Classification of Facial Expressions Using K-Nearest Neighbor Classifier

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Abstract. In this paper, we have presented a fully automatic technique for detection and classification of the six basic facial expressions from nearly frontal face images. Facial expressions are communicated by subtle changes in one or more discrete features such as tightening the lips, raising the eyebrows, opening and closing of eyes or certain combinations of them. These discrete features can be identified through monitoring the changes in muscles movement (Action Units) located near about the regions of mouth, eyes and eyebrows. In this work, we have used eleven feature points that represent and identify the principle muscle actions as well as provide measurements of the discrete features responsible for each of the six basic human emotions. A multi-detector approach of facial feature point localization has been utilized for identifying these points of interests from the contours of facial components such as eyes, eyebrows and mouth. Feature vector composed of eleven features is then obtained by calculating the degree of displacement of these eleven feature points from a non-changeable rigid point. Finally, the obtained feature sets are used for training a K-Nearest Neighbor Classifier so that it can classify facial expressions when given to it in the form of a feature set. The developed Automatic Facial Expression Classifier has been tested on a publicly available facial expression database and on an average 90.76% successful classification rate has been achieved.

1 Introduction

Facial expression is a visible manifestation of the affective state, cognitive activity, intention, personality and psychopathology of a person that plays a communicative role in interpersonal relations [1]. According to Mehrabian [2], the verbal part of a message contributes only for 7% to the effect of the message as a whole; the vocal part contributes 38%, while facial expression of the speaker contributes for 55% to the effect of the spoken message. This implies that the facial expressions form the major modality in human communication and can play an important role wherever humans interact with machines. Automatic recognition of facial expressions may act as a component of both natural human-machine interfaces [3] and its variation known

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as perceptual interfaces [4]. This can also be a possible application domain in behavioral science or medicine for automated analysis of human facial expressions.

Although humans can recognize facial expressions virtually without error or delay, reliable and fully automated expression recognition by machine is still a challenge. Automated systems for facial expression recognition usually take the form of a sequential configuration of processing blocks which adheres to a classical pattern recognition model [5]. The main blocks of such a system as identified by Chibelushi et al. [6] are: image acquisition, pre-processing, feature extraction, classification, and post-processing.

In this paper, we have presented a fully automatic technique for detection and classification of the six basic facial expressions from static face images namely, anger, disgust, fear, happiness, sadness and surprise as defined by Ekman [7]. The subsequent discussion of this paper has been organized into the following six sections: Section II outlines the related works in this field. Discussion about the features used in this work for representing facial expressions has been provided in Section III. Section IV elaborates the technique of obtaining feature set for each of the six facial expressions through detecting the eleven feature points. Section V gives an overview of the K-Nearest Neighbor Classification technique. Experimental results along with discussion on the performance of the system have been provided in Section VI and finally, Section VII concludes the paper.

2 Related Works

Due to its importance for application domains in human behavior interpretation and the human-computer interface, the automatic analysis and classification of facial expression has attracted the interest of many computer vision researchers. Since the mid 70s, different approaches have been proposed for automatic classification of facial expression from either static images or image sequences. Cottrell and Metcalfe [8] used a three layer back-propagation neural network for classifying facial expressions. They used features from the whole face by manually selecting the face region and normalizing it to 64×64 pixels. A pyramid-like feed-forward neural network has been used by Rahardja et al. [9] for classifying six basic facial expressions from hand-drawn face image. Their system can classify expressions successfully from the images of training data set but performance of their system on unknown data set is not reported. Kobayashi and Hara [10] used features obtained from 30 facial characteristics points to train their 60×100×100×6 neural network for classifying facial expression and achieved a success rate of 80%. Vanger et al. [11] proposed a system for classifying facial expressions using neural network by creating a prototype index for each of the emotion category through averaging all eye and mouth parts of 60 utilized static images. The claimed success rate for their system is 70%. Essa and Pentland [12] used an optical flow computation based 3D mesh model technique to track the muscle movement of face. Facial expressions were classified in their work using alternative similarity measurement. Hidden Markov Model based facial expression classifier was developed by Lien et al. [13] where tracking of feature points were performed using dense optical flow and edge detection. Pantic and Rothkrantz [14] performed rule-based classification of facial expressions by extracting features through geometric measurement among the landmarks located on the contours of eyebrows, eyes, nostrils, mouth and chin. Feng et al. [15] proposed a technique where local binary pattern has been used to represent a facial image and classification of facial expressions has been performed by linear programming technique.

