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Human Hidden Emotion Identification Techniques with Multi-Feature Face Recognition System

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This Paper explores the Technique to identify the psychology of a human being through Multi- feature Face Recognition system by Neural Network. The system works in three modes: Training, Classification and Matching – Emotion. In the training mode face images are normalized according to different emotions, extract appropriate face feature by using Principle and independent component analysis (PCA) & (ICA). The extracted features are then trained in parallel to partition in different face classes using Back-propagation neural network (BPNN). In classification, the trained face images are fed with new face image. Scored based strategy works with both PCA BPNN and ICA BPNN to classify given new face image according to trained face classes. In matching mode, the face image(s) is to be matched with the set of particular emotion and identify the emotion of the current face image.

Keywords: Emotion recognition, Multi feature face recognition, Neural Network, Scored Based Strategy.

Introduction

In communication field, face is one of the best features of human body for non-verbal communication. The entire face may reflect the hidden emotion of a human being. Basically a human being feels six types of emotions joy, sadness, anger, surprise, fear and disgust which can recognized from the movement of nose, eyes, eye- brows, lips, chin, and head. In face recognition, there are two major classes Holistic matching and feature based matching. Some organ individually reflects the emotion or their relationship with each other may expose the attitude. There are many methods for the recognition of emotion, like the Dynamic deformation template matching, Hidden Marcov Model, Fisher Faces respectively [1, 2, 3].

In real application the emotions are communicated by subtle changes in one or several discrete facial features, one addition or absence may change the interpretation of emotion. In order to capture the subtle change of facial emotion we propose to develop a computer vision system, in which the set of trained multi- feature face images of different emotions are stored. During interaction with the system, the system will match the current image with stored and the emotion will be exposed.

Proposed System

The proposed human emotion recognition system shown in figure (1) contains four different levels.

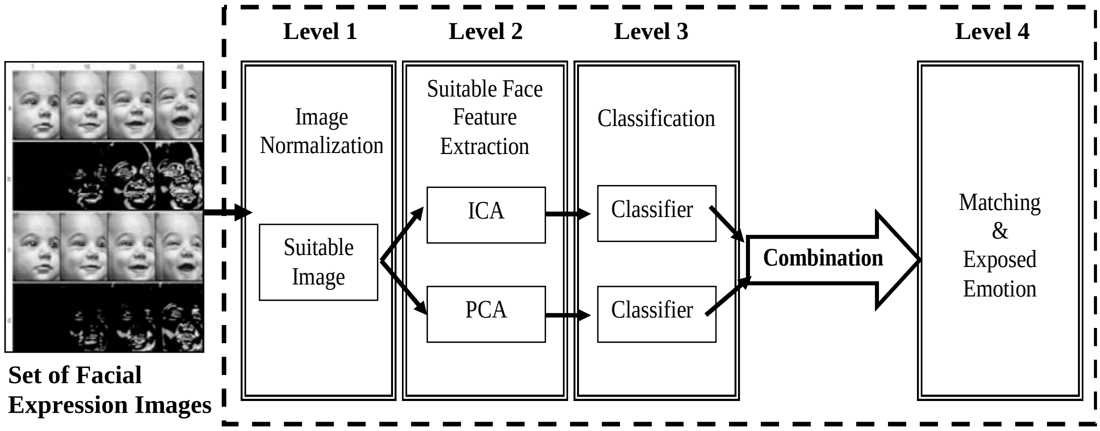


Figure 1: Multi-feature face recognition system for expose hidden emotion of a human being.

At the initial stage a set of facial expression image is entered in the proposed system. This set has been normalized at **Level 1** by applying different normalization methods [4]. At **Level 2** suitable face features have been extracted parallel by the methods PCA and ICA [5, 6]. In **Level 3** the images are classified into one of the possible emotions on the basis of chosen feature of normal face images. Here in this level work is done parallel as shown in Fig.1. After this process, both outputs of Neural Network Classifier (NNC) will be combined[7] and at **Level 4** system will match the final output with stored image sets and will expose the suitable emotion. The whole process is described as follows;

Level 1: Face Normalization

In this phase image is normalized by different available techniques like Affine Transformation, separation of rigid and non- rigid motion [2]. Without this phase we can't think about feature extraction.

