International Journal of Advanced Information in Engineering Technology (IJAIET) ISSN: 2454-6933
Vol.3, No.7, July 2016

Enhancing Facial Expression Recognition Using Tensor Approach And Log Gabor Filter

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***Abstract*—Smile detection is one of the expressions in face images captured in unconstrained real world scenarios is an interesting problem with many potential applications. Existing work detected expression of smile in face images by using AdaBoost and combined weak classifiers based on intensity differences to form a strong classifier. However, besides smiles other facial expressions such as Sad, Happiness, Anger, disguise of the face images are not detected. In order to address this, the proposed system detects these facial expressions along with the expression of smile in the face images. By using Features such as differences between pixels in the gray scale face images are used as simple features for smile detection and features form tensors of facial components are extracted respectively. Using the proposed framework, the components (in either RGB, YCbCr,CIELab or CIELuv space) of color images are unfolded to 2-D tensors based on multi-linear algebra and tensor concepts, from which the features are extracted by Log-Gabor filters. Mutual information quotient (MIQ) method as a feature selection is adopted to select the optimum features. These features are classified by using a support vector machine classifier. Experimental result provides better result on recognition when compare with the existing one**.

Keywords—AdaBoost, 2-Dtensors, Support Vector Machine

I. INTRODUCTION

Facial expression is the one of the most important features of transferring the emotions like happiness, sadness, surprise, anger, disgust, fear among people. In the last past years, Facial expression recognition has been doing so much research in computer vision community but smile detection has received less attention . However, Facial expression not only reflects the emotions, but also mental activities, social activities. Smile detection is an interesting problem with many applications. On the other hand, smile can be very useful for measuring the happiness, enjoyment .To detect the problem of smile, digital image processing is used to provide same as fast and objective results .In this paper, new techniques used for solving the problem of detection of smile. The intensity differences of pixel in the grayscale face image are used as features.

AdaBoost used for improving the performance of classifiers. Our approach is that the faces are correctly classified which have large pose variation. Therefore we investigate more on the detection of smile on the face which having large pose variations. And at the last, SVM (Support Vector Machine) used for better classification and also recognize the pattern. By using this we find the accuracy of variations of pose using as pair of pixels?

Image processing is any form of signal processing for which the input is an image, such as aphotograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Image processing refers to processing of a 2D picture by a computer. An image in the real worldis considered to be a function of two real variables, for example, a(x,y) with a as the amplitude (e.g. brightness) of the image at the real coordinate position (x,y). An image may be considered to contain sub-images sometimes referred to as regions-of-interest, ROIs, or simply regions. This concept reflects the fact that images frequently contain collections of objects each of which can be the basis for a region. In a sophisticated image processing system it should be possible to apply specific image processing operations to selected regions. Thus one part of an image (region) might be processed to suppress motion blur while another part might be processed to improve color rendition. Image enhancement refers to accentuation, or sharpening, of image features such as boundaries, or contrast to make a graphic display more useful for display analysis. This process does not increase the inherent information content in data. It includes gray level contrast manipulation, noise reduction, edge crisping and sharpening, filtering, interpolation and magnification, pseudo coloring, and so on. Image restoration is concerned with filtering the observed image to minimize the e effect of degradations. Effectiveness of image restoration depends on the extent and accuracy of the knowledge of degradation process as well as on filter design. Image restoration differs from image enhancement in that the latter is concerned with more extraction or accentuation of image features. Image compression is concerned with minimizing the number of bits required to represent an image. Application of compression are in broadcast TV, remote sensing via satellite,military communication via aircraft, radar, teleconferencing, facsimile transmission, for educational business documents, medical images that arise in computer tomography, magnetic resonance imaging and digital radiology, motion, pictures, satellite images, weather maps, geological surveys and so on.

