Facial Expressions Recognition in a Single Static as well as Dynamic Facial Images Using Tracking and Probabilistic Neural Networks

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Abstract. An efficient, global and local image-processing based extraction and tracking of intransient facial features and automatic recognition of facial expressions from both static and dynamic 2D image/video sequences is presented. Expression classification is based on Facial Action Coding System (FACS) a lower and upper face action units (AUs), and discrimination is performed using Probabilistic Neural Networks (PNN) and a Rule-Based system. For the upper face detection and tracking, we use systems based on a novel two-step active contour tracking system while for the upper face, cross-correlation based tracking system is used to detect and track of Facial Feature Points (FFPs). Extracted FFPs are used to extract some geometric features to form a feature vector which is used to classify input image or image sequences into AUs and basic emotions. Experimental results show robust detection and tracking and reasonable classification where an average recognition rate is 96.11% for six basic emotions in facial image sequences and 94% for five basic emotions in static face images.

Keywords: Active contours, Action Units, Facial Expressions, Probabilistic Neural Networks.

1 Introduction

Automated facial expression analysis using computer vision work could bring facial expressions into man-machine interaction.

Most computer-vision based approaches to facial expression analysis attempt to recognize only prototypic emotions. These prototypic emotional seem to be universal across human ethnicities and cultures and comprise happiness, sadness, fear, disgust, surprise, and anger. In everyday life, however, such prototypic expressions occur relatively infrequently. Instead, emotion is communicated by changes in one or two discrete features.

In order to make the recognition procedure more standardized, a set of facial muscle movements (known as Action Units) that produce each facial expression, was

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created by psychologists as Facial Action Coding System (FACS) [1]. Table 1 shows AUs used in this work that occur in the lower and upper face and are more important in describing facial expressions.

In recent years, there has been extensive research on facial expression analysis and recognition.

Pantic and Rothkrantz [2] proposed an expert system for automatic analysis of facial expressions from static face images. Their system consists of two major parts, the first one forms a frame work for hybrid facial feature detection and the second part of the system converts low level face geometry into high level facial actions.

Table 1. Some of FACS AUs used in this work

AU (Upper Face)	FACS description	AU (Lower Face)	FACS description
1	Raised inner brows	12	Mouth corners pulled up
2	Raised outer brows	15	Mouth corners pulled downwards
4	Lowered brows	17	Raised chin
5	Raised upper lid	20	Mouth stretched
6	Raised cheek	23	Lips tightened
7	Raised lower lid	24	Lip pressed
9	Wrinkled nose	25	Lips parted
-	-	26	Jaw dropped
-	-	27	Mouth stretched

Lien et al. [3] developed a facial expressions recognition system that was sensitive to subtle changes in the face. The extracted feature information, using a wavelet motion model, was fed to discrimination classifiers or hidden markov models that classified it into FACS action units. The system was tested on image sequences from 100 subjects of varied ethnicity. Average recognition accuracy for 15 AUs in the brow, eye and mouth regions was 81-91%.

Valstar et al. [4] used temporal templates which were 2D images, constructed from image sequences and showed where and when motion in the image sequences has occurred. A K-Nearest Neighbor algorithm and a rule-based system performed the recognition of 15 AUs occurring alone or in combination in an input face image sequences. Their proposed method achieved an average recognition rate of 76.2% on the Cohn-Kanade face image database.

Bartlett et al. [5] used Gabor filters using AdaBoost for feature selection technique followed by classification with Support Vector Machines. The system classified 17 AUs with a mean accuracy of 94.8%. The system was trained and tested on Cohn-Kanade face image database.

In this paper we develop an automatic facial expressions analysis and classification systems. Estimated positions of lips, eyes and eyebrows are determined by using a knowledge based system.

In the first frame of image sequences, 25 Facial Feature Points (FFPs) are automatically detected, using active contours for the lower face and gray level projection method for the upper face. A hybrid tracking system is used to track these FFPs in subsequent frames. An enhanced version of the conventional active contour tracking system is used for lip tracking and a cross-correlation based tracking system is used to track FFPs around eye, eyebrow and nose. Some geometric features are extracted, based on the position of FFPs in the first and the last frames. This features form a feature vector which is used for classifying of input image sequences into 16 AUs using Probabilistic Neural Networks (PNN). A rule-based decision making system is applied to AUs to classify input images into basic emotions.