Level 2: Feature Extraction

It is one of the most vital levels for this proposed system. It helps to derive meaningful representation of images by mapping high dimension input space into lower dimension feature space by which the classifier runs faster and consumes less memory. It may also improve the classification in revealing the intrinsic dimension of the observed pattern. To design a system with low to moderate complexity the feature vector should contain the most pertinent information about the face to be recognized. Face recognition should be able to withstand in face appearance and changing environment. The Multi- Feature face recognition system can have N different feature domains extracted from the normalized face images. Therefore this approach can extract more characteristics of Face images for classification purpose. For the study we consider N = 2 here.

[1] Principle Component Analysis (PCA)

PCA is based on an information theory approach that decomposes face images into small sets of feature images called "Eigenfaces" which may be thought of as principle component analysis of original training set of face images. In order to decompose, we have to extract relevant information from face image. A simple approach is to capture the variations from a collection of training face images, independent of any judgment of features(i.e. second order statistics of the data are de-correlated) and use this information to decode and compare individuals as shown in Fig.(2) and (3).

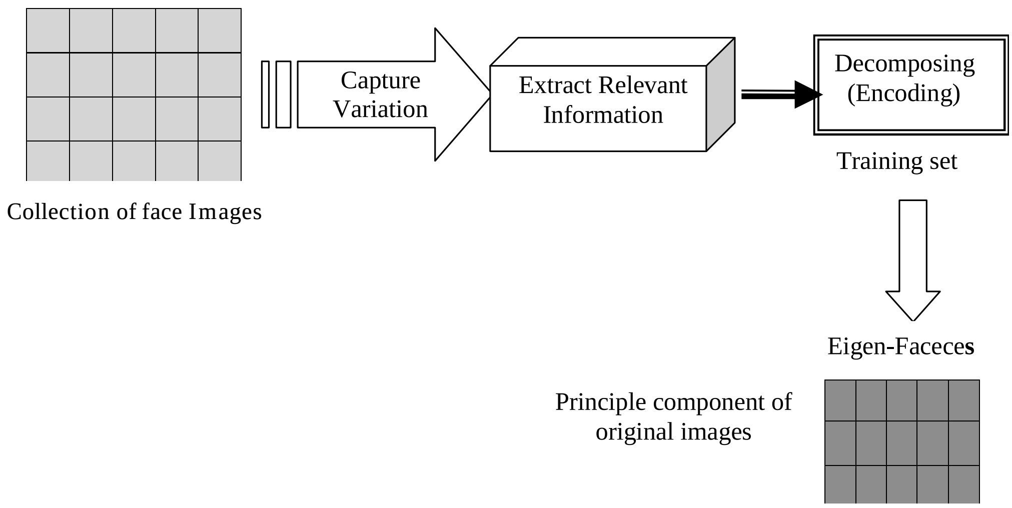


Figure 2: Decomposing the training face images.

Classification is performed by projecting an input face image into subspace known as a face space spanned by “Eigenfaces” and then classifying the input face image by comparing its position in a face space with the position of known individuals as shown in Fig. (3).

