency field feature based methods. Structure features includes lines and feature points which are sensitive to the captured resolution of palmprint and hence difficult to capture it. Frequency field features avoid the texture information causing instability in capturing of palm features. Sub-space methods include Eigen space based component analysis like PCA, ICA and LDA. Hai-feng Sang and Fang Liu (Sang et al, 2016) applied 2DPCA method for contactless defocused palmprint images over the database of 50 subjects. Euclidean distance based classifier was used for matching. However, success rate for defocused image was lower than that of clear image. To preserve the 2D information of images over 2DPCA subspace, 2D- locality preserving projections (2DLPP) is used on reduced features (Xin et al, 2007). 2DPCA is sensitive to illumination changes. Jinyu Guo et al (Guo et al. 2007) proposed a method using phase congruency with 2DPCA to tackle illumination problem. Similarly to overcome the noise in palmprint, local DCT based enhancement was integrated with 2DPCA on the enhanced images (Cui et al, 2010). Individual local mean 2DPCA is used to resolve the light illumination problem in face recognition ( Hacherangchai et al, 2019).

For comparing the accuracy results of the distance measurement, PCA is used to store the iris computing process ( Sari et al, 2018). They implemented this palmprint recognition algorithm on multimedia chip OMAP3530. To increase the accuracy over the illumination variation, entropy map and 2DPCA was proposed by Jinyu Guo et al (Guo et al, 2013). Arunkumar et al proposed improved histogram of oriented lines (IHoL) descriptor which is less sensitive to translation and illumination. It is also robust against small transformation variations. So the histogram values used in the work remains unchanged (Arunkumar and Valarmathy, 2016). Using PCA with improved HoL gives high recognition rates. Lie and Kim (Lie and Kim, 2016) proposed a method named Local Micro-structure Tetra Pattern (LMTrP) which obtains the advantages of direction and thickness. The superfluous features are removed using line-sharp filter. The given image is represented using single feature vector formed by concatenating local region histograms of the proposed descriptor LMTrP The dimensions are reduced by applying linear kernel based discrimination analysis. This method provides better stability against rotation and translation up to certain extent.

Palmprint features are extracted using principle component analysis and linear discriminant analysis. SVM classifier is used to for recognition. The author presented integration of palmprint features with features of other modalities to increase the accuracy. Instead of calculating histogram in spatial domain, Chaudhari (Chaudhari et al, 2012) transformed the image plane into Radon and histogram of Radon coefficients are used for matching the palmprints. The algorithm is robust to rotation and scaling invariance. Computationally simple algorithm is proposed by (Chaudhari et al,2013) ,where area and periphery of the polygon formed using the outermost coefficients of the Radon. PCA and radon transform used for face recognition (Hiremath et al, 2014). Probabilistic neural network, PCA and Radon transform gives equal error rate of 9.87% in training set of 10 images (Ooi et al, 2016). Using course to fine patchmatch for palm vein recognition approaches the state of the art results with improved time efficiency (Hernandez et al, 2019). Gumaei (Gumaei et al, 2018) proposed hybrid method for feature extraction which uses histogram of gradient and steerable guassian filter. They constructed efficient approach for palmprint recognition. For dimensionality reduction for extracted features is achieved using auto-encoder. The classification is done with regularized extreme learning machine.

Attallah et al (Atallah et al, 2018) used two different Haar wavelet decomposition components for feature extraction of palmprint image. These features are fused to give output. They used histogram of gradient and binarized statistical image features for fusion. The basic requirement for the palm print recognition algorithm is that features extraction must be robust to the environmental conditions. In 1DPCA, 2D image is transformed and represented as a point in high-dimensional vector. However, the formation from 2D to 1D breaks the correlation between the pixels in spatial domain. In this paper we have used 2DPCA. 2DPCA offers projection in 2D space and hence reduces the conversion time. HOG has inheritable advantages of illumination invariant and extract the local information from strong and lengthy lines. Thus PCA helps to characterize the lines and HOG fulfill the robustness of the extracted features. Therefore this paper proposes integration of 2DPCAand HOG for palm print identification. Later, SVM is used over the HOG transformed features for the classification..

**Proposed Algorithm:** Figure1 illustrates the proposed palmprint identification system. To train the SVM classifier (i.e. enrolment), A set of features from extracted using 2DPCA and HOG from all users are used. The classifier outputs each person. For the identification process, test palmprint is passed through same feature extraction process and SVM classifier. We used median filter to remove noise, also referred as pre-processing of palmprint. To process recognition step fast, size reduction plays an important role. Multi-spectral (band) images have tendency to be redundant at certain extent when spectral are adjacent to each other. PCA de-correlates these pixel values. Therefore PCA can be employed reducing image dimension and hence the computation cost. However, 1DPCA has weakness that it requires the conversion of 2D image into 1D vector. This process losses the correlation between the neighbor pixels and also increases the computation cost of conversion process. Therefore, 2DPCA which directly calculates the eigen-vectors form image is employed instead of matrix to vector conversion process (i.e. 1DPCA). 2DPCA works in row and column to reduce the dimension. 2DPCA calculation is as follows: Let A is a random matrix of size m x n, which represents m x n image. Considering the linear projection of A on X fields $y = AX$ where X is an n dimensional unit column vector and y is the projected feature on x. Characterization of the A vector using 2DPCA is as follows.