Facial expressions are the facial changes in response to a person's internal emotional states, intentions,or social communications. Facial expression analysis has been an active research topic for behavioral scientists. Facial expression analysis refers to computer systems that attempt to automatically analyze and recognize facial motions and facial feature changes from visual information. Sometimes the facial expression analysis has been confused with emotion analysis in the computer vision domain. For emotion analysis, higher level knowledge is required.

A smile is the most common facial expression that occurs in people's daily life. It often indicates pleasure, happiness, appreciation, or satisfaction. Detecting smiles can be used to estimate a person's mentalstate. Smile detection has many applications in practice, such as interactive systems (e.g., gaming), product rating, distancelearning systems, video conferencing, and patient monitoring.The machine analysis of facial expressions in general has been an active research topic in the last two decades. Most of the existing works have been focused on analyzing a set of prototypic emotional facial expressions, using the data collected by asking subjects to pose deliberately these expressions. However, the exaggerated facial expressions occur rarely in real-life situations. Spontaneous facial expressions induced in natural environments differ from posed expressions, i.e., both in terms of which facial muscles move and how they move dynamically. Recently, research attention has started to shift toward the more realistic problem of analyzing spontaneous facial expressions. As illustrated in some initial studies this is a challenging problem it seems very difficult to capture the complex decision boundary among spontaneous expressions. In this paper, we focus on smile detection in face images captured in real world scenarios.We present an efficient approach to smile detection, in which the intensity differences between pixels in the grayscale face images are used as simple features. AdaBoost then is adopted to choose and combine weak classifiers based on pixel differences to form a strong classier for smile detection. Experimental results show that our approach achieves similar accuracy to the state of the art method but is significantly faster. Automatic facial expression analysis can be applied in many areas such as emotion and paralinguistic communication, clinical psychology, psychiatry, neurology,pain assessment, lie detection, intelligent environments, and multimodal human computer interface (HCI). Our approach provides 85percentage accuracy by examining 20 pairs of pixels and 88percentage accuracy with 100 pairs of pixels. We match the accuracy of the Gabor feature based support vector machine using as few as 350 pairs of pixels. Varying illumination and pose are the two main difficulties for unconstrained face analysis. we also examine different illumination normalization methods and investigate the impact of pose variation.

Facial expression analysis includes both measurement of facial motion and recognition of expression. The general approach to automatic facial expression analysis (AFEA) consists of three steps:

1) Face acquisition
2) Facial data extraction and representation
3) Facial expression recognition

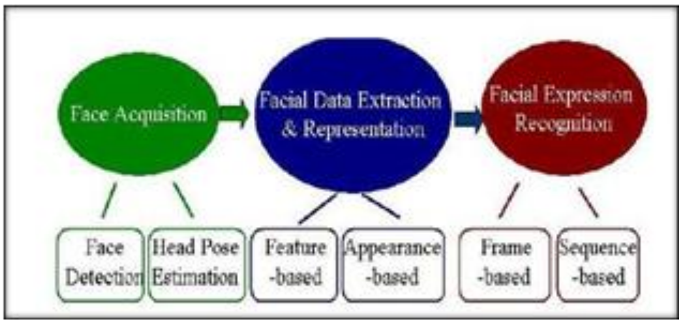

Fig.1 Basic structure of facial expression analysis systems

II. LIREATURE SURVEY

The State of the Art[1] method includes three basic problems related to facial expression analysis. These problems are: face detection in a facial image or image sequence, facial expression data extraction, and facial expression classification. For face detection there are two approaches: Holistic Approach, Analytic Approach. For feature extraction it may use either template based method or feature based method. For facial expression classification there are three methods: template based, neural network based and rule based classification.

Mainly authentic facial expression analysis[2] consist of two things:authentic expression database and facial expression recognition system. Authentic expression database is adatabase containing the emotions like joy, surprise, neutral, disgust.Facial expression recognition system mainly consist of three steps: face tracking, feature extraction and feature classification.