Proposed features and feature extraction method can also be applied to static images (except features for wrinkled nose). Last frame in image sequences which represents peak of facial expressions is used to train and test of static images recognition system. A local reference parameter is used to normalize extracted geometric features.

Most of the facial expression recognition systems use manually located FFPs in the first frame [3-5]. Our proposed system uses automatically detecting and tracking of feature points. Proposed hybrid tracking system shows robust tracking results both in upper and lower face, which only needs the rough estimated position of eye, eyebrow and mouth.

The system is trained and tested on 180 image sequences, consisting six basic facial expressions on Cohn-Kanade face image database [6].

2 Initial Position of Facial Features

Among the facial features, eye, eyebrow and mouth have important role in expressing facial emotions.

There are three steps in an automatic facial expression recognition system:

- Face detection
- Facial feature extraction
- Facial expression classification

Our proposed algorithm uses four points on top, down, left and right of the face as landmarks and determines automatically the initial position for facial features based on the face height and width using a knowledge-based system.

Knowledge-based system is formed from eyes, eyebrows and mouth position on 97 subjects in Cohn-Kanade face database. Based on this system, three rectangles are located on the face as the initial position for the mouth, the left and right eyes and eyebrows as shown in Fig. 1. These rectangles are big enough to assure that they cover these features in different facial images. Additional process is used for automatically detecting of accurate feature positions and extracting of 25 FFPs. Fig. 1 shows rectangles for initial positions as well as 25 upper and lower face FFPs.

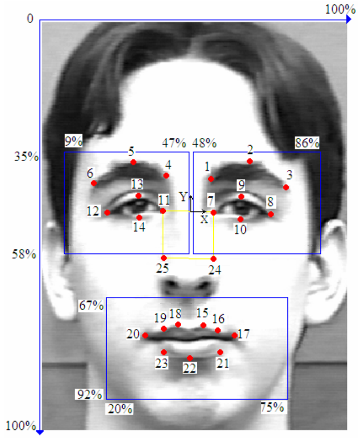

Fig. 1. Initial facial features position and 25 upper and lower face FFPs

2.1 Active Contours for Lip Localization

The active contour model algorithm, first introduced by Kass et al. [7], deforms a contour to lock onto features of interest within an image Usually the features are lines, edges, and/or object boundaries. An active contour is an ordered collection of **n** points in the image plane:

$$V = \{v_1, v_2, ..., v_n\}$$
$$v_i = (x_i, y_i), i = 1,2,...n \quad (1)$$

The points in the contour iteratively approach the boundary of an object through the solution of an energy minimization problem. For each point in the neighborhood of v_i, an energy term is computed:

$$E_i = E_{\text{int}}(v_i) + E_{ext}(v_i) \quad (2)$$

where $E_{\text{int}}(v_i)$ is an energy function dependent on the shape of the contour and $E_{ext}(v_i)$ is an energy function dependent on the image properties, such as the gradient and near point v_i.

The internal energy function used herein is defined as follows:

$$E_{\text{int}}(v_i) = cE_{con}(v_i) + bE_{bal}(v_i) \quad (3)$$

where $E_{con}(v_i)$ is the continuity energy that enforces the shape of the contour and $E_{bal}(v_i)$ is a balloon force that causes the contour to grow or shrink, **c** and **b** provide the relative weighting of the energy terms.

The external energy function attracts the deformable contour to interesting features, such as object boundaries, in an image. Image gradient and intensity are obvious characteristics to look at. The external energy function used herein is defined as follows:

$$E_{ext}(v_i) = mE_{img}(v_i) + gE_{grad}(v_i) \tag{4}$$

where $E_{img}(v_i)$ is an expression that attracts the contour to high or low intensity regions and $E_{grad}(v_i)$ is an energy term that moves the contour towards edges. Again, the constants, **m** and **g**, are provided to adjust the relative weights of the terms.

