



RESEARCH ARTICLE

Facial Expression Recognition Using SVM Classification in Perceptual Color Space

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Abstract— *Facial expression analysis is an important area of Human Robot Interaction (HRI) because facial expressions represent human emotions. Here, a new facial expression recognition system is introduced which uses tensor concept. Here perceptual color space is used instead of RGB color space since it cannot work well with illumination and pose variations. Also for classification purpose SVM classifier is used. The experimental results are compared using accuracy and the proposed method shows significant improvement in terms of these factors.*

Key Terms: - *Human Robot Interaction; Tensor; Perceptual color space; SVM classifier*

I. INTRODUCTION

Facial expression is a visible manifestation of the affective state, cognitive activity, intention, personality and psychopathology of a person. It plays a communicative role in interpersonal relations. Facial expressions, and other gestures, convey non-verbal communication cues in face-to-face interactions. These cues may also complement speech by helping the listener to elicit the intended meaning of spoken words. Mehrabian reported that facial expressions have considerable effect on a listening interlocutor; the facial expression of a speaker accounts for about 55 percent of the effect, 38 percent of the latter is conveyed by voice intonation and 7 percent by the spoken words. As a consequence of the information that they carry, facial expressions can play an important role wherever humans interact with machines. Automatic recognition of facial expressions may act as a component of natural human machine interfaces. For automatic facial expression recognition, the RGB color space may not always be the most desirable space for processing color information. This issue can be addressed using perceptually uniform color systems. Also for addressing the problem of applying 2D filtering to 3D image, the concept of tensor is introduced. This proposed face recognition system consists of a SVM classifier for improved accuracy and performance.

II. EXISTING METHODS

Many iris segmentation approaches has been explored till now. Approaches like Principal Component Analysis [1], Linear Discriminant Analysis [2], Independent Component Analysis [3] constitute a major part in the facial expression recognition techniques. These methods are 1-dimensional in nature. Therefore 2-dimensional Principal Component Analysis [4] is introduced. Since these techniques are applicable only in gray scale images, Global Eigen Approach [5] and Sub pattern Extended 2-dimensional Principal Component Analysis [6](E2DPCA) can be extended by traditional approaches to color space. Multilinear Image Analysis [7] introduced tensor concept which allows more than one factor variation in contradiction to PCA. Color Subspace Linear Discriminant Analysis [8] also uses tensor concept but in color space which improves the accuracy. For

achieving greater performance, another technique called Gabor Filter Bank [9] is used which outperforms all the other methods. Local Gabor Binary Pattern [10] has improved recognition rate than the gabor filter bank technique. Many studies have revealed that the overall performance is enhanced by color component embedding. But if RGB color space is used, accuracy depends on the angle and light source which reduces the recognition performance. Therefore RGB color space is not always suitable for color information processing. Perceptually uniform color systems can address this problem. Therefore a novel tensor perceptual framework [11] for facial expression recognition is introduced in this paper for better performance. This is done on perceptual color space and SVM classifier is used for better performance.

III. PROPOSED SYSTEM

In this paper, a tensor perceptual color framework for FER based on information contained in color facial images is introduced. Instead of RGB color space, perceptual color space is used for improving the performance. Further the classification is performed using support vector machine because the Support Vector Machine (SVM) performed better than the other classifiers and resolution of the face did not affect the classification rate with the SVM.