In fisher weight maps[3] method we use either local feature based approach or image vector based approach for feature extraction. Features of above 2 methods are integrated with a weight map to form feature vector. Bright pixels having positive large weight, dark pixels having negative large weight and gray pixels have zero weight.Classifying the image on the basis of pattern classification method.

III. PROPOSED SYSTEM

A detailed description on the implementation aspects of the proposed work is discussed in this chapter.

A. Proposed Work

In addition to facial expression of smile, the face images with different facial expressions such as Sad, Happiness, Angeranddisguise of the face images are recognized in proposed system. The present work focus on static color images and a holistic technique of the image-based method is used for feature extraction. The image based facial expression recognition systems consist of several components or modules, including face detection and normalization, feature extraction, feature selection, and classification. There are several image representation models in the color spaces used for image processing. The proposed work uses tensor perceptual color framework. In this, each color image can be represented as a 3-D, (i.e., horizontal, vertical, and color) data array. By using features such as differences between pixels in the gray scale face images are used as simple features for smile detection and geometric features such as shape and locations of facial components are extracted respectively. Using this proposed framework, the components (in either RGB, YCbCr, CIELab or CIELuv space) of color images are unfolded to 2-D tensors based on multilinear algebra and tensor concepts, from which the features are extracted by Log-Gabor filters. The mutual information quotient method is employed for feature selection. The selected features using the aforementioned MIQ technique are classified by a Support Vector Machine classifier.

IV. IMPLEMENTATION

A. Boosting Pixel Differences

A vital step in facial expression analysis is extracting effective features from original face images. Based on feature-point (e.g., mouthcorners) detection, geometric features can be exploited [4], [5].Another kind of features considers the appearance (skin texture) of the face [6], [7]. Appearance features are less sensitive to the errors in feature point detection and can encode changes in skin texture that are important for facial expression modeling.Appearance features are less sensitive to the errors in feature point detection and can encode changes in skin texture that are important for facial expression modeling. Appearance features look more promising for unconstrained facial expression analysis, and different features can be exploited. For example, the responses of Gabor filters at multiple spatial scales, orientations, and locations have been used traditionally [8] and have been proven successful for smile detection [9]. However, it is computationally ex-pensive to extract Gabor features. Also consider the features include the Haar wavelet features [10], LBP [11], and orientation histograms of gradients (edges) [12].In many practical applications, speed or computational efficiency is a key concern. Because of the limited computational resource, it is highly desired that the features used can be computed easily and efficiently. Baluja et al.[14], [15] introduced to use the relationship between two pixels' intensities as features. They obtained high accuracy on face orientation discrimination and gender classification by comparing the intensities of a few pixels.wepropose to use the intensity difference between two pixels as a simple feature.

AdaBoost [11] provides a simple yet e effective approach for stage wise learning of a nonlinear classification function. It combines the feature selection and classifier training steps in one process. AdaBoostlearns a small number of weak classifiers whose performance is just better than random guessing and boosts them iteratively into a strong classifier of higher accuracy. The process of AdaBoost maintains a distribution on the training samples. At each iteration, a weak classifier, which minimizes the weighted error rate, is selected, and the distribution is updated to increase the weights of the misclassified samples and reduce the importance of the others.

B. Experiments

1) Data

Experiments carried out on GENKI4Kdatabase. The database consists of 4000 images (2162 "smile" and 1828 "non smile"):

Fig.2 Examples of (top two rows) real-life smile faces and (bottom two rows)no smile faces, from the GENKI4K database.

some samples are shown in Fig. 2 As can be seen, the images span a wide range of imaging conditions, i.e. Consider both outdoors and indoors, as well as variability in age, gender, ethnicity, facial hair, and glasses [8].In our experiments, the images were converted to gray scale. The faces were normalized to reach a canonical face of 48*48 pixels, which was based on the manually labeled eyes positions. We partitioned the image set into four groups of 1000 images, with similar number of "smile" and "nonsmile" samples, and adopted a fourfold cross-validation. That is one group was used as testing data while the other groups as training data; the process was repeated four times foreach group in turn to be used for testing.