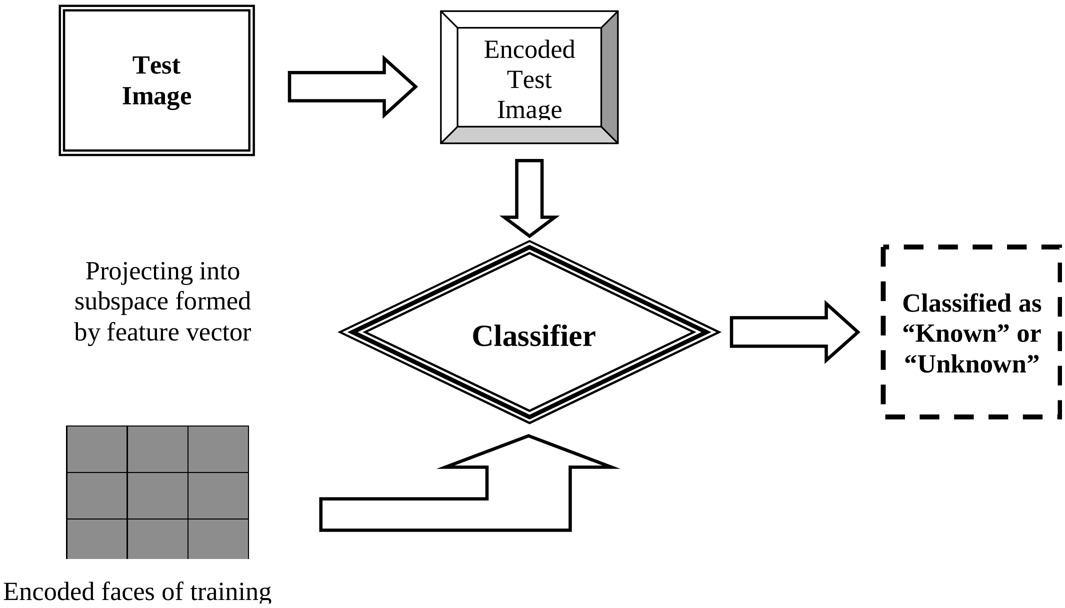


Figure 3: Classification of input face image.

The algorithm of this method is described as follows [5]:

Training Set

Step-1: Establishes the training set

Let $\{\alpha_i \,/\, i = 1, 2, ..., n\}$ be a training set

Where α is a face image (N^2).

Step-2: Calculate mean of all training samples.

$$\mu = \tfrac{1}{n}\sum_{i=0}^{n}\alpha_i$$

Step-3: Calculate the difference in images by subtracting the training set vector by the mean image. Let us call this matrix as the variation matrix. $A = [\eta_1, \eta_2, \eta_3, ..., \eta_n]$,

where $\eta = \alpha_i - \mu$

Step-4: Calculate eigenvectors and eigen values of covariance matrix AA^T.

$$C = \frac{\eta_1\eta_1^T + \eta_2\eta_2^T + ... + \eta_n\eta_n^T}{n}$$

As the covariance matrix C has dimensions of N^2 x N^2 , we need to calculate N^2 eigen vectors. For images of a significant size this is a large computational task. We can solve for the N^2 dimensional eigenvectors in this case by first solving the eigen vectors of an n x n matrix . i.e. AA^T

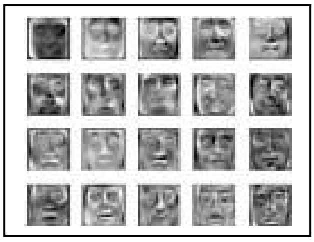
$$(A^T A)V_i = \lambda_i \ V_i$$

$$A(A^T A)V_i = A(\lambda_i \ V_i)$$

$$(AA^T)(AV_i) = \lambda_i (\mathrm{A} \ V_i)$$

where V_i and λ_i are eigenvectors and eigenvalues of the smaller (nxn) A^TA matrix respectively. The eigenvector of the larger AA^T matrix can be computed by calculating AV_i. the eigenvectors are stored in descending order of eigenvalues. They are shown in Fig.(4).

$$U_i = AV_i = [\eta_1, \eta_2, ..., \eta_n] * \begin{bmatrix} v_1^i \\ \vdots \\ v_k^i \\ \vdots \\ v_n^i \end{bmatrix} = \sum_{k=1}^{n} v_k^i \eta_k$$



Training set **Eigenface**

Figure 4: Eigenfaces have a face like appearance.

Step 4: Represent face image using eigen faces.

$$W_i = \frac{U_k^T(\alpha_i - \mu_i)}{\lambda_k}, \quad k = 1, \ 2, ..., \ n.$$

where Wi is a weight vector [i.e. W_i (l , i) denotes percent that first eigenface represents image i , W(2, i) denotes percent that second eigenface represents image i, and so on].

