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FACE RECOGNITION BASED ON SUB PATTERN METHOD USING SLANT TRANSFORM

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ABSTRACT
Face recognition using sub pattern method using slant transform is proposed in this paper. Face recognition is a popular technique for detection and identifying the face image from the face database. Slant transform is a good energy compaction and this transform possesses a discrete sawtooth basis vector which efficiently linear brightness variations along an image line. The image can be represented as sub parts to extract the minimum features from the image with the help of slant transform. Sub pattern slant transform used in image compression, filtering and coding. Face recognition using sub pattern slant transform gives better results as compared to existing techniques.

Keywords: Artificial neural networks (ANN), Soil contamination, pH, EC.

I. INTRODUCTION
The face recognition is a system which is widely used for identifying the face from the face database. In many Human Computer Interaction systems are expression Recognition and cognitive State/Emotional State Recognition. In many applications the face detection is widely used but major tasks are Out-of-Plane Rotation (facial expression, frontal, 45 degree, profile, upside down, Presence of beard, mustache, glasses etc.) and In-Plane Rotation (size, lighting condition, distortion, noise and compression). There are different types of approaches to recognize the face from the database. First approach is knowledge based method which encodes what constitutes a typical face, e.g., the relationship between facial features. Advantages of knowledge based method are easy to come up with simple rules, based on the coded rules, facial features in an input image are extracted first, and face candidates are identified, and work well for face localization in uncluttered background. Disadvantages are difficult to translate human knowledge into rules precisely: detailed rules fail to detect faces and general rules may find many false positives and difficult to extend this approach to detect faces in different poses: implausible to enumerate all the possible cases Second approach is feature invariant method which is used to find structure features of a face that exist even when pose, viewpoint or lighting conditions vary. Advantage of feature invariant method is applicable for features are invariant to pose and orientation change and disadvantages are difficult to locate facial features due to several corruption (illumination, noise, occlusion) and difficult to detect features in complex background. Third approach is template matching which is used to several standard patterns stored to describe the face as a whole or the facial features separately. Advantage of template method is simple but disadvantages are in the face image, template needs to be initialized near the face images and difficult to enumerate templates for different poses. Fourth approach is appearance based method which captures the representative variability of faces. There are different types of appearance based classifiers such as neural network, Principal Component Analysis (PCA), Support Vector Machine (SVM), Distribution-based method, Hidden Markov model and Human Visual System (HVS) etc. Finally top-to-down approach which represents any face using a set of human-coded rules.

Basics concepts of principal component analysis (PCA), Human Visual System (HVS) and Slant transform are discussed in section II. Proposed method is discussed in section III. Experimental results are presented in section IV. Concluding remarks are discussed in section V.

II. SLANT TRANSFORM
Shibata and enomoto have introduced orthogonal transform containing four and eight matrices for data vector length of slant transform. a slant vector is a discrete sawtooth waveform decreasing in uniform steps over its length, which is suitable for efficiently representing gradual brightness changes in an image. To develop an image slant transform matrices processing the following properties are orthogonal set of basis vectors, sequency property, one constant basis, high energy compaction, one slant basis vector, variable size transform and computational algorithm.
The slant transflrom matrix of order two consisting of a constant and a slant basis vector is given by

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$$S_2 = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

Bthe slant matrix of order eight is obtained by the operation

$$\mathbf{S}_n = \frac{1}{\sqrt{2}}\left[\begin{array}{cccccc} 1 & 0 & \boldsymbol{0} & 1 & 0 & \boldsymbol{0} \\ a_n & b_n & & -a_n & b_n & \\ \multicolumn{2}{c}{\boldsymbol{0}} & \mathbf{I}_{n-1} & \multicolumn{2}{c}{\boldsymbol{0}} & \mathbf{I}_{n-1} \\ 0 & 1 & \boldsymbol{0} & 0 & -1 & \boldsymbol{0} \\ -b_n & a_n & & b_n & a_n & \\ \multicolumn{2}{c}{\boldsymbol{0}} & \mathbf{I}_{n-1} & \multicolumn{2}{c}{\boldsymbol{0}} & \mathbf{I}_{n-1} \end{array}\right]\begin{bmatrix} \mathbf{S}_{n-1} & \boldsymbol{0} \\ \boldsymbol{0} & \mathbf{S}_{n-1} \end{bmatrix}$$

