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Face and Expression Recognition under Illumination and Occlusion Using GSRRR and ICP Framework

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ABSTRACT: Facial expression is an effective way for humans to communicate since it contains critical and necessary information regarding human affective states. It is a critical part of affective computing systems that aim to recognize and therefore better respond to human emotions. Automatic recognition of facial expressions can be an important component in human-machine interfaces, human emotion analysis, and medical care. However, the task of automatically recognizing various facial expressions challenging. As a result, facial expression recognition has become a prominent research topic in human-computer interaction, as well as in the fields of image processing, pattern recognition, machine learning, and human recognition. A server sets up a database with training facial images from all expression classes. Since all images represent the face, it is necessary to extract discriminative features of these images that correspond to different expression classes in order to simplify the classification. A client requesting facial recognition service would supply a test image whose expression it desires to recognize. This test image would be encrypted in order to prevent the server from being able to gain access to its actual private contents. we can evaluate the facial expressions in various viewpoints. Our experimental result shows good performance in real time applications.

KEYWORDS: Face recognition, Expression recognition, Affective computing, and Facial expressions.

I. INTRODUCTION

With the rapid development of human–machine interaction, affective computing is currently gaining popularity in research and flourishing in the industry domain. It aims to equip computing devices with effortless and natural communication. The ability to recognize human affective state will empower the intelligent computer to interpret, understand, and respond to human emotions, moods, and possibly intentions. This is similar to the way that humans rely on their senses to assess each other’s affective state. Many potential applications, such as intelligent automobile systems, game and entertainment industries, interactive video, indexing and retrieval of image or video databases, can benefit from this ability.

Our research has contributed to: (1) Designing new ways for people to communicate affective-cognitive states, especially through creation of novel wearable sensors and new machine learning algorithms that jointly analyze multimodal channels of information; (2) Creating new techniques to assess frustration, stress, and mood indirectly, through natural interaction and conversation; (3) Showing how computers can be more emotionally intelligent, especially responding to a person's frustration in a way that reduces negative feelings; (4) Inventing personal technologies for improving self-awareness of affective state and its selective communication to others; (5) Increasing understanding of how affect influences personal health; and (6) Pioneering studies examining ethical issues in affective computing.

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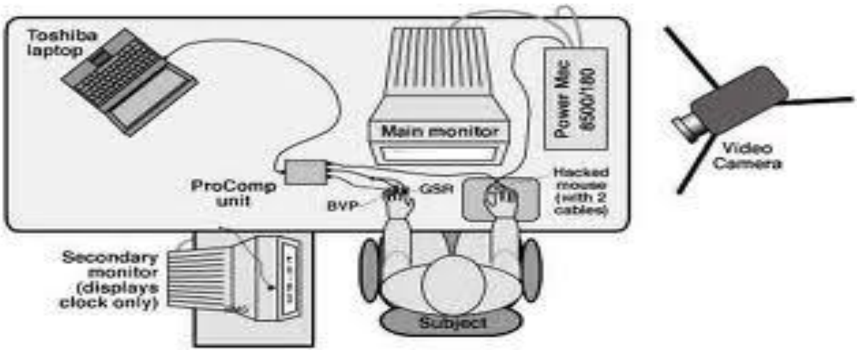

Figure 1: Affective computing functions

II. TECHNOLOGIES OF AFFECTIVE COMPUTING

A) Emotional Speech

One can take advantage of the fact that changes in the autonomic nervous system indirectly alter speech, and use this information to produce systems capable of recognizing affect based on extracted features of speech. For example, speech produced in a state of fear, anger or joy becomes faster, louder, precisely enunciated with a higher and wider pitch range. Other emotions such as tiredness, boredom or sadness, lead to slower, lower-pitched and slurred speech. Emotional speech processing recognizes the user's emotional state by analysing speech patterns. Vocal parameters and prosody features such as pitch variables and speech rate are analysed through pattern recognition.

B) Facial Affect Detection

The detection and processing of facial expression is achieved through various methods such as optical flow, hidden Markov model, and neural network processing or active appearance model. More than one modalities can be combined or fused to provide a more robust estimation of the subject's emotional state.

C) Facial Action Coding System

Defining expressions in terms of muscle actions A system has been conceived in order to formally categorize the physical expression of emotions. The central concept of the Facial Action Coding System, or FACS, as created is Action Units (AU). They are, basically, a contraction or a relaxation of one or more muscles. However, as simple as this concept may seem, it is enough to form the base of a complex and devoid of interpretation emotional identification system.