As can be inferred from the literature review, most of the previous works depend greatly on manual initialization of the landmark points or facial regions used for representing facial expressions as well as for feature extraction. In this work, we have attempted to eliminate this problem by automatic detection of the used landmark points. Besides this, a small subset of the previously used landmark points has been utilized in this work that has less tendency of being failed during the detection process and thus contributes significantly in improving the performance of the facial expression classifier.

3 Features for Facial Expression Classification

To enable a machine learning technique to learn as well as to classify the patterns of facial expressions successfully, salient properties of the facial expression have to be passed through it as features during both the learning and classification stages. Although each part of human face somehow contributes in producing the non verbal facial expressions, participation of certain face regions are stronger comparative to that of the others. These regions are the eyebrows, eyes and mouth. In this work of detection and classification of human facial expressions, we have considered only the features that are concentrated around these regions.

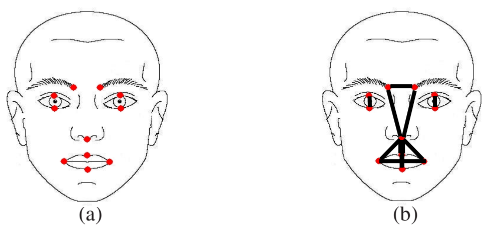

Fig. 1. (a) Feature points used for capturing the facial actions (Action Units) (b) distances that have been used as features by the K-NN classifier for classifying facial expression

Considering the technique of how humans perceive emotions from the face of other humans, we have selected total eleven points (Fig. 1.a) on human face that can detect the movement of eyebrows, eyelids and mouth providing useful information about the involved action units (AU). A set of eleven measurements are performed among these eleven feature points to estimate the level (strength) of activation of the triggered action units using midpoints of nostrils as the base point (Fig. 1.b). This set $\{D_1, D_2, D_3, D_4, D_5, D_6, D_7, D_8, D_9, D_{10}, D_{11}\}$ represents one of the six basic human emotions and is used as a set of feature by the classifier for training as well as classifying facial

Table 1. Description of the distances used as features by the K-Nearest Neighbor classifier for classifying facial expression

Distance	Description of Distances Used as Features
D_1 and D_2	Distance of the right and left eyebrow inner corners from the mid point of nostrils
D_3	Distance between the inner corners of right and left eyebrows
D_4 and D_5	Distance between the mid points of the upper and lower eyelids of left and right eyes
D_6 and D_7	Distance of the right and left mouth corners from the mid point of the nostrils
D_8 and D_9	Distance of the mid upper lip and mid lower lip from the mid point of the nostrils
D_{10}	Distance between the mid points of upper and lower lips
D_{11}	Distance between right and left mouth corners

expressions. Brief description of the measurements, used for generating feature set of facial expressions, is given in Table-1.

4 Detection of Feature Points and Obtaining the Feature Vector

The task of feature point extraction has been performed in two separate stages. At the first stage, feature regions of human faces are isolated using an anthropometric face model based technique specified in [16].

