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Adaptive Human Machine Interface Approach for Face Recognition

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Abstract: **-- Feature extraction is one of the challenging issues in face recognition and matching process. Here we proposea novel method for dense featureextraction in face recognition.This methodology consists of two steps. In first step, encoding scheme is defined that shifts high dimensional data into compact representation by maximizing intra user correlation. In second step an adaptive feature matching is done for image classification which works for images with different scaling limits. This methodology is implemented on local facial database. We introduce a novel human-machine interface based on movements of head pose. This human machine interface works by detecting facial features from live cam and then tracking face features.Movement and actions of cursor are performed by using facial feature tracking. We prove that our methodology yields better results compared to state-of-art criteria, our method performs better at noisy condition, illumination changes, complex background and at different head poses.**

Keywords: **-- Face recognition, intra-user correlation.**

I. INTRODUCTION

The safety of persons, goods or information is one of the major preoccupations our societies today. Also, the great weakness of the current means of identity verification is clear here:[1] the identity of a person is directly related to what it owns (a passport, magnetic badge,etc…). However, a badge can be stolen, guessed password or broken by brute strength algorithms: this leads to identity theft.

Recently, face recognition has attracted much research efforts due to the progresses of local descriptors[2] and increasing demands of real-world applications, such as face tagging on the desktop or the Internet1. There are two main kinds of face recognition tasks:[3-4] face identification (who is who in a probe face set, given a gallery face set) and face verification.

Since face verification is a binary classification problem on an input face pair, there are two major components of a verification approach: face representation and face matching. The extracted feature (descriptor) is required to be not only discriminative[10-15] but also invariant to apparent changes and noise. The matching should be robust to variations from pose, expression, and occlusion. These requirements render face recognition a challenging problem.

Currently, descriptor-based approaches have been proven to be effective face representations producing best performance. Ahonen et al. proposed to use the histogram of Local Binary Pattern (LBP)[13] to describe the micro-structures of the face. LBP encodes the relative intensity magnitude between each pixel and its neighboring pixels. It is invariant to monotonic photometric change[11] and can be efficiently extracted. Since LBP is encoded by a handcrafted design, many LBP varieties have been proposed to improve the original LBP. SIFT or Histogram of Oriented Gradients (HOG)[20-23] is other kinds of effective descriptors using handcrafted encoding. The atomic element in these descriptors can be viewed as the quantized code of the image gradients. Essentially, different encoding methods and descriptors have to balance between the discriminant power and the robustness against data variance.

However, existing handcrafted encoding methods suffer two drawbacks. On one hand, manually getting an optimal encoding method is difficult. Usually, using more contextual pixels [17] (higher dimension vector) can generate a more discriminative code.. It means that the resulting code histogram will be less informative and less compact, degrading the discriminant ability of the descriptor.The rest of this paper is organized as follows. Section II first reviews the current state-of-the-art methods. Today, the keyboard, the mouse and the remote control are used as the main interfaces for transferring information and commands to computerized equipment. In some applications[16] involving three-dimensional information, such as visualization, computer games and control of robots, other interfaces based on trackballs, joysticks and datagloves are being used. In our daily life, however, we humans use our vision and hearing as main sources of information about our environment. Therefore, one may ask to what extent it would be possible [19] to develop computerized equipment able to communicate with humans in a similar way, by understanding visual and auditive input. Our proposed mitigation scheme is described in Section III. Then experimental results are reported in Section IV to demonstrate the superior performance of our framework. Finally, conclusions are presented in Section V.

II.EXISTING METHOD

The existing methods used forrepresenting local features for face recognition include Gabor wavelets, Local Binary Patterns (LBP) and Scale Invariant Feature Transform (SIFT) [2].

Gabor wavelets

Face recognition is one of the most important applications of Gabor wavelets. The face image is convolved with a set of Gabor wavelets and the resulting images are further processed for recognition purpose. The Gabor wavelets are usually called Gabor filters in the scope of applications.