2) Baseline

In [8], Gabor features achieve superior performance on smile detection. Therefore, Gabor features were considered as the baseline in this paper. We utilized a bank of Gabor filters at eight orientations and effective spatial frequencies. The outputs of the 40 Gabor filters were down sampled by a factor of 4 [8]; therefore, the dimensionality of the Gabor feature vector is 23040. Another representation we considered is LBP. LBP features have shown promising performance for face analysis in recent years. Following [12], we divided face images of 48*48 pixels into 16 sub regions of 12 and the 59-label LBP 12 pixels,(8*2*2) operator was adopted to extract LBP.In some literature, the raw pixel values are used directly for face representation. Here, we also examined the raw pixel intensities for smile detection. An SVM was adopted as the classifier, which has proven effective in the existing studies [8].Gabor features provide the accuracy of 89.55percentage, whereas LBP features achieve 87.10percentage.Although Gabor features produce better results than LBP, considering that the dimensionality of LBP features O (10^3) is much lower than that of Gabor features O (10^5), LBP is more promising for practical applications. We also observe that, even with the gray scale pixel values, a linear SVM can achieve the performance of 80.38percentage, although the standard deviation is larger than the Gabor and LBP features.

C. Illumination Normalization

Illumination normalization methods are applied to see the impact of illumination variation. Histogram Equalization(HE) method is used for the illumination normalization.HE is a simple and widely used technique for normalizing illumination effects. Other illumination normalization methods are:

1) Single-scale Retinex (SSR):It is photometric normalization technique, which smooth's the image with a Gaussian filter to estimate the luminance function.
2) Discrete cosine transform (DCT):Sets a number of DCT coefficients corresponding to low frequencies as zero to achieve illumination invariance.
3) LBP:LBP operators is their tolerance against monotonic illumination changes; therefore, LBP can be used as a preprocessing lter to remove illumination effects.
4) Tan Triggs: Tan and Triggs proposed a series of steps to counter the effects of illumination variation, local shadowing, and highlights while still preserving the essential elements of visual appearance.

D. Color Space Conversion

After face detection stage, the face images are scaled to the same size (e.g., 64×64 pixels). The color values of face images are then normalized with respect to RGB values of the image. The purpose of color normalization is to reduce the lighting effect because the normalization process is actually a brightness elimination process.

Given an input image of N1 × N2 pixels represented in the RGB color space, $\mathbf{x} = \{\mathbf{x}^{n3}$ [n1, n2]| $1 \le n1 \le N1$, $1 \le n2 \le N2$, $1 \le n3 \le 3\}$, the normalized values,x^{n3}_{norm} [n1, n2], are defined by

$$\mathbf{x^{n3}_{norm}[n1,n2]} = \frac{\mathbf{x^{n3}[n1,n2]}}{\sum_{n3=1}^{3}\mathbf{x^{n3}[n1,n2]}}$$

A color image represented by T is a tensor of order 3 and T ∈ R $\prod_1^3 N_n$ where N_1 is the height of the image, N_2 is the width of the image, and N_3 represents the number of color channels.

$$\mathbf{T} \in \mathbf{R}\prod_1^3 \boldsymbol{N_n} \to \mathbf{T^1} \in \mathbf{R^{N_1\times(N_2\times N_3)}}$$

$$\mathbf{T} \in \mathbf{R}\prod_1^3 \boldsymbol{N_n} \to \mathbf{T^2} \in \mathbf{R^{N_2\times(N_1\times N_3)}}$$

$$\mathbf{T} \in \mathbf{R}\prod_1^3 \boldsymbol{N_n} \to \mathbf{T^3} \in \mathbf{R^{N_3\times(N_1\times N_2)}}$$

The 3-D color image is unfolded to obtain 2-D tensors based on multiline analysis criteria, which are suitable for 2-D feature extraction filters. These tensors are used for feature extraction and classification.