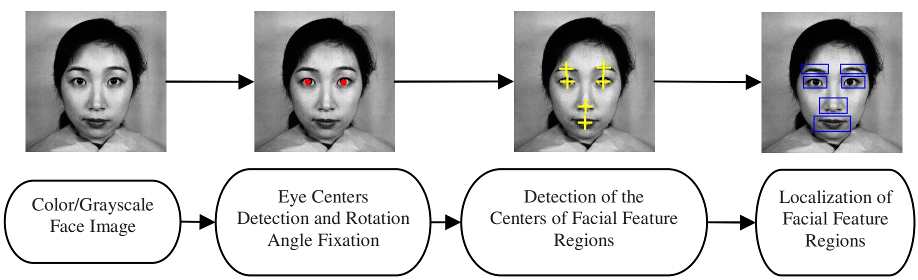

Fig. 2. Detection of facial feature regions using anthropometric face model based technique. Eye centers are detected first. Location of other facial feature regions are then identified and isolated using distance between two eye centers as the principle parameter of measurement.

In this method, centers of the two eyes are first identified using a generalized framework for robust, real-time object detection [17]. Eye, eyebrow and mouth regions of the face images are then isolated using the distance between two eye centers as the principal parameter of measurement. Results of applying the facial feature regions localization technique over a face image is given in Fig. 2.

During the second stage, a hybrid image processing technique is applied over these isolated feature regions for detecting the specific eleven feature points (Figure 1.a). Feature set, representing a specific facial expression is then obtained using Euclidian distance based measurement performed among these feature points (Table-1).

4.1 Facial Feature Point Detection

Searching for the eleven facial feature points is done separately within each of the areas returned by the facial feature region identifier [16]. Steps constituting the searching process for identifying the eleven feature points are described below:

4.1.1 Mid Upper and Lower Eyelid Detection

The eye region is composed of dark upper eyelid with eyelash, lower eyelid, pupil, bright sclera and the skin region that surrounds the eye. The most continuous and non deformable part of the eye region is the upper eyelid, because both pupil and sclera change their shape with various possible situations of eyes, especially when the eye is closed or partially closed due to various facial expressions. So, inner and outer eye corners are determined first by analyzing the shape of the upper eyelid, and are used later on for locating the mid upper and mid lower eyelid. To avoid the erroneous detection of the eye feature points, discontinuity in upper eyelid region must be avoided. It can be done by changing the illumination of the upper eyelid so that it differs significantly from the surrounding region. This has been carried out by saturating the intensity values of all the pixels towards zero that constitutes the lower 50% of the image intensity cumulative distribution (Fig. 3.b). The adjusted image is then converted to binary one (Fig. 3.c) using the threshold value obtained from the following iterative procedure [18].

1. Pick an initial threshold value, t
2. Calculate the two mean intensity values from the histogram (m_1 and m_2) using the pixels' intensity values that fall below and above the threshold t.
3. Calculate new threshold. $t_{new} = (m_1 + m_2) / 2$.
4. If the threshold has stabilized $(t = t_{new})$, this is the appropriate threshold level. Otherwise, t become t_{new} and reiterate from step 2.

Contour that covers the largest area is then isolated (Fig. 3.d) using the 8-connected contour following algorithm specified in [19]. For right eye, the inner eye corner is the right most point of the contour and outer eye corner is the leftmost point of the contour (Fig. 3.e). For left eye, right most point over the contour becomes the inner corner and leftmost point becomes the outer corner. The whole eye contour region is then divided vertically into three equal parts and searching for the upper and lower mid eyelid is then done within the mid division. For each value of x coordinate $\{x_1, x_2, x_3,\ldots,x_n\}$ that falls within this mid division, there will be two values of y coordinate: one from the upper portion of the eye contour $\{y_{11}, y_{12}, y_{13},\ldots,y_{1n}\}$ and another from the lower portion of the eye contour $\{y_{21}, y_{22}, y_{23},\ldots,y_{2n}\}$. Distance between each pair of points $\{(x_i, y_{1i}), (x_i, y_{2i})\}$ is then calculated. The maximum distance, calculated from the two points that are closest to the midpoint of inner and outer eye corner, is considered as the amount of eye opening and provides the mid points of the upper lower eyelids respectively (Fig. 3.f).