2.1.1 Two-Step Lip Active Contour

We develop a lip shape extraction and lip motion tracking system, based on a novel two-step active contours model. Four energy terms are used to control motion of control points. The points in the contour iteratively approach the outer mouth edges through the solution of a two-step energy minimization problem. One of the advantages of the proposed method is that we do not need to locate the initial snake very close to lip edges. At the first step active contour locks onto stronger upper lip edges by using both high threshold Canny edge detector and balloon energy for contour deflation. Then using lower threshold image gradient as well as balloon energy for inflation, snake inflates and locks onto weaker lower lip edges. In this stage upper control points were fixed and only lower points inflates to find lower lip edges. Fig. 2 and Fig. 3 show flowchart of proposed two- step algorithm and results.

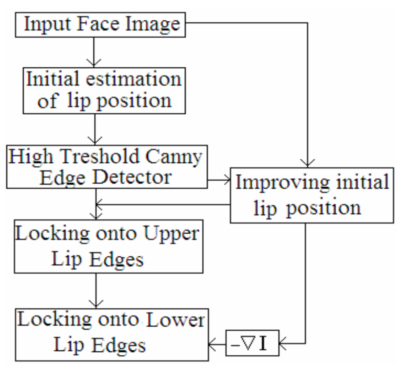

Fig. 2. Two-step active contour algorithm

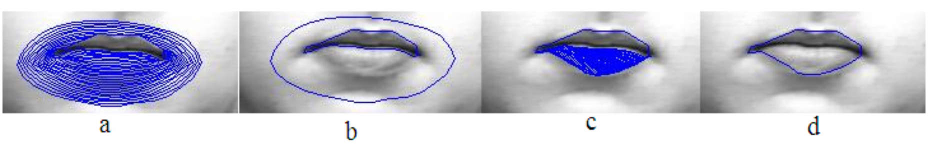

Fig. 3. Two-step lip tracking a) deflating initial snake and finding upper strong edges b) initial and final snake at the end of the first step c) fixing 14 upper control points and inflating 14 lower points to find lower weak edges d) final lip contour

In image sequences two-steps active contour is applied in the first frame (which is supposed that mouth is not open) and then the final snake is used as an initial snake in the next frame. Fig. 4 shows some results of tracking in image sequences.

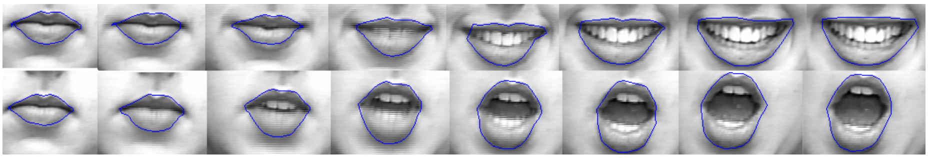

Fig. 4. Lip tracking in image sequences using proposed algorithm

2.2 Detecting FFPs in Eye and Eyebrow

We used gray-level projection method to separate eye, eyebrow and possible hair regions. Using local Min-Max methods on the gray-level, proper thresholds are determined to separate eye, eyebrow and hair regions in the initially located rectangle.

By using horizontal projection and selecting a proper threshold, eye and eyebrow regions in left and right upper faces can be separated. Also hair region is removed using vertical projection and gray level threshold for hair region. After determining eyes and eyebrows and using horizontal Sobel edge detection as well as horizontal and vertical scanning methods, 4 FFPs in eye corners and 3 FFPs in eyebrows are detected. Fig.5 shows vertical and horizontal gray-level projections, thresholds for hair region and eye-eyebrow separation and detected FFPs.

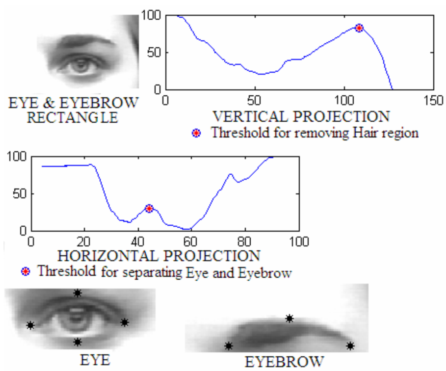

Fig. 5. Vertical and horizontal gray-level projection

3 Hybrid Tracking System

We used our enhanced two-step version of active contours to track lower face FFPs and cross correlation-based tracking system for upper face FFPs in image sequences.