To classify an input image following steps are performed.

Step 5: Convert test image into vector μ.

Step 6: Maps test image into Eigenfaces "face space".

$W_k = U_k^T(.-.), \quad k = 1, 2, ..., n.$

The weights form a feature vector,

$$\bullet^{T} = [\ W_1\ W_2\ ...\ W_{n'}\ ]$$

The feature vectors obtained from training set is used to train the neural network and feature vector of test image is used to simulate the neural network.

[2] Independent Component Analysis

Second technique is ICA; one seeks to obtain completely independent components, which constitute complete faces. The basic idea is that any face image is a unique linear combination of these independent components.

$$R = AU \Rightarrow U = W_1 R, \quad \text{where} \quad W_1 = A^{-1}$$

Here, R = face images,

A = unknown mixing matrix and

U = statistically independent

It is important that these components should not only be de-correlated but completely independent from the point of view of higher order statistics as well. We have used an algorithm proposed by Bell and Sejnowski [8] for separating the statistically independent components of a dataset. The training face images are decomposed into statistically independent components known as a basic images as shown in Fig.(5). This information is used to encode the input face images and compare individuals as shown in Fig.(3).

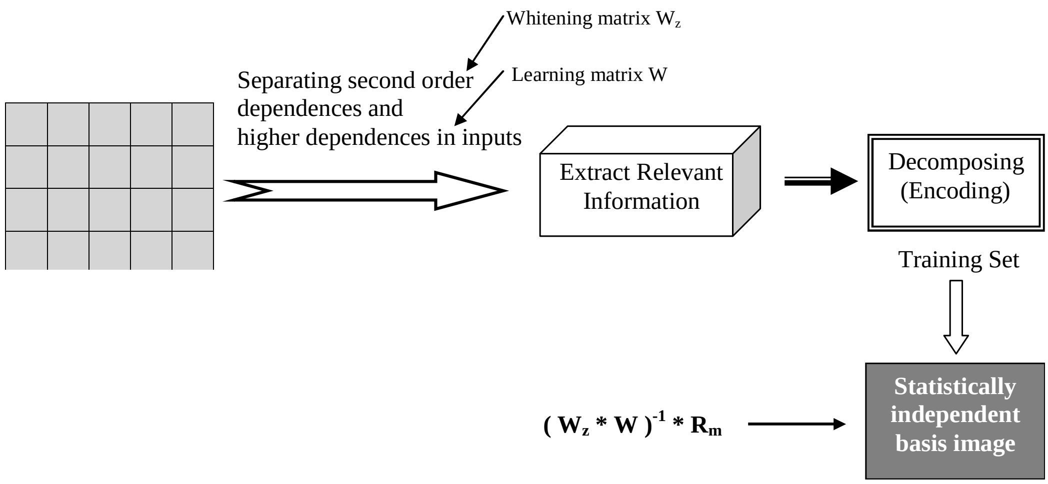


Figure 5: Decomposing the training face images into statistically independent component.

The algorithm of ICA is as follows:

The ICA algorithm produces a matrix WI = W * W_Z, where Wz is a whitening matrix and W is a learning matrix. Here we are assuming that dimension reduction is already applied on training images either by LDA or PCA.

Training Set

Step I: Perform "Sphering" (step prior to learning) on training set

Centering:

The row means are subtracted from the dataset, R, and then R is passed through the whitening filter.

Whitening:

$W_z = U \times (E)^{-1/2}$ where U and E are eigenvectors and eigenvalues respectively.

This step removes both the first and the second order statistics of the data; both the mean and covariance are set to zero and the variances are equalize.