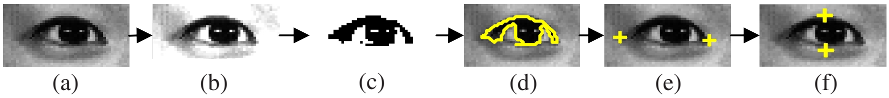

Fig. 3. Mid upper and lower eyelid detection (a) eye region (b) intensity adjustment (c) binarization (d) isolated eye contour (e) inner and outer eye corner detection (f) detected mid points of the upper and lower eyelids

4.1.2 Detection of Inner Eyebrow Corners

Aside from the dark colored eyebrow, eyebrow regions also contains relatively bright skin portion. Sometimes, this region is also partially occulted with hair. Since dark pixels are considered as background in digital imaging technology, the original image is complemented to convert the eyebrow region as the foreground object and rest as the background (Fig. 4.b).

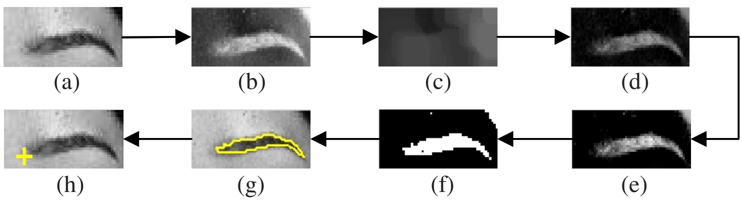

Fig. 4. Inner eyebrow corners detection (a) eyebrow region (b) complemented eyebrow image (c) estimated background (d) background subtraction (e) intensity adjustment (f) binary eyebrow region (g) eyebrow contour (h) detected inner eyebrow corner

Morphological image opening operation is then performed over the complemented image with a disk shaped structuring element of 10 pixel radius for obtaining the background illumination (Fig. 4.c). The estimated background is then subtracted from the complemented image to have a comparatively brighter eyebrow over a uniform dark background (Fig. 4.d). Intensity of the resultant image is then adjusted on the basis of the pixels' cumulative distribution to increase the discrimination between the foreground and background (Fig. 4.e). Binary version of this adjusted image (Fig. 4.f) is obtained by thresholding it using Otsu's method [20] and all the available contours of the binary image are detected using the 8-connected contour following algorithm specified in [19]. The eyebrow contour, which is usually the largest one, is then identified by calculating the area covered by each contour (Fig. 4.g). For left eyebrow, the point on the contour having the minimum values along x and y coordinates simultaneously is considered as the inner eyebrow corner. Similarly, for the right eyebrow, point on the eye contour that has the maximum values along x axis and minimum value along y axis simultaneously is considered as the inner eyebrow corner (Fig. 4.h).

4.1.3 Detection of the Midpoint of Nostrils

Nostrils of a nose region are the two circular or parabolic objects having the darkest intensity (Fig. 5.a). For detecting the centre points of nostrils, separation of this dark part from the nose region is performed by filtering it using a Laplacian of Gaussian (LoG) as the filter. The 2-D LoG function centered on zero and with Gaussian standard deviation σ has the form:

$$LoG(x,y) = -\frac{1}{\pi\sigma^4}\left[1-\frac{x^2+y^2}{2\sigma^2}\right]e^{-\left(\frac{x^2+y^2}{2\sigma^2}\right)}$$

The LoG operator calculates the second spatial derivative of an image. This means that in areas where the image has a constant intensity (*i.e.* where the intensity gradient is zero), the LoG response will be zero. In the vicinity of a change in intensity, however, the LoG response will be positive on the darker side, and negative on the lighter side.