1) Feature Extraction

In this module, a bank of 24 Log-Gabor filters is employed to extract the facial features. The polar form of 2-D Log-Gabor filters in frequency domain is given by

$$\mathbf{H(f,\theta) = exp}\left\{\frac{-\left[\ln\frac{f}{f0}\right]^2}{2\left[\ln\frac{\sigma_f}{f0}\right]^2}\right\}\mathbf{exp}\left\{\frac{-(\theta-\theta_o)^2}{2\sigma_\theta^2}\right\}$$

whereH(f, θ) is the frequency response function of the 2-D Log-Gabor filters, f and θ denote the frequency and the phase/angle of the filter, respectively, f_0 is the filter's center frequency and $\theta_0$thefilter's direction. The constant $\sigma_F$defines the radial bandwidth B in octaves and the constant $\sigma_\theta$defines the angular bandwidth ΔGin radians

$$\mathbf{B= 2}\sqrt{\frac{2}{\ln 2}}\times|\mathbf{ln}(\frac{\sigma_f}{f_0})|,\ \mathbf{\Delta\Omega = 2\sigma_\theta}\sqrt{\frac{2}{\ln 2}}$$

the ratio σ_f / f_0 is kept constant for varying f_0, B is set to one octave and the angular bandwidth is set to ΔΩ= π/4 radians. This left only $\sigma_f$to be determined for a varying value of f_0. Six scales and our orientations are implemented to extractfeatures from face images. This leads to 24 filter transfer functions representing different scales and orientations. The image filtering is performed in the frequency domain making the process faster compared with the spatial domain convolution. After the 2-D fast Fourier transform (FFT) into the frequency domain, the image arrays, **x**, are changed into the spectral vectors, **X** and multiplied by the Log-Gabor transfer functions $\{H_1, H_2. H_{24}\}$, producing 24 spectral representations for each image. The spectra are then transformed back to the spatial domain via the 2-D inverse FFT. This process results in a large number of the feature arrays.

2) Feature Selection

The feature selection module is required to select the most distinctive features. The optimum features are selected using minimum redundancy maximum relevance algorithm based on mutual information (IM). The mutual information quotient (MIQ) method for feature selection is adopted to select the optimum features. According to MIQ feature selection criteria, if a feature vector has expressions randomly or uniformly distributed in different classes, its MI with these classes is zero. If a feature vector is strongly different from other features for different classes, it will have large MI.

Let F denotes the feature space, C denotes a set of classes C = {c1, c2, . . . ,ck}, and $\mathbf{v_t}$denotes the vector of N observations for that feature

$$\mathbf{v_t} = [\mathbf{v_t^1}, \mathbf{v_t^2}, \dots\dots.\mathbf{v_t^N}]^\mathbf{T}$$

where$v_t$is an instance of the discrete random variable V_t. The MI between features $V_t$and$V_s$is given by

$$\mathbf{I(V_t; V_s)} = \sum_{\mathbf{v_t \epsilon v_s}}\sum_{\mathbf{v_s \epsilon v_s}}\mathbf{p(v_t, v_s)log}\frac{\mathbf{p(v_t,v_s)}}{\mathbf{p(v_t)p(v_s)}}$$

where $p(v_t, v_s)$ is the joint probability distribution function (PDF) of $V_t$andV_s, $p(v_t)$ and $p(v_s)$ are the marginal PDFs of $V_t$andV_s, respectively, for $1 \le t \le N_f$, $1 \le s \le N_f$, and N_f is the input dimensionality, which equals the number of features in the dataset. The MI between $V_t$andC can be represented by entropies

$$\mathbf{I(V_t;C) = H(\ C) - H(\ C|V_t)}$$

Where

$$\mathbf{H(\ C) = -\sum_{i=1}^{k} p(c_i)\ log(\ p(c_i))}$$

$$\mathbf{H(\ C|V_t) = -\sum_{i=1}^{k}\sum_{v_t \epsilon V_t} p(c_i, v_t) log(p(\ c_i|v_t))}$$