III. METHODS

In this work, we empirically study facial representation based on Local Binary Pattern (LBP) features for person-independent facial expression recognition. LBP features were proposed originally for texture analysis, and recently have been introduced to represent faces in facial images analysis. The most important properties of LBP features are their tolerance against illumination changes and their computational simplicity. We examine different machine learning methods, including template matching; Linear Discriminate Analysis (LDA) to reduce the facial feature points and create the GSRRR model to labelling the facial expression with class labels. We implement the KRRR technique to find head poses from real time facial images. Finally, the model response corresponding to the expression class label vector is calculated and the expression category of the testing facial image can be obtained based on it. This method having different advantages. Because all the facial features are finally concatenated into a high-dimensional feature vector to represent the facial image. Head pose estimation will be used to select appropriate KRRR model parameters for synthesizing multi-view facial feature vectors.

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A) Facial image Acquisition

In this phase, we capture the face image or upload the datasets. The uploaded datasets contains 2D face images. In face registration we can identify the faces which are captured by web camera. Then web camera images known as 2D images. And we perform the pre-processing steps such as gray scale conversion, invert, and border analysis, detect edges and region identification. The Greyscale images are also called monochromatic, denoting the presence of only one (mono) color (chrome). The edge detection is used to analyse the connected curves that indicate the boundaries of objects, the boundaries of surface markings as well as curves that correspond to discontinuities in surface orientation.

B) Features Extraction

In this phase we can implement Local binary pattern technique to extract features from face image. The LBP feature vector, in its simplest form, is created in the following manner: First divide the examined window into cells (e.g. 16x16 pixels for each cell). Next for each pixel in a cell, compare the pixel to each of its 8 neighbours (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise. Third step where the centre pixel's value is greater than the neighbour's value, write "1". Otherwise, write "0". This gives an 8-digit binary number (which is usually converted to decimal for convenience).In fourth step compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the centre).Next optionally normalize the histogram. Finally concatenate (normalized) histograms of all cells. This gives the feature vector for the window.

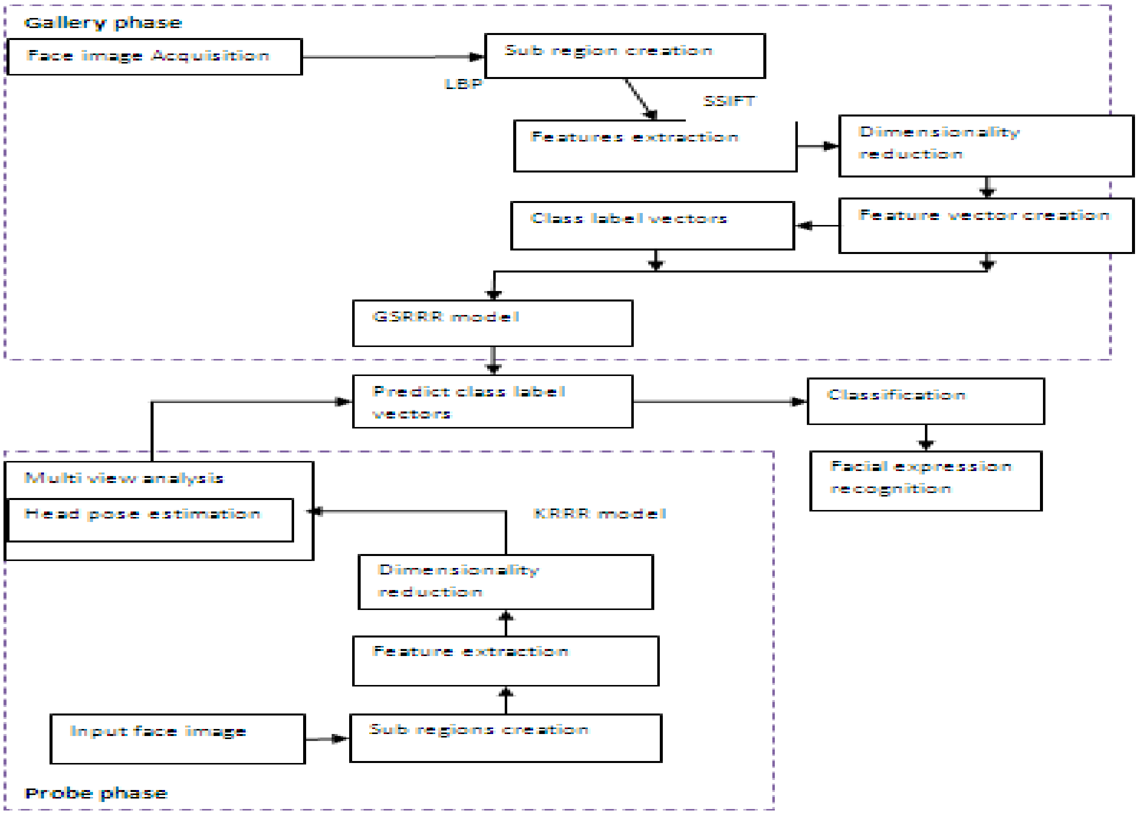

Figure 2: System Architecture

C) Dimensionality Reduction

In this phase implement linear discriminant analysis (LDA) method for reducing the dimensionality of feature vectors. All the transformed feature vectors belonging to the same facial image are then concatenated into a vector to represent the facial image. The objective of LDA is to perform dimensionality reduction while preserving as much of

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the class discriminatory information as possible. In order to find a good projection vector, we need to define a measure of separation between the projections.