Discrete Wavelet transform is usually wire t by Bank filter iteration, however, for a fixed number of zero points, it does not give a discrete time scale that is optimal with respect to time localization. This article discusses the implementation and properties of orthogonal DWT, with two zero points and with improved time localization framework is not based on filter Bank, iteration, and different filters are used for each scale. For large scale support discrete basis functions approaches 2/3, that the respective roles of the Bank of filters of the iteration. This Foundation, a private case class bases described Alpert, retains an octave band feature and piecewise linear (but not complete). Closed form expressions for filters are given, the effective implementation of the conversion explained, and improved noise reduction example shows. This basis, being the polygonal, reminiscent of a transformation to which it is compared.

III. PROPOSED METHOD

Proposed Algorithm

Proposed method is presented below:

1. There are N face images belonging to M persons in the training set; $N = N_1+N_2+N_3+\ldots N_M$. where M is the total images.
2. Images size is represented as no. of rows and columns (A1×A2). By using sub-pattern method Each face image is first partitioned into S equally sized, these sub-pattern images are transformed into corresponding column vectors with dimensions of d = (A1×A2)/S using non-overlapping method.
3. In the first step calculate mean value of sub-pattern images.
4. Each sub-pattern matrix is multiplied with slant matrix using slant transform. Slant matrix size should be equal to the sub-pattern matrix.
5. Then find the largest Eigen vector features from the square matrix. Each of them can be expressed in the form of d-by-L Eigenvector matrix.
6. Similarly same procedure for all sub matrices.
7. Afterwards, S extracted local sub feature weights of an individual vertically are synthesized into a global feature.
8. At final stage necessary to identify a new test image, this image also partitioned into S sub-pattern images. Each of them is represented as C test i and it's vertically centered.
9. Finally, the identification of the test image is done by using nearest neighbor classifier with cosine measure, in which the cosine of the angle between the test image and each training image in the database.

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IV. EXPERIMENTAL RESULTS

Feature extraction process

Recognition performance in terms of average recognition rate and recognition time of the proposed face recognition system is tested by conducting experiments on Yale data base [7]. A face database set was constructed by selecting 40 images of 4 individuals, ten images per person. These images of a person used for training and testing. Experimental results are tabulated in Table 1. Since the recognition accuracy of the subpattern image, several sizes of sub-pattern images are used in our experiments as shown below: 56×46(S=4), 28×23(S=16), 14×23(S=32), 7×23(S=64), and 4×23(S=112). In this, Eigen values vertical, horizontal, and whitened are considered.