where H(C) is the entropy of C, H(C|**Vt**) is the conditional entropy of C on $\mathbf{V_t}$, and k is the number of classes (for six expressions, k = 6). The features ($\mathbf{V_d}$) for desiredfeature subset, S, of the form <S; c> where S⊂F and c ⊂C are selected based on solution of following problems

$$\mathbf{V_d = argmax_{V_t}} \left\{ \frac{\mathrm{I}(V_t;C)}{\frac{1}{|S|}\sum \mathrm{I}(V_t;V_s)} \right\} \mathbf{V_t \epsilon \bar{S}, V_s \epsilon S}$$

Where $\bar{S}$ is the complement feature subset of S, |S| is the number of features in subset S and I (V_t;V_s) is the MI between the candidate feature (V_t) and the selected feature (V_s). Based on (10), the MI between selected feature and intra-class features is maximized whereas the MI between the selected feature and inter-class features is minimized, respectively. These features are used for emotion classification.

3) Classification Using SVM

Support Vector Machines (SVMs) are a machine learning system that is directly based on a branch of mathematics called statistical learning theory, which became properly formalized in the last decade. SVMs have successfully been applied to a number of classification tasks and tend to often outperform classic neural network approaches, their application to facial expression analysis and emotion classification so far has been limited. The aim of this classification is to apply SVMs to automated facial expression classification.

Machine learning algorithms are systems that receive input data during a training phase, then build a decision model according to the input and generate a function that can be used to predict a future data.By given a set

$$\mathbf{D=\{(x_i, y_i)\}_{i=1}^{l}}$$

of labeled training examples, where

$$\mathbf{y_i \in \{-1,1\}}$$

Learning systems typically try to find a decision function of the form

$$\mathbf{F(x) = sgn([w.x]+b)}$$

where*w*is a vector of weights and *b* is called bias, that yields a label ∈ {-1, 1} (for the basic case of binary classification) for an unseen example *x*, which have the smallest generation error.SVMs technique performs projection the original set of variables *x* in higher dimensional feature space:

$$\mathbf{x \in R^d \rightarrow z(x) \equiv (\emptyset_1(x), \ldots . \emptyset_n(x)) \in R^{2n}}$$

where a linear algebra and a geometry may be used to separate data that is only separable with nonlinear rules in an input space. By formulating the linear classification problem in the feature space, the solution will have the form

$$\mathbf{f(x) = sgn(} \sum_{i=1}^{l} \alpha_i y_i \mathbf{K(x,x_i)+b)}$$

associates with using the kernel functions, allowing an efficient computation of inner products directly in a feature space, by given a nonlinear mapping Φ that embeds input vectors into a feature space, kernels have the form

$$\mathbf{k(x,z) = [\emptyset(x).\emptyset(}z\mathbf{)]}$$

where the α_i are Lagrange multipliers of a dual optimization problem. It is possible to show that only small number coefficients $\alpha_i$are different from zero, and since every coefficient corresponds to a particular data point, this means that the solution is determined by the data points associated to the nonzero coefficients. These data points, which are called, support vectors. These induce sparseness in the solution and give rise to efficient approaches to optimization. Once a decision function is obtained, classification of an unseen example x amounts to checking which of the two subspaces defined by the separating hyperplane the example lies in.

V. PERFORMANCE EVALUATION

A. Experimental Results

The system is implemented using MATLAB programming language. For this purpose MATLAB 2013a is installed.