A.Analytic approaches

Some feature points are detected from the face, especially the important facial landmarks such as eyes, noses, and mouths. These detected points are called the fiducial points, and the local features extracted on these points, distance and angle between these points, and some quantitative measures from the face are used for face recognition. The main advantage of analytic approaches is to allow for a flexible deformation at the key feature points so that pose changes, different angles of view can be compensated for.

B.Holistic approaches

In contrast to using information only from key feature points, holistic approaches extracts features from the whole face image. Normalization on face size and rotation is a really important pre-processing to make the recognition robust. The Eigenface based on Principal Component Analysis (PCA) [6] and the fisher face based on Linear Discriminant Analysis (LDA) [7] are two of the most well-know holistic approaches.However they have the downside of being non-orthogonal, so efficient decomposition into the basis is difficult.

Local Binary Pattern (LBP):

LBP is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis.The existing Local Binary Pattern (LBP) operators have three disadvantages:

a) They produce rather long histograms, which slow down the recognition speed especially on large-scale face database;
b) Under some certain circumstance, they miss the local structure as they don't consider the effect of the center pixel;
c) The binary data produced by them are sensitive to noise.

Scale Invariant Feature Transform (SIFT)

SIFT is an image descriptor for image-based matching and recognition. The SIFT descriptor is invariant to translations, rotations and scaling transformations in the image domain and robust to moderate perspective transformationsand illumination variations. Experimentally, the SIFT descriptor has been proven to be very useful in practice for image matching and object recognition under real-world conditions.In its original formulation, the SIFT descriptor comprised a method for detecting interest points from a grey-level image at which statistics of local gradient

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directions of image intensities were accumulated to give a summarizing description of the local image structuresin a local neighborhood around each interest point, with the intention that this descriptor should be used for matching corresponding interest points between different images.

a)Still quite slow.

b)Generally doesn't work well with lightingchanges and blur.

III. PROPOSED MITIGATION SCHEME

To overcome the above limitations, we propose a successful encoding strategy that transforms thick elements into a minimal component representation, while in the meantime improving the discriminative power. This is accomplished by compressing facial elements to form a compact representation of features. The proposed encoding scheme maximizes the correlation between the features. Here we had taken the multiple features to address all the variations like aging conditions, expressions and lighting changes. By combining these multiple features we can derive different face descriptors so that we can apply our encoding scheme to multiple scales.

The human face is an uneven structure, so the classification of non-linearly structured elements became very difficult. To address this issue, we proposed other method called adaptive matching framework. Before the kernel based classifiers are used for classification but those are limited by the risk of over fitting. Our method classifies better than the previous method by using a classification model trained by nearby samples. The samples of the non-linear structure are linear.The development of the Adaptive Matching Framework can partitioned into two stages. In the initial step, a progression of preparing subsets is built by over and again examining the preparation information.

In the second step, a progression of linear sub-classifiers is prepared in view of the preparation subsets produced in the initial step and consolidated to form a decision. We require the examined information focuses to lie in a nearby district, such that they have a locally straight property. To accomplish this, a specimen is first chose from the whole preparing dataset and after that its K-nearest neighbors are consolidated to structure an arbitrary subset. Each element has five nearest points which are measured by the Euclidean distance. Then a weighted graph is constructed and the edges are combined to form the disjoint sets. In the second step we measure the geodesic distance. Here the training samples are updated. After this LFDA approach is applied to divide the features into slices of equal length and a unified sub space analysis is applied.