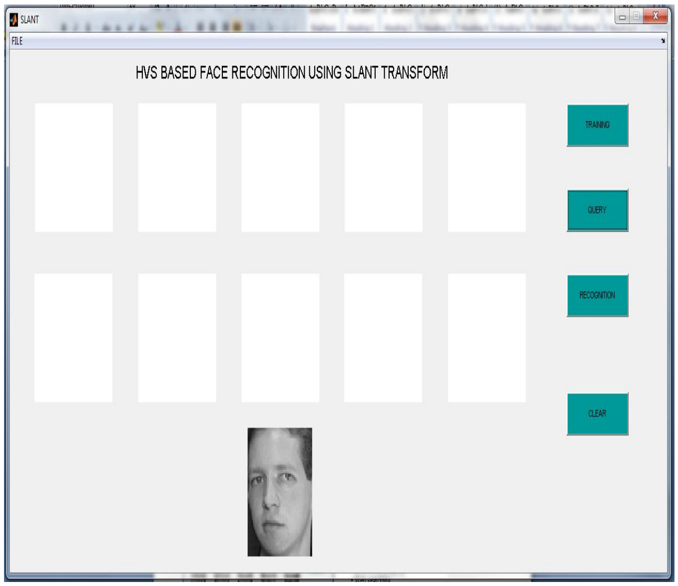

Figure2: Query image

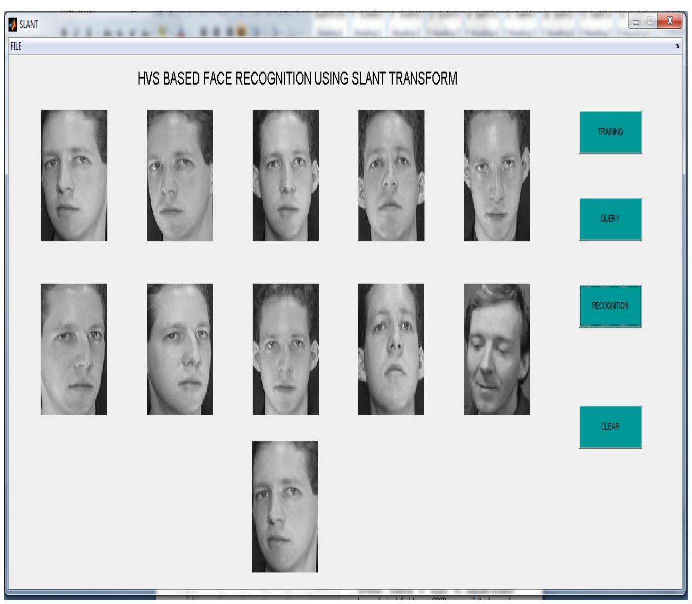

Figure3: Retrieval result

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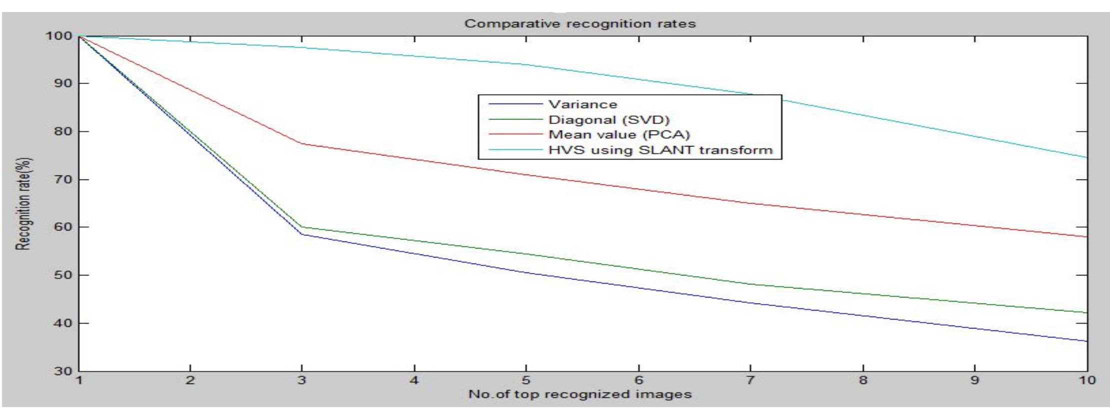
Recognition rate

HVS based face recognition using slant transform method performance in terms of average recognized rate is shown in table 1. Figure 4 indicates the superiority of the efficiency for HVS method using slant transform for face recognition system with minimum features. This method has better recognition performance than over remaining methods in terms of average recognized rate.. Retrieval time is also less.

	No. of top recognized matches				
	1	***3***	***5***	***7***	***10***
Variance	*100*	*58.5*	*50.5*	*44.2*	*36.25*
Diagonal (SVD)	*100*	*60*	*54.5*	*48.2*	*42.25*
Mean value (PCA)	*100*	*77.5*	*71*	*65*	*58*
SLANT transform (Proposed)	***100***	***97.5***	***94***	***87.85***	***74.5***

Table 1: Recognized efficiency on face database

Comparative recognition rates:



V. CONCLUSIONS

In this paper, architecture for 2- dimensional DWT with its VLSI implementation has been proposed. Image fusion has attracted more attention due to increasing demands of clinical and other applications for they can support more accurate information than any individual source image. The

2nd International Conference on Communications & Signal Processing, April, 2013. 156 architectures are representative of many design styles and range from highly parallel architectures. Here an average technique based reconfigurable system is designed using the EDK tool. Hardware architectures has been implemented as a coprocessor in an embedded system. In addition, the hardware cost of this architecture is compared for benchmark images. This type of work using EDK can be extended to other applications of embedded system.

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