D) GSRRR model framework

In this stage, the GSRRR model is used to describe the relationship between the expression class label vectors and the corresponding synthesized multi-view facial feature vectors. A learning algorithm is proposed to solve the regression coefficient matrices of GSRRR.

IV. IMPLEMENTATION AND RESULTS

A) Multi view Facial Expressions analysis

a) Local Binary Pattern

Local Binary Pattern (LBP) features have performed very well in various applications, including texture classification and segmentation, image retrieval and surface inspection. The original LBP operator labels the pixels of an image by thresholding the 3-by-3 neighbourhood of each pixel with the centre pixel value and considering the result as a binary number.

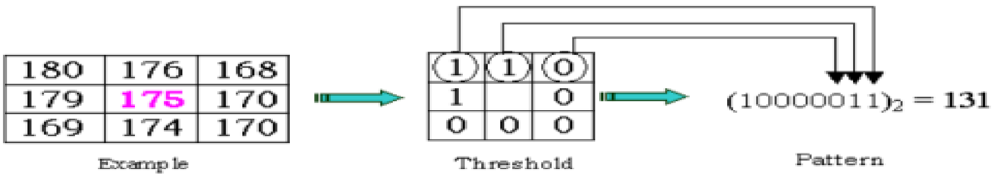

Figure 3: Local Binary pattern

The 256-bin histogram of the labels computed over an image can be used as a texture descriptor. Each bin of histogram (LBP code) can be regarded as a micro-texton. Local primitives which are codified by these bins include different types of curved edges, spots, flat areas, etc. Each face image can be considered as a composition of micro-patterns which can be effectively detected by the LBP operator. To consider the shape information of faces, they divided face images into M small non-overlapping regions R0, R1... RM. The LBP histograms extracted from each sub region are then concatenated into a single, spatially enhanced feature histogram defined as:

$$H_{i,j} = \sum_{x,y} I(f_l(x,y) = i) I((x,y) \in R_j)$$

Where i = 0, ... , L-1, j = 0, ..., M-1. The extracted feature histogram describes the local texture and global shape of face images.

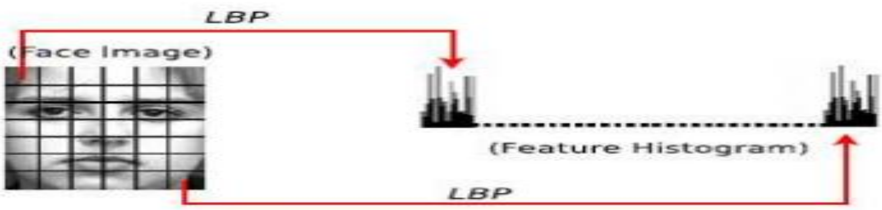

Figure 4: Extract feature Histogram

b) Sparse SIFT features

SSIFT is an approach for detecting and extracting local feature descriptors that are reasonably invariant to changes in illumination, scaling, rotation, image noise and small changes in viewpoint. Detection stages for SSIFT features are as follows:

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(1) Scale-space extreme detection: The first stage of computation searches over all scales and image locations. It is implemented efficiently by means of a difference of- Gaussian function to identify potential interest points that are invariant to orientation and scale.
(2) Key point localization: At each candidate location, a detailed model is fit to determine scale and location. Key points are selected on basis of measures of their stability.
(3) Orientation assignment: One or more orientations are assigned to each key point location on basis of local image gradient directions. All future operations are performed on image data that has been transformed relative to the assigned scale, orientation, and location for each feature, thereby providing invariance to these transformations.
(4) Generation of key point descriptors: The local image gradients are measured at the selected scale in the region around each key point. These gradients are transformed into a representation which admits significant levels of local change in illumination and shape distortion.