Here the face recognition depends upon the highest matching score. For this we had taken a gallery of faces and a probe face. The matching score can said to be high when the mean of the trained samples had the minimum distance to the probe face. The proposed methods which are used for feature extraction and matching are advantageous in terms of efficiency, accuracy and implementation. If we combine these methods with existing ones then we get more compact representation of features to derive the best feature descriptor. As an extension to this, a human machine interface is developed here that is the movements of cursor on the monitor can be controlled by the movements of the face. For that the procedure is as follows:

A Webcam is placed in front of the user, focusing on the user’s face. A motion extraction algorithm based on RGB, which is user independent, is used to extract the facial motion from the video. This motion is used to move the mouse pointer that is controlled in a fashion relatively similar to standard mouse devices. This system can be used with great accuracy even when the user has exiguous cephalic motion control.

The multimodal system is aimed for the disabled people, which need other kinds of interfaces than ordinary people. In the developed system the interaction between a user and a computer is performed by head movements. To process these data streams the modules of speech

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recognition and head tracking were developed. This system was applied for hands-free operations with Graphical User Interface in such tasks as Internet communications and lunchingapplications. We showed theoretically and practically that this technology could be used to operate computers hands-free.

IV.RESULTS

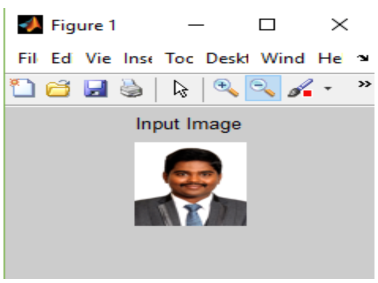

