Multimodal Biometrics by Direct Fusion of Face and Palm Print Features
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Abstract— Multimodal biometrics has recently attracted substantial interest for its high performance in biometric recognition system. The face and Palm print is a reliable biometric characteristic with high usability. With the increasing demand very highly accurate and robust as well as clear face and palm print authentication system, multimodal image has been employed to acquire more discriminative information and increase the anti spoof capability of face and palm print. In this paper, introducing multimodal biometrics for face and palm print images using fusion techniques at the feature level. In this study, propose to build a modified multistage LBP histogram for a palmprint image. The palmprint image is divided into several regions from which the LBP feature distributions are extracted and concatenated into an enhanced feature vector to be used as a image descriptor. In this model of paper, the biometric system gives an explanation for each model. Also, the modalities of biometrics are discussed as well as focused on two different modalities :Palm-Print, Fusion

Index Terms—Palm-print, fusion, face.

I. INTRODUCTION

Biometric technology is an automatic method to recognize a person based on single modal biometrics or combination of multimodal biometrics characteristics. The technology has become the foundation for extensive array of highly secure identification and personal verification solutions. In recent years, multimodal biometrics has become increasingly important, particularly because single modal biometrics has reached its bottleneck; i.e. non-universal, noisy sensor data, large intra-user variations and susceptibility to spoof attacks. Multimodal biometrics is believed to have supplementary information between different modalities that increases recognition performance in term of accuracy and ability to overcome the limitations of single biometrics. To use multimodal biometrics, one has to allocate a combination technique that is able to fuse this information provided by different modalities. Modalities such face, fingerprint and hand geometry at matching score level is utilized [1]. And there are different methods for recognition of these modalities. As far as facial analysis is concerned, a computer vision approach to automatically extract visual features from just the frontal view of the face without needing any markers. The visual front-end is based on active appearance models. The active appearance models based system allows reliable extraction of shape and appearance specific facial features which subsequently use for articulator inversion. The use of canonical correlation analysis which is well-suited for linear model estimation with the limited data corresponding to each specific class model. In few multimodal systems combining face and body gesture for emotion recognition have attempted to model the temporal dynamics of the combined face and body affective behavior and their relationship, and tackled the phase synchronization issue for data fusion.

a) Palm Print
The human palm means the inner area between the fingers and wrist. The area of palm print compared to fingerprint is much larger, and then it can extract more features than a fingerprint. The palm print is similar to the fingerprint in ridges and valleys but the palm has also principle lines and wrinkles which can be acquired with a lower resolution scanner.

b) Face
Face recognition is the popular way for the humans to recognize each other. The face is the front part of a head from chin to the forehead. Face recognition can be used in surveillance application because the face is one of the few biometric traits that can be recognized by people at distance.

II. LITERATURE SURVEY

There are various methodologies of a multimodal Biometrics by direct fusion of face and palm print features.

RELATED WORK:-

The fusion method at feature level by using a combination of two modalities face and palm print images, which are used by Linear Projection Analysis methods such as principal component analysis (PCA) [1], [4], [5], Linear Discriminate Analysis (LDA) [1], [4] which reduces the dimension of original data have been proposed Canonical Correlation Analysis (CCA) [2], Active Appearance Models (AAMs) [2], FABO system [3], Locality Preserving Projections (LPP) [4], Video-Base fusion system [5], Online Multispectral
palm print System [6] have been demonstrated. However [1] failed to address the fusion of non linear feature otherwise better result could have been obtained. Principal lines for palm print and eigenface for face is considered white final decision is made based on threshold value. The method of hidden Markov Model, Canonical Correlation Analysis (CCA) which used the Active Appearance Models (AAMs) [2] for conjunction from audio features such as Mel Frequency Cepstral Coefficient (MFCCs) have been studied while they could analyze explain fusion schemes better suited to audiovisual speech inversion. The system based on vision recognize affective state from face and palm print movement and the Decision-level fusion method using module of FABO system [3] have been suggested but it does not illustrate directed affective body action appearance and timing from spontaneously occurring behavior natural and realistic setting. The fusion at feature level on laplacian palm have been obtained by applying Locality Preserving Projections (LPP) on fused image doesn’t address the General Registration Method. Fusion rule Max rule and Sum rule are used to integrated information from ESFI (Enhanced Side-face Image) and GFI (Gait Energy Image) they not clarify the giant recognition method based on GEI but is affected by shape of Face and palm print to some extent. It is sensitive to noise and facial expression [5]. An online multispectral Face and palm print system for real-time biometric authentication system using palm line orientation code as feature have been illustrated [6]. Where it Evaluate palm print verification using spectral signal spectrum of Red, Green, Blue and NIR (Near Infrared) where fusion of only two or three band have been suggested and Multispectral fusion has not been address [6].

An overview of our proposed approach is illustrated in Fig. 1. First, the MPC image is obtained by gradient normalization. To acquire the palm vein texture image, k-means method is adopted for the MPC image segmentation. Subsequently, we perform MPR matching on the obtained palm vein texture image and both the MF and Matching score 1 are obtained. In addition, the LBP code is calculated directly from the MPC image, and LBP histogram matching is performed on the MF to obtain Matching score 2. The final recognition results are achieved by the score-level fusion strategy on the formerly obtained matching scores. Rigorous experiments demonstrate that our proposed method attains superior recognition performance and reduces the influence from irrelevant palm regions.