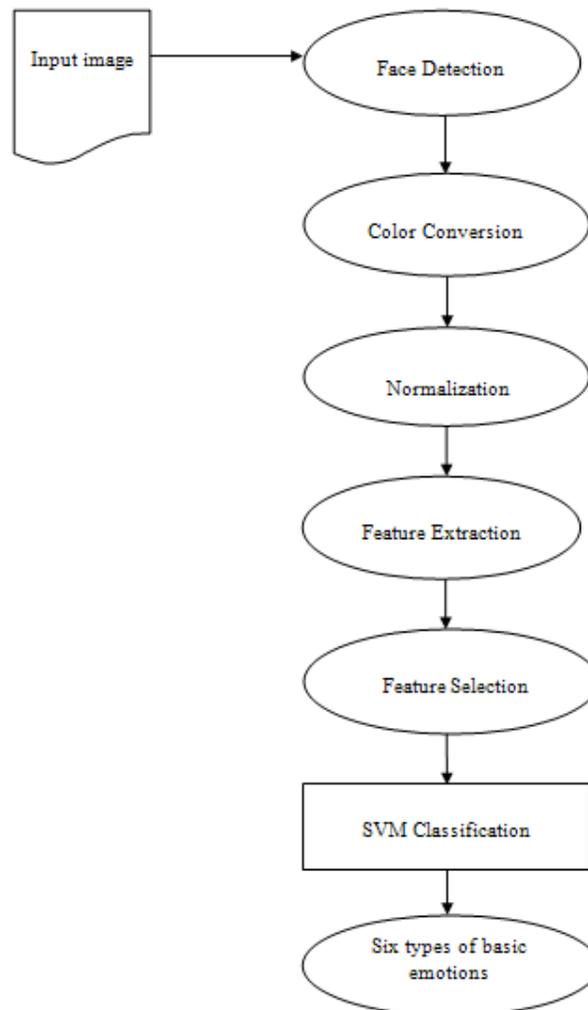


Fig. 1 System Architecture

A. Face Detection

The aim of this module is to obtain face images. The face area of an image is detected using the Viola–Jones method based on the Haar-like features and the AdaBoost learning algorithm. The Viola and Jones method is an object detection algorithm providing competitive object detection rates in real-time. It was primarily designed for face detection. The features used by Viola and Jones are derived from pixels selected from rectangular areas imposed over the picture, and exhibit high sensitivity to the vertical and the horizontal lines. After face detection stage, the face images are scaled to the same size (e.g., 64×64 pixels).

B. Color Conversion

There is several image representation models in the color spaces used for image processing. The RGB color space is commonly used in image processing and pattern recognition systems. This color space can be used to generate other alternative color formats including: YCbCr, CIE Lab, and CIE Luv. Although recent research has shown improved performance by embedding the color components, the effectiveness of color information in the RGB color space in terms of recognition performance depends on the type and angle of light source, often making recognition impossible. Therefore, the RGB color space may not always be the most desirable space for processing color information. This issue can be addressed using perceptually uniform color systems. To convert from RGB to perceptual color spaces (CIE Lab or CIE Luv), the RGB color space is converted to XYZ color space, which is then converted to perceptual color spaces.

C. Normalization

The purpose of color normalization is to reduce the lighting effect because the normalization process is actually a brightness elimination process. The local normalization technique is performed to reduce the effect of illumination for facial expression images. To see the effect of illumination on images in different color spaces, the illumination pattern is applied to original color facial images. The image under illumination is given by product of normal image and illumination pattern. All the images are normalized using and unfolded in horizontal mode.

D. Feature Extraction

Various methods of feature extraction have been studied and compared in terms of their performance, including principal component analysis, independent component analysis, linear discriminant analysis (LDA), the Gabor filter bank, etc. However, the Gabor filters have two major limitations, i.e., the maximum bandwidth of Gabor filters is limited to approximately one octave, and the Gabor filters are not optimal to achieve broad spectral information with the maximum spatial localization. Furthermore, the Gabor filters are bandpass filters, which may suffer from loss of the low and the high-frequency information. To achieve the broad spectral information and to overcome the bandwidth limitation of the traditional Gabor filter, Field proposed Log-Gabor filter. The response of the Log-Gabor filter is Gaussian when viewed on a logarithmic frequency scale instead of a linear one. This allows more information to be captured in the high-frequency areas with desirable high pass characteristics. In this contribution, a bank of 24 Log-Gabor filters is employed to extract the facial features. Six scales and four orientations are implemented to extract features 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 spacial 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 $\{H_1, H_2, \dots, H_{24}\}$, producing 24 spectral representations for each image[11]. 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, which are not suitable to build robust learning models for classification.

E. Feature Selection

Since the number of features resulted from the previously discussed feature extraction process is fairly large, the feature selection module is required to select the most distinctive features. In other words, the feature selection module helps to improve the performance of learning models by removing most irrelevant and redundant features from the feature space. The optimum features are selected using minimum redundancy maximum relevance algorithm based on mutual information (MI). The mutual information quotient (MIQ) method for feature selection is adopted to select the optimum features[11]. 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. 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.