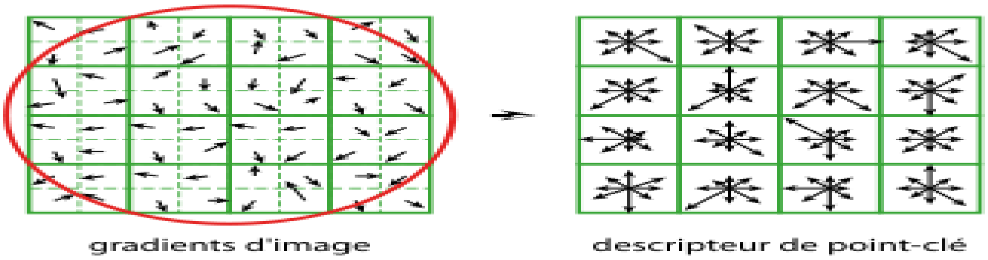

Figure 5: Sparse SIFT feature

c) Linear Discriminative Analysis

Linear Discriminate Analysis (LDA) has been successfully applied to face recognition which is based on a linear projection from the image space to a low dimensional space by maximizing the between class scatter and minimizing the within-class scatter. LDA allows objective evaluation of the significance of visual information in different features of the face for identifying the human face. The LDA also provides us with a small set of features that carry the most relevant information for classification purposes. Linear Discriminate Analysis (LDA) has been successfully applied to face recognition which is based on a linear projection from the image space to a low dimensional space by maximizing the between class scatter and minimizing the within-class scatter.
(1) Class-dependent transformation: This type of approach involves maximizing the ratio of between class variance to within class variance. The main objective is to maximize this ratio so that adequate class separability is obtained. The class-specific type approach involves using two optimizing criteria for transforming the data sets independently.
(2) Class-independent transformation: This approach involves maximizing the ratio of overall variance to within class variance. This approach uses only one optimizing criterion to transform the data sets and hence all data points irrespective of their class identity are transformed using this transform. In this type of LDA, each class is considered as a separate class against all other classes.
d) Group Sparse Reduced Rank Regression Model: The reduced rank regression model is a multivariate regression model with a coefficient matrix with reduced rank. The reduced rank regression algorithm is an estimation procedure, which estimates the reduced rank regression model. It is related to canonical correlations and involves calculating Eigen values and eigenvectors.

B) RESULTS

To evaluate the performance of our proposed method, facial expression real time datasets are used for the experiment. The facial region is detected in the input sequence using the face detection method with local patterns. The normalized results of the original sequences show that the LBP patterns of all input images are widely spread to cover the entire gray scale by local normalization; and the distribution of pixels is not too far from uniform. The overall performance of the system is considerably improved by incorporating local normalization. The fiducial points are then detected and tracked automatically in the facial region. As the location of each fiducial point is at the centre of a 16×16 pixel neighbourhood window, and the feature vectors for point detectors are extracted from this region, we consider detected points displaced within five pixels from the corresponding ground-truth facial points as successful detections. The overall system performance of recall 92.45% and precision 90.93% is achieved simultaneously in terms of false alarm rates. The proposed method has a better performance on both efficiency and accuracy.

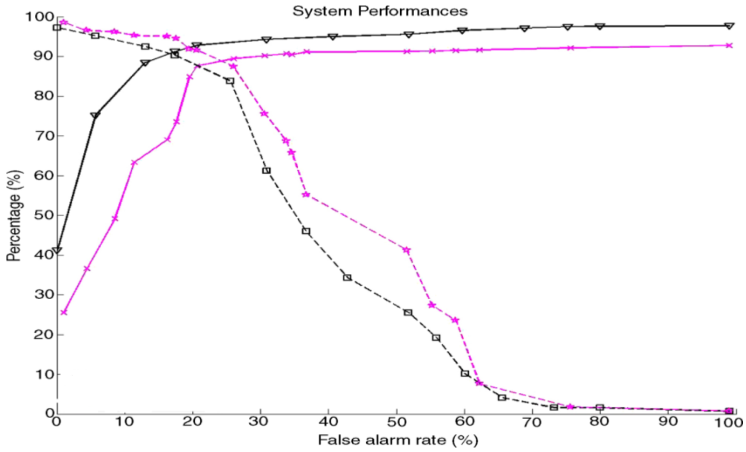

Figure 6: Result Graph

V CONCLUSION

In this project proposed Group Sparse Reduced-Rank Regression algorithm. Considering an expressive face as a superposition of a neutral face with expression component, we proposed an algorithm to decompose an expressive test face into its building components. For this purpose, we first generate grids for captured face using local binary patterns. Knowing that the face component of the test face has sparse representation in the face database and the expression part can be sparsely represented using the expression database; we decompose the test face into these feature vectors. The elements of the test face along with the vectors are then used for face and expression recognition. For this purpose, the separated components are sparsely decomposed using vectors while the grouping structures of the vectors are enforced into the sparse decomposition. The experimental results on both databases showed that the proposed method achieves competitive recognition performance compared with the state of the art methods under same experimental settings and same facial feature. As a future direction, we plan to model occlusions better, so that the overall performance of the system can be increased. We extend our work to less limited registration approach and Independent of nose visibility. Then Occlusion invariant recognition system has following aspects, Automatic occlusion detection and removal, Discriminative features other than depth information and also implement this concept analyzes expression in various illumination conditions.

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