1) Dataset Description

The performance of the proposed system is evaluated using frontal view facial images from BU-3DFE. The database presently contains 100 subjects (56% female, 44% male), with age ranging from 18 years to 70 years old and a variety of ethnic/racial ancestries, including White, Black, East-Asian, Middle-east Asian, Indian, and Hispanic Latino. The database has images, which are not relevant to six main facial expressions. Therefore, these images are ignored and not used in testing and training set. Totally, 2400 facial expression images are selected from the database. The original resolution of the images is 512 × 512. However, the resolution of the images is normalized to different resolutions for several experiments. Fifty percent of the images are used for the training set and the rest for the testing set. The RGB facial images are transformed to other color spaces (YCbCr ,CIELab, and CIELuv). All the images are normalized and unfolded in horizontal mode. A bank of 24 Log-Gabor filters is used to extract the features from unfolded 2D tensors representing color facial images, which are concatenated and employed for the MIQ algorithm to generate the feature vector. These features are classified by a SVM respectively.
The results are shown in the following tables. Accuracy value obtained for proposed Log Gabor with SVM is as follows.

TABLE I. ACCURACY COMPARISON GRAPH

Methods	Gabor +SVM	LBP+ SVM	Raw Pixel Value+ SVM	Pixel Comparison + Adaboost	2DTensor 2DLog Gabor With SVM
Accuracy	89.5	87.5	85.6	90.1	93.7

The following graph shows the accuracy result for the proposed method with the existing methods is shown below:

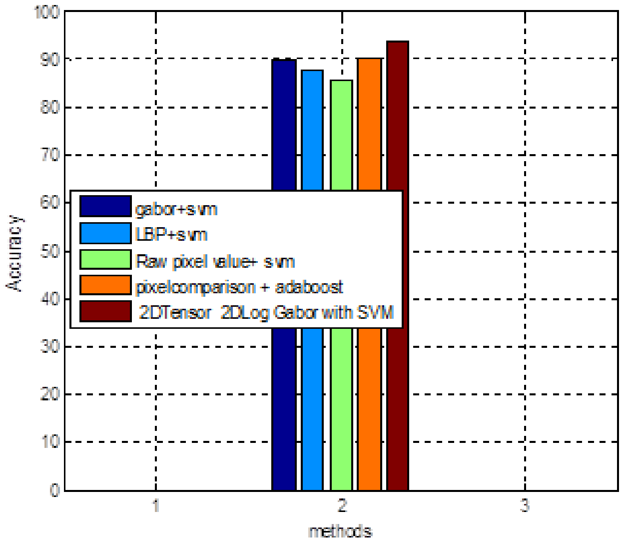

Fig.3 Accuracy comparison graph

The above graph in Figure 3 shows that the Accuracy comparison of the methods such as Gabor with SVM, LBP with SVM, Raw pixel value with SVM, Pixel comparison with AdaBoost and 2DTensor -2DLog Gabor with SVM. The Accuracy is measured in % at Y-axis and methods are depicted in the X-axis. The Accuracy values of the 2DTensor -2DLog Gabor with SVM are higher than the all other methods (Gabor with SVM, LBP with SVM, Raw pixel value with SVM, Pixel comparison with AdaBoost). Finally the proposed algorithm of the 2DTensor - 2DLog Gabor with SVM achieves a higher level of the Accuracy value rather than the other algorithm.

VI. CONCLUSION

In the present work, facial expression includes Sad, Happiness, Anger, disguise of the face images is proposed along in addition with the smile detection .Facial expression can be recognized in the perceptual color space of 2D Tensors. Facial features such as differences between pixels and features from 2D tensor can be extracted by using Illumination normalization method and a bank of 24 Log-Gabor filters, and the optimum features were selected based on MIQ algorithm. The selected features using the aforementioned MIQ technique are classified by a SVM classifier. An efficient classifier namely Support vector machine (SVM) is used to classify the different expressions of the face image. The images under slight illumination variation were used to test robustness of the Facial Expression Recognition system performance. Experimental result provides better recognition accuracy when compare with the existing work.

VI. FUTURE WORKS

Future research includes the application of the algorithms on large scale real world dataset as well as the repetition of the study of different types of occlusion on facial expression recognition.

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