Fig. 1. Input image

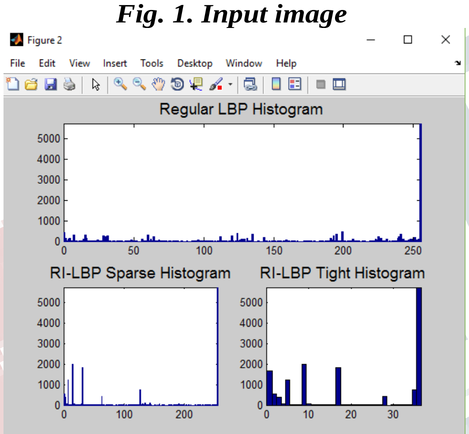

Fig.2.Regular LBP histogram

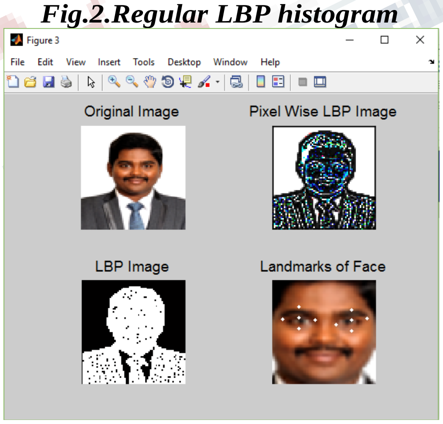

Fig.3.Difference between original and LBP images, Landmarks of Face

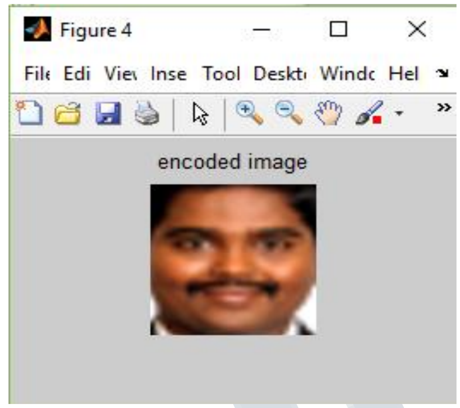

Fig.4.Decoded image

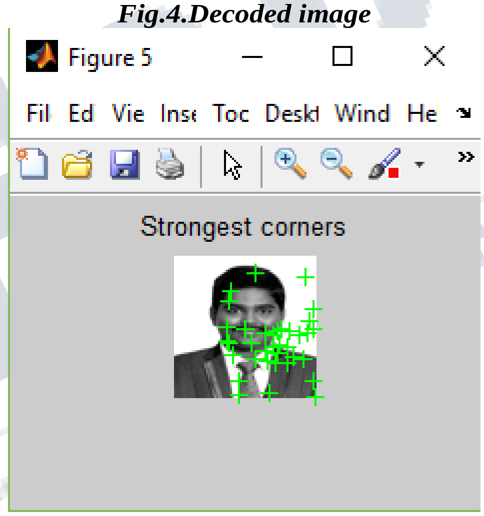

Fig. 5. Strongest corners of image

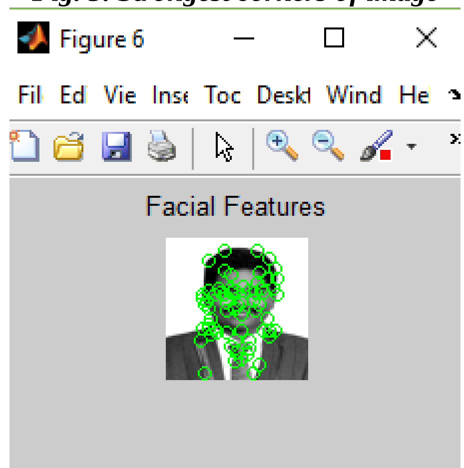

Fig.6.Facial features

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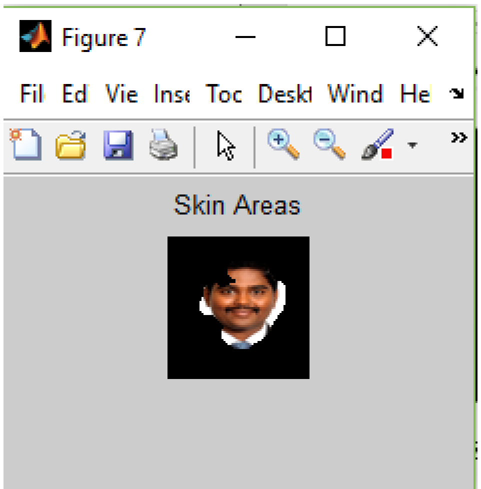

Fig.7.Skin area of the face

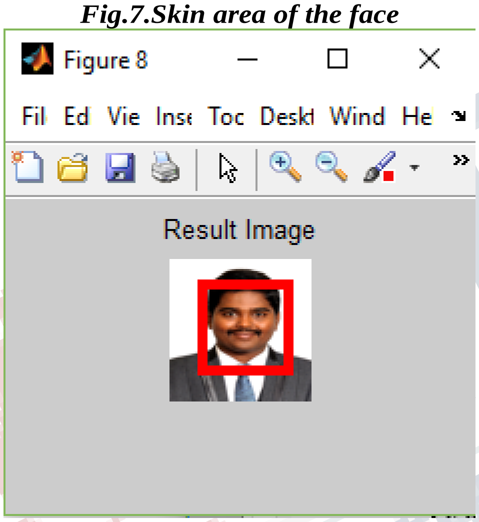

Fig.8.Recognised face image

V.CONCLUSIONS

In this paper, we proposed a novel encoding scheme, which is used for feature extraction motivated by the recent advancementsin the field of face recognition. This scheme is used to represent the data into a compact form. In addition, we proposed a novel method called adaptive matching framework which is used for image classification. This can be done by matching the features. We have Performed experiments on FERET databases to evaluate the effectiveness ofthe proposed feature extraction and classification schemes under different scenarios.Our results clearly demonstrate the robustness of the proposed emotion recognition system, especially inchallenging scenarios that involve illumination changes, occlusion, and pose variations. The limitations includethe higher computational cost for feature extraction and classification as well as the need to optimize manyparameters. Furthermore, there is still a large room for improvement in the recognition accuracy. Our prototype exhibits accuracy and speed, which are sufficient for many real time applications and which allow handicapped users to enjoy many computer activities.

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