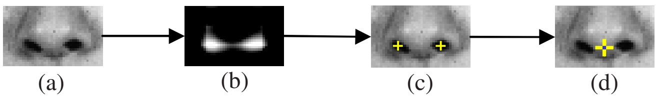

Fig. 5. Detection of the midpoint of nostrils from isolated nose region (a) isolated nose region (b) filtered by LoG (c) detected nostrils (d) midpoint of nostrils

This means that at a reasonably sharp edge between two regions of uniform but different intensities, the LoG response will be zero at a long distance from the edge as well as positive just to the one side of the edge and negative to the other side. As a result, intensity of the filtered binary image gets complemented and changes the nostrils as the brightest part of the image (Figure 5.b). Searching for the local maximal peak is then performed on the filtered image to obtain the centre points of the nostrils. To make the nostril detection technique independent of the image size, the whole process is repeated varying the filter size starting from 10 pixel, until the number of peaks of local maxima is reduced to two (Figure 5.c). Midpoints of the nostrils are then calculated by averaging the coordinate values of the identified nostrils (Figure 5.d).

4.1.4 Feature Point Detection from Mouth

The simplest case of mouth feature points detection occurs when mouth is normally closed. However, complexities are added to this process by situations like when mouth is wide open or teeth are visible between upper and lower lips due to laughter or any other expression. These two situations provides additional dark and bright region respectively in the mouth contour and makes the feature point detention process quite complex.

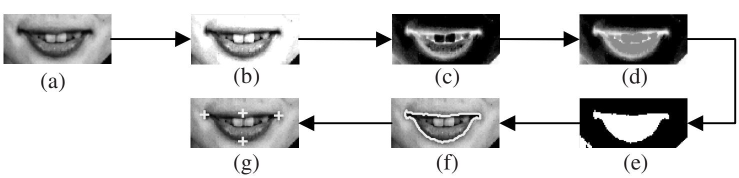

Fig. 6. Feature point detection from mouth region (a) isolated mouth region (b) intensity adjustment (c) complemented mouth region (d) filled image (e) binary mouth region (f) detected mouth contour (g) detected feature points from mouth region

To handle these problems, contrast stretching on the basis of the cumulative distribution of the pixels is performed on the image for saturating the upper half fraction of the image pixels towards higher intensity value. As a result, lips and other darker region become darker while the skin region becomes comparatively brighter providing a clear separation boundary between the foreground and background (Fig. 6.b). A flood fill operation is then performed over the complemented image to fill-up the wholes of mouth region (Fig. 6.d). After this, the resultant image is converted to its binary version using the threshold value obtained by the procedure given in [18]. All the contours are then identified applying the 8-connected contour following algorithm specified in [19] and mouth contour is isolated as the contour having the largest area (Fig. 6.f). The right mouth corner is then identified as a point over the mouth contour having the minimum x coordinate value, and the point which has the maximum x coordinate values is considered as the left mouth corner. Middle point (X_{mid}, Y_{mid},) of the left and right mouth corner are then calculated and upper and lower mid points of mouth are obtained by finding the two specific points over the mouth contour which has the same x coordinate as that of (X_{mid}, Y_{mid},) but minimum and maximum y coordinates respectively.

4.2 Obtaining the Feature Vector

Once all the eleven feature points are detected, a set of eleven measurements (Table 1) is performed over these points to obtain the feature vector that represents a specific facial expression. The obtained feature vector(s) is/are then fed into the facial expression classification system for training as well as classification of the represented unknown facial expression.

5 Overview of K-NN Classifier

K-Nearest Neighbors (K-NN) is a well-known and widely used instance-based classification algorithm [21], [22]. The basic idea behind this classification paradigm is to compute the similarity between a test object and all the objects in the training set, select the k most similar training set objects, and determine the class of the test object based on the classes of this k nearest neighbors. One of the advantages of K-NN is that it is well suited for multi-modal classes as its classification decision is based on a small neighborhood of similar objects. As a result, even if the target class is multimodal (i.e., consists of objects whose independent variables have different characteristics for different subsets), it can still lead to good classification accuracy.