Step 2: Calculate W iteratively

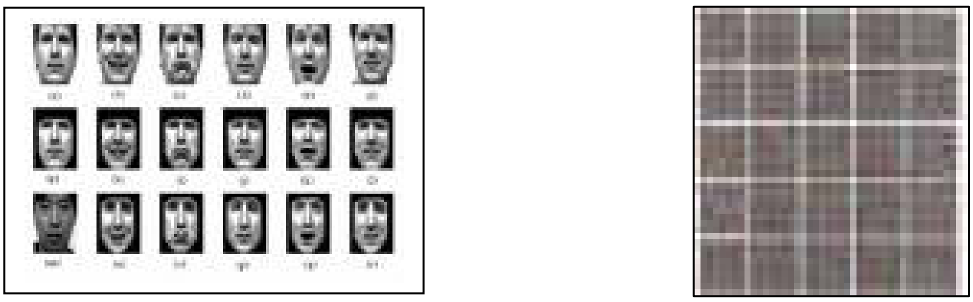
In order to calculate W, we have to pass a sequence of training data until old value of W and new value of W points in same direction[8].

Step 3: Calculate W_I

$W_I = W * W_z$

Step 4: Calculate basis image (independent component). They are shown in Fig.(6).

$B = R * W_I^{-1}$



Training set **Independent component**

Figure 6: Statistically independent component.

To classify an input image following steps are performed.

Step 5: Project Test image into eigenfaces (if dimension reduction applied prior to ICA)

Step 6: Compute coefficient B_{test}

$B_{test} = R_{test} * W_1^{-1}$

Both B and Btest are used as feature vector to train the neural network and simulate the neural network respectively.

Level-3: Classification

Neural networks have been employed and compared to conventional classifiers for a number of classification problems. The results have shown that the accuracy of the neural network approache is equivalent to, or slightly better than, other methods. Also, due to the simplicity, generality and good learning ability of the neural networks, these types of classifiers are found to be more efficient [7]. The most popular neural network algorithm is back propagation algorithm (a type of gradient decent method), we have used multi-layer feed-forward neural network on which back-propagation algorithm performs, as follows

Multi-layer feed-forward neural network

It can approximate almost any regularity between its input and its output. The weights are adjusted by supervised training procedure called back-propagation (BP). Error is defined as the root means square of differences between real and desired outputs from the NN. A typical architecture for a feed-forward network has a number of layers as shown in Fig.(7).

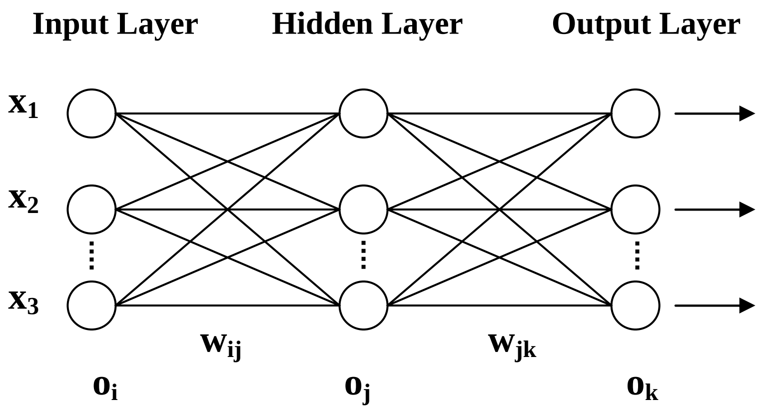


Figure 7: Multi-layer feed-forward network.

A training sample, $X = (x_1, x_2, ..., x_i)$, is fed to input layer. Weighted connections exits between each layer, where Wij denotes the weight form a unit j in one layer to a unit i in the previous layer. We have an input layer (i) consisting of input nodes and an output layer (k) consisting of output nodes. The input nodes are connected to the output nodes via one or more hidden layers (j). The nodes in the network are connected together, and each of the links has a weight associated with it. The output value from a node is a weighted sum of all the input values to the node. By changing the different weights of the input values we can adjust the influence from different input nodes. For face recognition the input nodes will typically correspond to image pixel values from the face image. The output layer will correspond to classes or individuals in the database. Each unit in the output layer can be trained to respond with + 1 for a matching class and -1 for all others. In practice real outputs are not exactly + 1 or -1, but vary in the range between these values. Classification is done by finding the output neuron with the maximal value. Then a threshold algorithm can be applied to reject or confirm the decision.