Among the facial expressions, mouth has high flexibility and hard to track its shape and deformation. The use of active contours is appropriate especially when the feature shape is hard to represent with a simple template. Nevertheless, the initial active contour must be located very close to the desired feature. This problem is removed using a novel two-step active contour algorithm. In the first frame, the initial active contour is located using an estimated mouth position and lock on the outer mouth edges using two-step active contours. This contour is used as initial contour in subsequent frames (Fig. 4).

Because of openness of mouth in some static images, the proposed two-step active contour could not be applied and we used the traditional and one-step contours to detect mouth shape in static images.

Active contours method has some problems to use in upper face features. Contours are very sensitive to shadows around eyes and eyebrows.

We used a cross-correlation based tracking system for upper face features. Each upper face FFP is considered as the center of a 11×11 flow window that includes horizontal and vertical flows. Cross-correlation of 11×11 window in the first frame with a 21×21 search window at the next frame is calculated and the position by maximum cross-correlation value for two windows, were estimated as the position of the feature point for the next frame [8] [9].

Fig.6 shows detecting and tracking of upper face FFPs for surprise and disgust expressions.

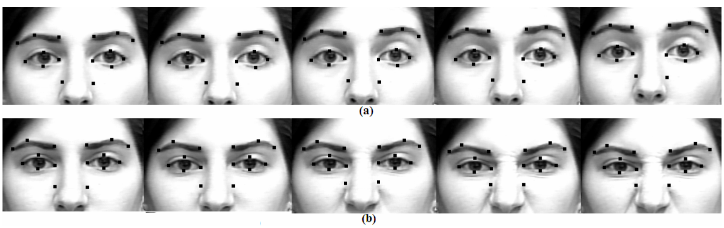

Fig. 6. Tracking of upper face FFPs a) Surprise expression b) Disgust expression

4 Feature Vector Extraction

Extracted feature points are used to extract some geometric feature points to form a feature vector for upper and lower face features.

The following features are extracted for lower face:

- Openness of mouth: average vertical distance of points 15-22 and 18-22 (Fig. 1).
- Width of mouth: horizontal distance of points 17 and 20.
- Chin rise: vertical distance of point 22 from origin.
- Lip corners distance: average vertical distance of points 17 and 20 from origin
- Normalized quadratic curvature parameters for points 15, 16 and 17.
- Normalized quadratic curvature parameters for points 17, 21 and 22.

To calculate and normalize curvature parameters, origin is transferred to point 17 that reduces curvature parameters from 3 to 2, also horizontal distance of points 17 and 22, is normalized to one.

Calculated features form a 8×1 feature vector which is used for classification of lower face action units.

The following features are extracted for upper face:

- Openness of eye: vertical distance of points 9-10 and 13-14.
- Height of eyebrow 1: vertical distance of points 1 and 4 from origin.
- Height of eyebrow 2: vertical distance of points 2 and 5 from origin.
- Inner eyebrow distance: horizontal distance of points 1 and 4.
- Nose wrinkle: vertical distance of points 7-24 and 11-25.
- Normalized quadratic curvature parameters for points 1, 2 and 3.
- Normalized quadratic curvature parameters for points 4, 5 and 6.

To calculate and normalize curvature parameters, origin is transferred to point 2 and 5 in left and right eyebrow that reduces curvature parameters from 3 to 2; also horizontal distance of points 1-3 and 4-6, is normalized to one.

Points 24 and 25 are determined by a square with two vertices on points 7 and 11. These two points are used to track nose wrinkle which is a discriminant feature for disgust expression (Fig. 6). This feature can not be calculated in static images and our proposed system can not detect disgust expression in static images. As it has been shown in Fig.7, without recognizing wrinkled nose (AU9), disgust expression is very close to anger or sad expressions.

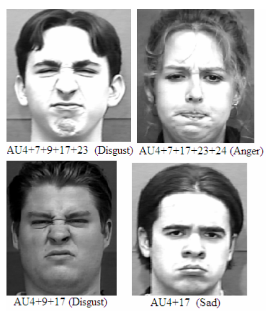

Fig. 7. Comparing Disgust with Sad and Anger expressions

Calculated features form a 9×1 feature vector in image sequences and a 8×1 feature vector in static images which are used for classification of upper face action units.