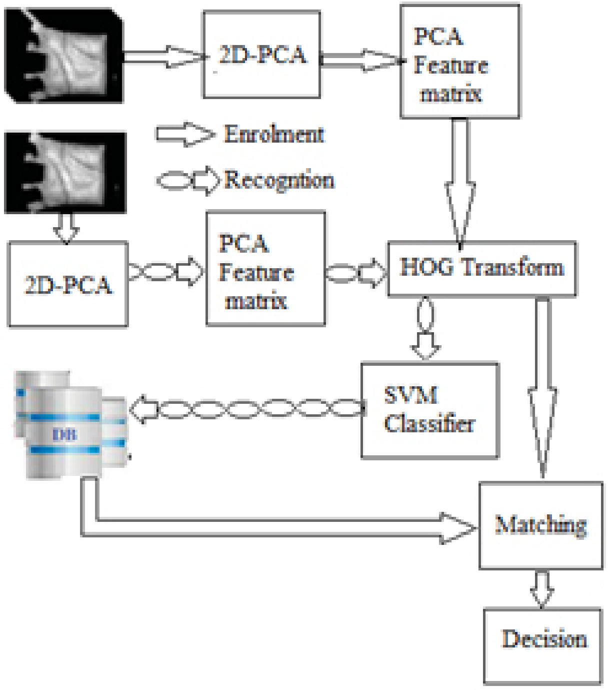
Considering that there are c pattern classes in the space $R^{m \times n}$ and the sample space includes images $\{X_1, X_2......X_n\}$ where, $X_i \in R^{mxn}$ and each sample belongs to a class j where $j \in \{1, 2, ....c\}$. The total scatter matrix can be defined as $S_T = (1/N)\sum_{k=1}^{N}(X_K - \bar{X})(X_K - \bar{X})^T$, where N indicates the number of samples and $\bar{X} = (1/N)\sum_{k=1}^{N} X_k$ is the mean of all training samples.

In 2DPCA algorithm, the optical projection vector $A_{opt}$ satisfies with

$$A_{opt} = \arg\max \left| A^T S_T A \right| = [A_1, A_2, .....A_m] \quad (1)$$

Where $\{A_i \mid i = 1, 2, ....m\}$ are orthogonal eigenvectors of $S_T$ corresponding to the largest m eigen values, respectively.

Figure 1: Proposed Palmprint Matching System




In biometric recognition, the classification plays an important role. All classification algorithms analyses the various image features. These typical image features are characterized and isolated in the training phase and this partition is used to classify biometric in testing phase. Further, priori knowledge based statistical processes are used in supervised classification and clustering approach is used in un-supervised classification. Some of them are Maximum likelihood, K-means clustering, Support vector machine, Neural network, decision tree classifier etc. The choice of classifier depends on the type and size of database and features extraction method. In biometric recognition, the size of data base is too large and hence SVM is the most suitable choice for the large sets of images. In comparison with NN, SVM offers simple geometric interpretation and provides sparse solution reducing mathematical complexity. SVM with linear kernel is used as it provides fast speed. Hence SVM is used in the proposed approach.

The success of the classifier strongly depends on extracted features from the palmprint. Principle lines and wrinkle in the palmprint are the strongest features. During the palmprint acquisition process, the translation and rotation are encountered problems. HOG extracts the orientation features of the gradient (i.e. lines) in spatial domain. Further, extracted features are scale and illuminationinvariant. Therefore HOG features are the best choice for SVM based classifier. The HOG features transform for vector image X can be written as

$$\varphi_\theta(X) = Db * \left[(g_\theta * X)\Theta(g_\theta * X)\right] \quad (2)$$

Where $g_\theta$ is oriented edge filter, b is blurring function and D is the sparse selection matrix to achieve histogram. This operation is performed over the bank of edge filters and responses from each filter are concatenated to obtain final feature vector.

$$\varphi_\theta(X) = [\varphi_1(X), \varphi_2(X)\ldots\ldots\ldots\varphi_\theta(X)] \quad (3)$$

Further equation 2 can be expressed as second order interaction (Bristow et al, 2014) in the form of

$$\varphi_\theta(X) = DBM\left(G_\theta \otimes G_\theta\right)\left(X \otimes X\right) \quad (4)$$

Where M is the selection matrix, B and G are convolutional matrices prototype. In equation 4, the $BM(G_\theta \otimes G_\theta)$ can be viewed as filter bank applied to second order statistics of image data. Thus HOG provides second order covariance and filter bank based prior information. This prior information helps SVM to classify the features successfully. In addition, the second order covariance of image is enough to discriminate one biometric image from other biometric image. Overall, these features are used as input on SVM classifier. Combining with HOG extraction with 2DPCAand SVM training, the process includes following steps: 2DPCA, features extraction using HOG, training and detection.