F. SVM Classification

In this module to perform automated expression recognition, system needs to deal with the issues of face localization, facial feature extraction and the training as well as the classification stages of the SVM. In the previous approaches, LDA classifier is used, but for improving the performance SVM is used. For each expression, a vector of displacements is calculated by taking the euclidean distance between landmark locations in a neutral and a peak frame representative of the expression. The labeled vector of displacements of each example expression supplied is used as input to an SVM classifier, resulting in a model of the training data, which is subsequently used to dynamically classify unseen feature displacements. The result is then returned to the user. SVMs are maximal margin hyper plane classifiers that exhibit high classification accuracy for small training sets and good generalization performance on very variable and difficult to separate data. During a number of interactive sessions with various users, we evaluated our system by considering classification performance for the six basic emotions. Given some training data \mathcal{D} , a set of n points of the form,

$$\mathcal{D} = \{(\mathbf{x}_i, y_i) \mid \mathbf{x}_i \in \mathbb{R}^p, y_i \in \{-1, 1\}\}_{i=1}^n$$

where the y_i is either 1 or -1, indicating the class to which the point \mathbf{x}_i belongs. Each \mathbf{x}_i is a p -dimensional real vector. We want to find the maximum-margin hyperplane that divides the points having $y_i = 1$ from those having $y_i = -1$.

IV. EXPERIMENTAL RESULTS

The experimental result given here illustrates that the proposed method using SVM classifier provides comparatively better performance in terms of accuracy than the existing systems.

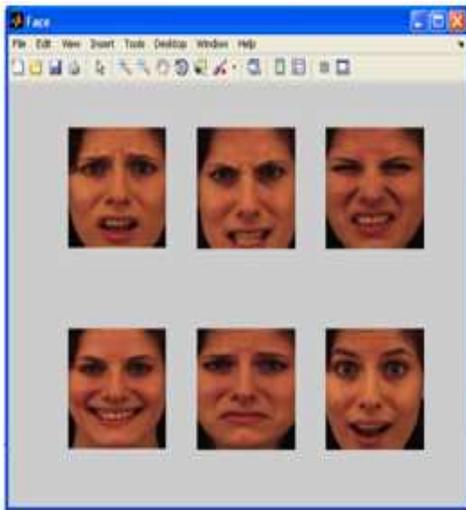


Fig. 2 a) Face detection

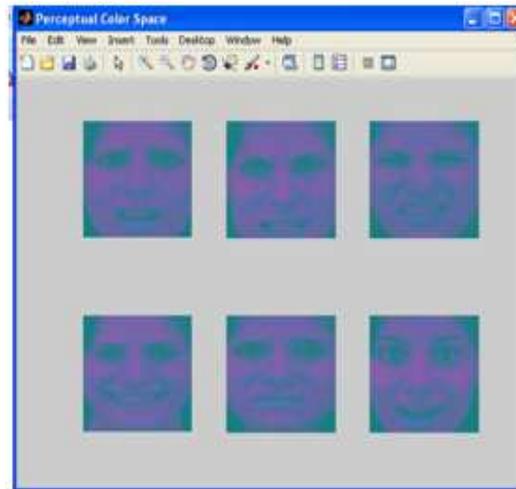


Fig. 2 b) Color Conversion

An input image is given and face area is detected from the given image using Viola-Jones method. The face area of an image is detected using the Viola-Jones method based on Haar-like features and the Ada Boost learning algorithm. The detected face images are converted from RGB color space to perceptual color space. The purpose of color normalization is to reduce the lighting effect because the normalization process is actually a brightness elimination process. After image preprocessing, features are extracted from the normalized output. Feature extraction is done using gabor filter. The input image is classified in to one of the six different expressions. For each expression, a vector of displacements is calculated by taking the euclidean distance between landmark locations in a neutral and a peak frame representative of the expression. The labeled vector of displacements of each example expression supplied is used as input to an SVM classifier, resulting in a model of the training data, which is subsequently used to dynamically classify unseen feature displacements. The result is then returned to the user.