Mid-Point between inner eye corners is determined as origin.

In the image sequences, calculated features (except curvature parameters) in the first and the last frames are normalized using the following equation:

$$Norm\_fature = (Last\_frame - First\_frame) / First\_frame \tag{5}$$

Last frame in image sequences which represents peak of facial expressions is used to extract curvature parameters.

In the static images, distance of inner eye corners (distance of points 7 and 11 in Fig. 1) is used as a local reference to normalize extracted geometric features to remove the effect of subject-camera distance.

5 PNN Classifier

Probabilistic Neural Networks (PNN) is a variant of the Radial Basis Function Neural Networks (RBFNN) and attempts have been carried out to make the learning process in this type of classification faster than normally required for the multi-layer feed forward neural networks.

The construction of PNN involves an input layer, a hidden layer and an output layer with feed forward architecture. The input layer of this network is a set of **R** units, which accept the elements of an **R**-dimensional input feature vector. The input units are fully connected to the hidden layer with **Q** hidden units (RBF units). **Q** is the number of input/target training pairs. Each target vector has **K** elements. One of these elements is **1** and the rest are **0**. Thus, each input vector is associated with one of **K** classes.

When an input vector is presented in the input layer, the hidden layer computes distances from the input vector to the training input vectors, and produces a vector whose elements indicate how close the input is to a training input. The output layer sums these contributions for each class of inputs to produce its net output as a vector of probabilities. Finally, a compete transfer function on the output of the output layer picks up the maximum of these probabilities, and produces a **1** for that class and **0** for the other classes [9].

6 Experimental Results

The Cohn-Kanade database consists of expression sequences of subjects, starting from a neutral expression and ending with the peak of the facial expression. Subjects sat directly in front of the camera and performed a series of the facial expressions that included the six primary and also some single AUs. We used a subset of 180 image sequences containing six basic emotions for 30 subject emotions. Those AUs which are important to the communication of the emotion and were occurred at least 25 times in our database are selected. This frequency criterion ensures sufficient data for training and testing. For each person there are on average of 12 frames for each expression (after eliminating alternate frames). Image sequences for the frontal views are digitized into 640×490 pixel array with 8 bits grayscale [6].

6.1 Recognition of Upper and Lower Face AUs in Image Sequences

We used the sequence of 144 (80%) subjects as training sequences, and the sequence of the remaining 36 (20%) subjects as test sequences. This test is repeated five times, each time leaving different subjects out. The number of the input layer units in the lower face PNN classifier is equal to 8, the number of extracted features, the number of the hidden layer units equals to 144×9, the number of training pairs and that of the output layers is 9, which corresponds to selected 9 lower face AUs.

The number of the input layer units in the upper face PNN classifier is equal to 9, the number of the hidden layer units equals to144×7, and that of the output layers is 7, which corresponds to the selected 7 upper face AUs.

Table 2 shows the recognition rate of lower and upper face AUs.

Table 2. Recognition results for lower and upper face AUs in image sequences

Lower Face AUs		Upper Face AUs	
AU12	31/35 %88.57	AU1	52/65 % 80
AU15	27/29 %93.10	AU2	35/39 %89.74
AU17	73/82 %89.02	AU4	77/91 % 84.61
AU20	26/30 %86.67	AU5	30/32 %93.75
AU23	24/29 %82.76	AU6	31/38 % 81.58
AU24	23/32 %71.88	AU7	51/56 % 91.07
AU25	52/59 %88.14	AU9	30/31 % 96.77
AU26	6/10 %60.00	-	-
AU27	20/22 %90.91	-	-
Average	282/328 %85.98	Average	306/352 %86.93

Comparing to some related works [10, 11], results are encouraging.

6.2 Recognition of Six Basic Facial Emotions in Image Sequences

After classifying facial expressions into AUs, we tried to classify them to basic emotions which comprise happiness, sadness, fear, disgust, surprise, and anger.

There is no unique AUs combination for these emotions. Based on manual FACS codes for Cohn-Kanade database, a rule-base is constructed to classify facial expressions based on analyzed lower and upper face AUs. Table 3 shows this rule-bases and Table 4 shows classification results.