## RESULTS AND DISCUSSION

We experimented with Hong Kong polyU palmprint datasets. Total 3800 gray scale palm images of 190 palms are used in the dataset. The resolution of the image is 72 pixels per inch. From total sets, 50% images are used for enrolment and rest are used to test. As pre-processing step, median filtering is applied to remove noise from palmprint. 25 largest Eigenvectors are used in 2DPCAtransformation. The HOG features are also tested with K- Nearest Neighborhood. 2DPCA is applied to 128 x 128 palmprint. The window size of 3x3 is used for feature extraction. HOG features are calculated by assembling the histogram with 9 bins and range of 20 degrees per bin. These feature vectors are normalized for SVM classification. In the experiment, verification process consist of one to one comparison and identification process consist of comparison of one to all is carried out. SVM is binary classifier. The bias value for SVM training model is kept in auto mode to get best bias value. Fig 2 presents the effect of 2DPCA projection for accuracy of identification. Large number of projections provides better accuracy and after 30 projections, the KNN and SVM both achieved same accuracy. Table 1 represents the comparison of obtained accuracy with other model. Inclusion of HOG with 2DPCA in the proposed algorithm provides better accuracy (i.e. 96.36%) in comparison with other 2DPCA or 1D PCA algorithms.

Figure 2: Analysis of 2dpca Projection Over Accuracy

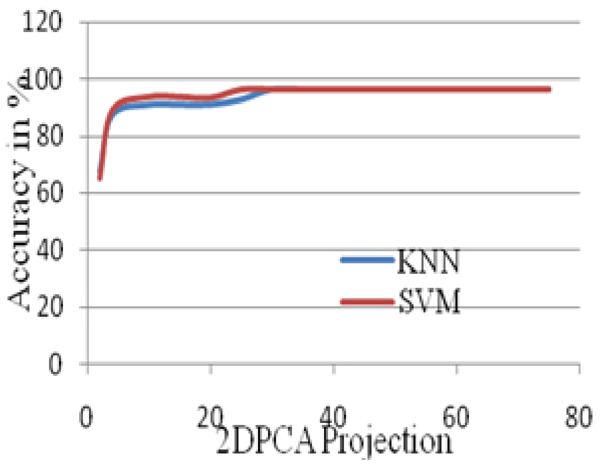



Table 1. Accuracy Comparison of the Proposed Model With Other Models

| Method | Accuracy |
|---|---|
| Proposed 2DPCA + HOG + SVM | 96.36 |
| Proposed HOG + K- Nearest Neighbor | 92.72 |
| HOG +PCA + SVM (Arunkumar et al, 2010) | 95 |
| HOG + PCA (Jia et al, 2014) | 95.37 |
| 2DHOG + 2DPCA (Jia et al, 2014) | 95.68 |
| Pseudo-Zernike Moments+ Naive Bayes Classification (Lakshmi et al, 2010) | 79.24 |
| Legendre Moments+ Naive Bayes Classification (Lakshmi et al, 2010) | 80.45 |
| Chebyshev Moments+Naive Bayes Classification (Lakshmi et al, 2010) | 51.27 |
| Pseudo–Zernike Moments + BBN (Lakshmi et al, 2012) | 90.1 |
| Legendre Moments + BBN (Lakshmi et al, 2012) | 92.5 |
| Chebyshev Moments + BBN (Lakshmi et al, 2012) | 54.9 |
| IHoL + PCA (Arunkumar et al, 2016) | 94.2 |
| PCA+LDA+SVM (Vinodkumar, 2016) | 83.5 |

## CONCLUSION

This paper proposes the biometric recognition using HOG and SVM. To reduce the dimensionality, 2DPCA is used in comparison with 1DPCA to save time and to preserve the locality of the features. Use of HOG method improves the robustness and increases the feature distinguishing capability.SVM having inherent advantages for large set of databases is used.In addition, The HOG preserves the locality with second order statistic and it is the key parameter for the success of SVM over KNN.Thus HOG is the perfect the feature extraction method supporting SVM. Experiments results show that the proposed system improves detection accuracy while maintaining a relatively satisfactory speed.

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