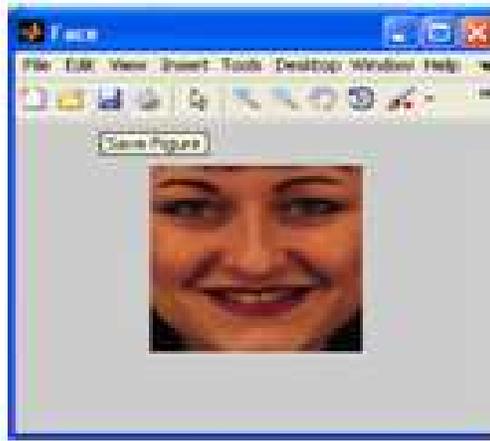


Fig. 2 c) Input Image



Fig. 2 d) Output

The accuracy rate of expression recognition for both existing, as well as the proposed method has been provided in the given below diagram.

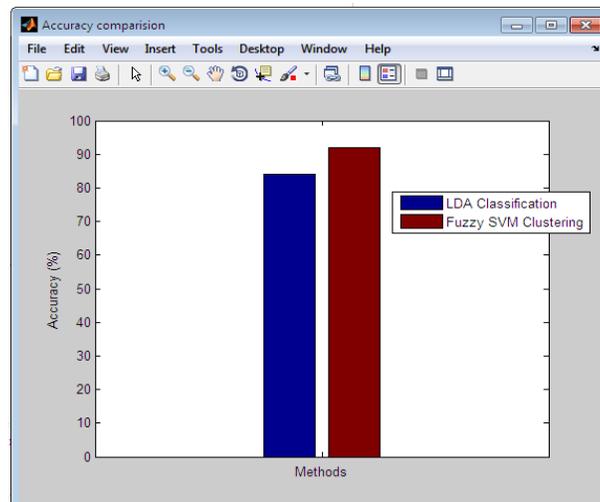


Fig. 3 Accuracy rate of existing and proposed system

V. CONCLUSIONS

A facial expression recognition system in perceptual color space using SVM classification is proposed here. Based on this, the RGB color images were first transformed to perceptual color spaces after which the horizontal unfolded tensor was adopted to generate the 2-D tensor for feature extraction. The 2-D tensor was normalized before the features were extracted using a bank of 24 Log- Gabor filters, and the optimum features were selected based on MIQ algorithm. Then given input image is classified in to six different expressions using SVM classifier. The performance is compared with the existing systems using accuracy, precision and recall.

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REFERENCES

- [1] L. Sirovich and M. Kirby, "Low Dimensional Procedure for Characterization of Human Faces," J. Optical Soc. Am., vol. 4, pp. 519-524, 1987.
- [2] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigenfaces vs. Fisherfaces: recognition using class specific linear projection," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 711-720, Jul. 1997.
- [3] B.A. Draper, K. Baek, M.S. Bartlett, J.R. Beveridge, "Recognizing Faces with PCA and ICA," Computer Vision and Image Understanding: special issue on face recognition, in press.
- [4] J. Yang, D. Zhang, A. F. Frangi, and J. Y. Yang, "Two-dimensional PCA: A new approach to appearance-based face representation and recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 26, no. 1, pp. 131-137, 2004.
- [5] L. Torres, J. Reutter, and L. Lorente, "The importance of the color information in face recognition," in Proceedings. 1999 International Conference on Image Processing, 1999. ICIP 99., vol. 3. IEEE, 1999, pp. 627-631.
- [6] Chen S., Sun Y. and Yin B., "A Novel Hybrid Approach Based on Sub-pattern Technique and Extended 2DPCA for Color Face Recognition," 11th IEEE International Symposium on Multimedia, pp. 630-634, 2009.
- [7] M. Thomas, C. Kambhamettu and S. Kumar, (2008), Face recognition using a color subspace LDA approach, Proceedings - International Conference on Tools with Artificial Intelligence.
- [8] M. A. O. Vasilescu and D. Terzopoulos, "Multilinear image analysis for facial recognition," in Proc. Int. Conf. Pattern Recognit., Quebec City, QC, Canada, Aug. 2002, pp. 511-514
- [9] Barbu, T, Gabor filter-based face recognition technique, Proceedings of the Romanian Academy, vol.11, no. 3, pp. 277 - 283, 2010.
- [10] S. Moore and R. Bowden, "Local binary patterns for multi-view facial expression recognition," Comput. Vis. Image Understand., vol. 115, no. 4, pp. 541-558, 2011.
- [11] S. M. Lajvardi and H. R. Wu, "Facial Expression Recognition in Perceptual Color Space" IEEE Transactions on Image Processing, vol. 21, no. 8, pp. 3721-3732, 2012.