Table 3. Rule-bases for basic emotions classification

IF	**THEN**
(AU23=1 OR AU24 =1) AND AU9=0	Anger
AU9=1	Disgust
(AU20=1 AND AU25 =1) OR (AU20=1 AND AU26 =1)	Fear
AU12=1	Happiness
AU15=1 AND AU17 =1	Sadness
AU27=1 OR (AU5=1 AND AU26 =1)	Surprise

Table 4. Recognition rate of six basic emotions in image sequences

Anger	27/30 90%
Disgust	30/30 100%
Fear	30/30 100%
Happiness	30/30 100%
Sadness	26/30 86.67%
Surprise	30/30 100%
Average	173/180 96.11 %

Comparing to some related works [11, 12, 13], results are encouraging.

6.3 Recognition of Upper and Lower Face AUs in Static Images

Our proposed system can not detect wrinkled nose (AU9) and disgust expression in static images.

Last frame in image sequences which represents peak of facial expressions is used to train and test of static images recognition system. We left out input images for disgust expression.

We used the images of 120 (80%) subjects as training sequences, and the remaining 30 (20%) subjects as test images. This test is repeated five times, each time leaving different subjects out. The number of the input layer units in the lower face PNN classifier is equal to 8, the number of extracted features, the number of the hidden layer units equals to 120×9, the number of training pairs and that of the output layers is 9, which corresponds to selected 9 lower face AUs.

The number of the input layer units in the upper face PNN classifier is equal to 8, the number of the hidden layer units equals to120×6, and that of the output layers is 6, which corresponds to the selected 6 upper face AUs.

Table 5 shows the recognition rate of lower and upper face AUs.

Comparing to some related works [14], results are resonable.

Table 5. Recognition results for lower face AUs in static images

Lower Face AUs		Upper Face AUs	
AU12	31/35 %88.57	AU1	45/65 % 69.23
AU15	26/29 %89.66	AU2	29/39 %74.36
AU17	46/60 %76.67	AU4	43/64 % 67.19
AU20	18/30 %60.00	AU5	26/32 %81.25
AU23	18/26 %69.23	AU6	14/31 % 45.16
AU24	18/30 %60.00	AU7	24/33 % 72.73
AU25	42/55 %76.36	-	-
AU26	7/10 %70.00	-	-
AU27	22/22 %100	-	-
Average	228/297 %76.77	Average	181/264 %68.56

6.4 Recognition of Five Basic Facial Emotions in Static Images

Table 6 shows recognition results for five basic expressions (leaving out the disgust expression) using the same rule-base (Table3) and lower and upper face AUs in static images.

Table 6. Recognition rate of five basic emotions in static images

Anger	30/30 100%
Fear	23/30 76.67%
Happiness	30/30 100%
Sadness	29/30 96.67%
Surprise	29/30 96.67%
Average	141/150 94 %

7 Conclusion

In this paper we developed an automatic facial expressions analysis and classification systems with high success rate. Our image and video analysis includes automatic feature detection, tracking and the results are directly used for facial emotion classification based on AUs analysis and classification. An average recognition rate of 96.11% was achieved for six basic emotions in facial image sequences.

In the first frame, 25 Facial Feature Points (FFPs) were automatically detected, using active contours for lower face and gray level projection method for upper face. A hybrid tracking system was used to track these FFPs in subsequent frames. An enhanced version of active contour tracking system was used for lip tracking while a cross-correlation based tracking system was used to track FFPs around eyes and eyebrows.

Some geometric features were extracted, based on the position of FFPs in the first and the last frames. This features formed a feature vector which was used for classification of input image sequences into 16 AUs, using PNN. A rule-based decision making system was applied to AUs to classify input images into six basic emotions.

Proposed features and feature extraction method can also be applied to static images (except features for wrinkled nose) using a local reference to normalize these features in order to remove the effect of subject-camera distance. An average recognition rate of 94% was achieved for five basic emotions in static face images.

While most of the facial expression recognition systems use manually located FFPs in the first frame, our proposed system used automatically detection and tracking of feature points. Proposed hybrid tracking system showed robust tracking results both in upper and lower face, which only needed the rough estimated position of eye, eyebrow and mouth. Our proposed new features improved AUs recognition rate as well as six basic emotions recognition rate.

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