Multi-layer feed-forward neural network based classifier design is explained as follows

The nodes in hidden layer and number of hidden layer are selected by trial and error; here we use one hidden layer with 70 neurons.

Step 1: Assemble training data (both input and output)

It takes input as Eigen faces (U) (0nly first n' > n) and Basic Independent components (F) for PCA and ICA system respectively, and output as array (259 x 37) (259 face images and 37 feature considered)

Step 2: Create neural network and initialize it's parameter.

Step 3: Train the neural network as mentioned in [7].

Step 4: Simulate the network response to an input image (s).

Output of both neural networks is transmitted to combiner (Combination process).

Combination Process

If the score functions are directly comparable or if there exists at least an acceptable transformation scheme to make the involved classifiers comparable, score based strategies are good ways for decision process. In this paper, NN is used as a classifier for both systems, so naturally outputs of both systems are in same format, and we select score based strategy as combiner [10].

Level-4: Matching and Exposed Emotion

As we noted earlier there are nearby 70 emotions are felt by human being [11], are listed below in table. Here, we take the image sequence of emotions, which are mostly reflected by facial expression like: joy, sadness, anger, surprise, fear, disgust and so on. These are noted as E_1, $E_{2, \ldots\ldots\ldots,}$ E_n and a normal face sequence which is denoted as E_0 as shown in above Fig.(8). In this Level, the image classified by Neural Network in the previous level is matched by the system with all the image sequence of emotions. Here, system finds the association between stored group of image and classified face image (CFI). After compression the highly associated emotion will be displayed. At this level it is important to discuss that the CFI may consist the characteristics of more than one emotion or it’s a combination of emotions. In this case CFI is matched with all the groups of emotion image and displayed that emotion whose proportion of characteristics is more matched compared to the others with CFI. So with this procedure we can easily find the emotion with facial expression.