In K-NN classification, training patterns are plotted in d dimensional space, where d is the number of features present. These patterns are plotted according to their observed feature values and are labeled according to their known class. An unlabelled test pattern is plotted within the same space and is classified according to the most frequently occurring class among its k most similar training patterns; its nearest neighbors. The most common similarity measure for K-NN classification is the Euclidian distance metric, defined between feature vectors $\vec{x}$ and $\vec{y}$ as:

$$euc(\vec{x}, \vec{y}) = \sqrt{\sum_{i=1}^{f} (x_i - y_i)^2}$$

where, f represents the number of features used to represent each pattern. Smaller distance values represent greater similarity. Classification occurs after identifying the k most similar training points to a query point. Rather than using a standard voting scheme, the algorithm used here assigns class labels to query points using a weighted scheme based upon each neighbor's proximity to the query point [23]. Let d be a distance measure, and $x_1, x_2, x, \ldots, x_k$ be the k nearest neighbors of x arranged in increasing order of $d(x_i,x)$. So x_1 is the first nearest neighbor of x. Dudani [23] proposes to assign a weight w_i to the i-th nearest neighbor x_i defined as:

$$w_i = \begin{cases} \frac{d(x_k,x)-d(x_i,x)}{d(x_k,x)-d(x_1,x)}, & \text{if } d(x_k,x) \neq d(x_1,x) \\ 1, & \text{if } d(x_k,x) = d(x_1,x) \end{cases}$$

Pattern x is assigned to the class for which the weights of the representatives among the k nearest neighbors sum to the greatest value. This rule was shown to yield lower error rates by Dudani [23] than those obtained using the voting K-NN rule.

6 Experimental Results

As specified earlier, K-Nearest Neighbor (K-NN) technique has been used for the recognition part of our Automatic Facial Expression Classification System. Performing experimentation with different values of k, we have observed that $k = 3$ is the best choice for our work. The developed Automatic Facial Expression Classifier has been tested using the Japanese Female Facial Expression (JAFFE) Database [24]. This publicly available database contains 213 images each representing 7 different facial expressions (6 basic facial expressions + 1 neutral) posed by 10 Japanese female models. Each image of this database was rated on 7 emotion adjectives by 60 Japanese subjects. “Leave-One-Out” criteria has been maintained in training the classifier and for each subject, six feature vectors calculated from the image of each of the six basic facial expressions, were used during the training session. The remaining images, that were left unused during the training session, have been used to verify the performance of the Automatic Facial Expression Classification System and on an average, successful recognition rate of 90.76% have been achieved. Performance of the K-NN based Automatic Facial Expression Classifier has also been compared with that of the two other classifiers namely Back-propagation Neural Network Classifier and Naive Bayes Classifier. Obtained results are summarized in Table 2.

Table 2. Accuracy of the automatic facial expression classifier in classifying facial expression

	Recognition Accuracy (%) on JAFFE Database		
Expression	K-NN (K=3)	Neural Network	Naive Bayes Classifier
Anger	88.58	82.48	84.27
Disgust	86.75	79.45	82.84
Fear	84.52	76.74	80.58
Happiness	96.14	89.45	89.26
Sad	89.93	79.67	72.64
Surprise	98.66	91.32	94.69
Average	90.76	83.19	84.05

7 Conclusion

We have discussed the development technique of an automatic facial expression classification system that incorporates a hybrid image processing based facial feature point detection method along with K-Nearest Neighbor algorithm as classifier. As shown in the experimental results, the system performs better when K-NN is used as classifier rather than Neural Network or Naive Bayes Classifier and provides an average successful recognition rate of 90.76%. Use of only eleven feature points has enabled the system to be computationally time effective compared to the other systems that works by identifying more feature points. Beside this, incorporation of the anthropometric model based facial feature regions localization technique [16] has further reduced the computational time of our system by confining the search space of he eleven feature points. Since aggregation of emotional information in human-computer interfaces allows much more natural and efficient interaction paradigms to be established, we believe that the developed automatic facial expression classifier can play an increasing role in building effective and intelligent multimodal interfaces for next generation.

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