III. PALM VEIN ROI SEGMENTATION

The process involves various preprocessing steps, such as ROI extraction and normalization of transformation, rotation, and scaling, that must be performed to preserve the vascular patterns against variations of displacement, angle, and scaling. Our proposed palm vein ROI segmentation scheme is illustrated in Fig. 2. First, a modified OTSU method [38] was used to extract hand contours from grayscale palm vein images. Next, the radial distance function (RDF) between a reference point and contour points was used to locate the peak points and valley points of the palm, which can be taken as landmarks for extraction of ROI from grayscale palm vein images. Finally, we perform scaling and rotation normalization on the extracted ROI to obtain the final palm vein ROI to be matched.

OUR WORK:-

![Diagram](image-url)

Fig. 1. Schematic overview of the proposed approach
IV. LINEAR BINARY PROCESS

The original LBP operator labels the pixels of an image by thresholding a $3 \times 3$ neighborhood of each pixel with the center value and considering the results as a binary operator. Converting the binary code into a decimal one. Figure shows an illustration for the basic LBP-Based on the operator, each pixel of an image is labeled with an LBP code. The 256-bin histogram of the labels contains the density of each label and can be used as a texture descriptor of the considered region. The procedure of interacting LBP approach can obtain the relationship among the original LBP operator. The LBP code of the center pixel in the neighborhood is obtained by pixels of a facial image in a larger scale, which can contain more face features with the cost of increasing data redundancy.

\[
LBP_{P,R} = \sum_{p=1}^{P} S(g_p - g_c)2^{p-1}
\]

where $g_c$ is the gray value of the central pixel, $g_p$ is the value of its neighbors, $P$ is the total number of involved neighbors and $R$ is the radius of the neighborhood. Suppose the coordinate of $g_c$ is $(0, 0)$, then the coordinates of $g_p$ are $(R\cos(2\pi p/P), R\sin(2\pi p/P))$. Above fig. gives examples of the circularly symmetric neighbor sets for different configurations of $(P, R)$. The gray values of neighbors that are not in the center of grids can be estimated by interpolation.

\[
S(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}
\]

If the texture image is of size $N \times M$. After identifying the LBP pattern of each pixel $(i, j)$, a histogram is built to represent the whole texture image:

\[
H(k) = \sum_{i=0}^{N} \sum_{j=0}^{M} f(LBP_{P,R}(i, j), k), k \in [0, K]
\]

where $K$ is the maximal LBP pattern value. The U value of an LBP pattern is defined as the number of very spatial transitions (bitwise 0/1 changes) in that pattern

\[
U(LBP_{P,R}) = \left| \sum_{p=1}^{P} s(g_p - g_{c_p}) - s(g_{c}-g_{c}) \right|
\]

For example, the LBP pattern 00000000 has a U value of 0 and 01000000 has a U value of 2. The uniform LBP patterns refer to the patterns which have limited transition or discontinuities ($U \leq 2$) in the circular binary presentation [10]. It was verified that only those “uniform” patterns are fundamental patterns of local image texture [10]. In practice, the creating from, PR LBP to 2, u PRL BP (superscript “u2” means that the uniform patterns have a U value of at most 2), which has $P^2+3$ distinct output values, is implemented with a lookup table of 2P elements. The dissimilarity of sample and model histograms is a test of goodness-of-fit, which could be measured with a nonparametric statistic test. In this study, the
dissimilarity between a test sample $S$ and a class model $T$ is measured by the chi-square distance:

$$D(S, T) = \sum_{n=1}^{N} \frac{(S_n - T_n)^2}{S_n + T_n}$$

where $N$ is the number of bins,
$S_n$ are the values of the sample,
$T_n$ are model images at the $n$th bin.

V. FUSION OF FACE AND PALM PRINT

Currently most of the feature level fusion in multimodal biometric which combines face and palmprint modalities uses concatenation method to fuse the information extracted from both modalities. Concatenation method which serially combined the holistic feature vector produces a new fused feature vector which has a large feature dimensionality. The new fused feature vector may contain noise and redundant information that can affect the discrimination power of the feature vector. Furthermore, when limited number of training images is available, accurate estimation of model parameters for high dimensional feature vector will not be possible. In the previous feature level fusion, concatenation is performed after preprocessing method such as Gabor transform where the feature vector becomes larger than the original image. High dimensional fused feature vector is then reduced to smaller dimensionality by using linear projection method such as Principle Component Analysis (PCA) and Linear Discriminant Analysis (LDA).

Most of the feature level fusion uses holistic features of face and palmprint images. While holistic features contain information of the whole image, they also include high frequency components that are not useful for fusion purpose. In contrast, fusion of low frequency components is expected to give higher degree of discrimination power, thus Discrete Cosine Transform (DCT) analysis can be used to extract the information into several frequency bands. Local region in the face and palmprint images may also hold important information to distinguish among different persons, therefore, fusion process using local features is expected to be superior to those using holistic features. Furthermore, information fusion using local features produces low dimensional fused feature vector compared to the holistic feature fusion. As a result, an accurate statistical model can be estimated using a large amount of fused feature vector extracted from each local region of the face and palmprint images.

VI. CONCLUSION

This paper explores the use of local binary pattern for palmprint verification based on texture. This indicates that feature is extracted by local binary pattern. Chi square dissimilarity test and Pearson correlation similarity test calculate the matching score among two different feature sets. Discrimination function evaluates the threshold value which decides the class of the input image. Experimental analysis for variation in ROI, Thus the individual score of two traits (face & palmprint) are combined at classifier level and trait level to develop a multimodal biometric system.

REFERENCES

[1] Wenxiong Kang, Qiuxia Wu “Contactless Palm Vein Recognition Using a Mutual Foreground-Based Local Binary Pattern” IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY, VOL. 9, NO. 11, NOVEMBER 2014