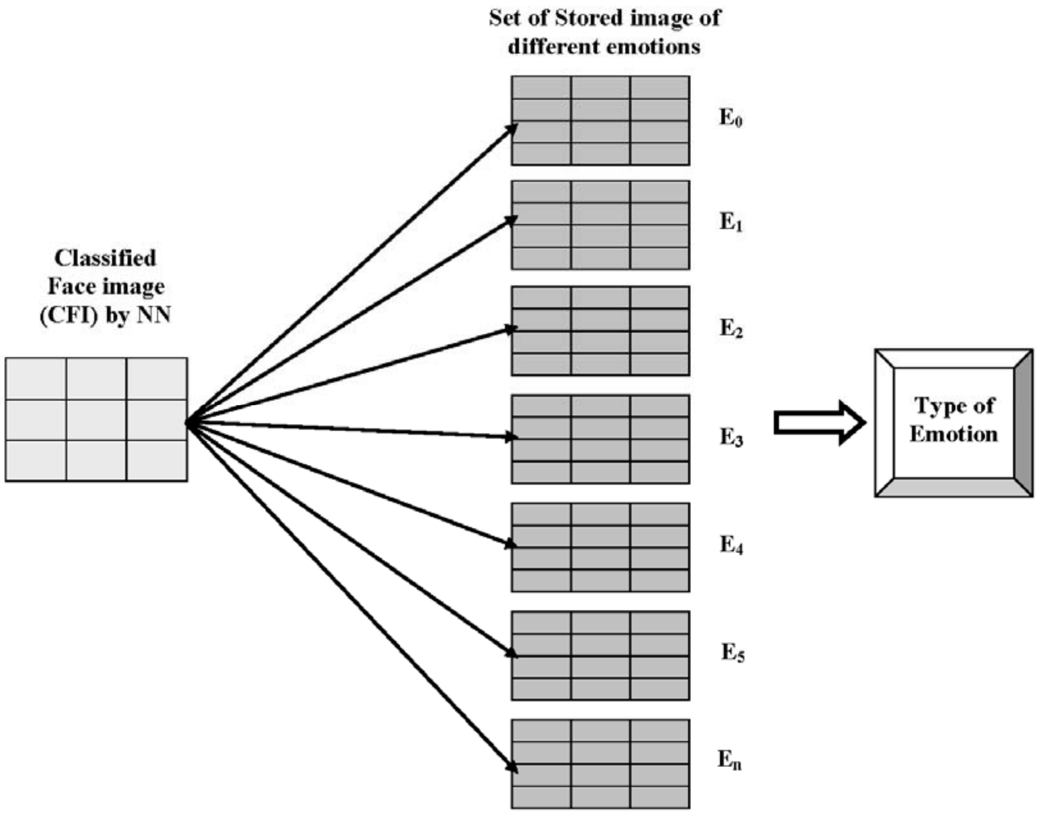


Figure 8: Emotion identification.

Emotions list
Acceptance · Affection · Alertness · Ambivalence · Anger · Angst · Annoyance · Anticipation · Anxiety · Apathy · Awe · Boredom · Calmness · Compassion · Confusion · Contempt · Contentment · Curiosity · Depression · Desire · Disappointment · Disgust · Doubt · Ecstasy · Embarrassment · Empathy · Emptiness · Enthusiasm · Envy · Epiphany · Euphoria · Fanaticism · Fear · Frustration · Gratification · Gratitude · Grief · Guilt · Happiness · Hatred · Homesickness · Honesty · Hope · Hostility · Humiliation · Hysteria · Inspiration · Interest · Jealousy · Kindness · Limerence · Loneliness · Love · Lust · Melancholia · Nostalgia · Panic · Patience · Pity · Pride · Rage · Regret · Remorse · Repentance · Resentment · Righteous indignation · Sadness · Saudade · Schadenfreude · Sehnsucht · Self-pity · Shame · Shyness · Suffering · Surprise · Suspicion · Sympathy · Wonder · Worry

Conclusion

Above proposed system is working in four different levels to identify different human emotions which will be highly beneficial to study human psychology through facial expressions with psychology theory.

Reference

[1] Yuille A. L., Cohen D. S. and Hallianan P. W., "Feature Extraction from Faces Using Deformable Templates", International Journal of Computer Vision, 8(2), pp. 99- 111 (1992).

[2] Nefian A. V., "A Hidden Markov Model-Based Approach for Face Detection and Recognition", Ph. D. Thesis, Georgia Institute of Technology (1999).

[3] Lu, K. Plataniotis N., and Venetsanopoulos A. N., Face recognition using LDA-Based algorithms", IEEE Transactions on Neural Networks, vol. 14, pp. 195-200, Jan- 2003.

[4] Heseltine1 T., Pears N., and Austin J., "Evaluation of Image Pre-Prcessing techniques for eigenface based face recognition", The Proceedings of the Second International Conference on Image and Graphics, SPIE, 4875, pp. 677-685 (2002).

[5] Turk, M., and Pentland "Eigenfaces for recognition", A., Journal of Cognitive Neuroscience, Vol. 3, pp. 71-86, (1991).

[6] Bartletta M. S., Ladesb H. M, and Sejnowskic T J., "Independent component representations for face recognition", Proceedings of the SPIE, Symposium on Electronic imaging: Science and Technology conference on Human Vision and Electronic Imaging III, volume 3299, San Jose, CA, pp. 528- 539, (1998).

[7] Haddadnia J., K.Faez K., Moallem P., " Neural Network Based Face Recognition with Moments Invariant", IEEE Int. Conf. On Image Processing, Vol. I, pp. 1018 1021, Thessaloniki, Greece, 7-10 October 2001.

[8] Yang M.H., Kriegman D., N. Ahuja N. "Detecting faces in images: a survey", PAMI 24(1): 34-58,(2002).

[9] Bell A. and Sejnowski T."An information maximization approach to blind separation and blind deconvolution", Neural Computation, 7(6): 1129-1159, 1995.

[10] Achermann B. and Bunke H., "Combination of Classifier on Decision level for Face recognition" Institute of information, university Bern, IAM- 96-002, January 1996.

[11] http://en.wikipedia.org/wiki/List_of_emotions.