Analysis of Facial Expressions Based on Silhouettes

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Abstract

Non-verbal communication plays an important role in human communication. At the Delft University of Technology there is a project running on the automatic recognition of facial expressions. The developed system ISFER (Integrated System for Facial Expression Recognition) consists of modules suited for the analysis of a frontal view of the face. As the obtained results are still far from being perfect we present in this paper a new complementary approach based on a lateral view of the face. The underlying model is based on the silhouette of the facial profile with 10 characteristic points on specific places. The points are chosen so that using Matlab tool we can assess their locations as extreme points on the silhouette. From this information emotional facial expressions can be classified up to some degree using expert systems or neural networks. The new model and results of testing are reported in this paper.

1 Introduction

About 70% of human communication is based on non-verbal communication such as facial expressions and body movements. In long distance communication there is a need to use real-time multimedia. But adding moving pictures to text or speech puts a high demand on the technical infrastructure. A strong reduction of the huge amount of data is necessary. One approach to achieve the above goal is to perform a real-time automatic analysis of the pictures with facial expressions and to transfer only the extracted features or parameters. At the side of the receiver the image can be reconstructed again [1].

Since 1992, the Knowledge Based Systems group of TU Delft is researching the automatic analysis of facial expressions [2]. In the course of the years a lot of working prototypes have been developed for different parts of the process of analyzing the face. Some of these prototypes are based on neural networks and fuzzy logic, while others are based on image processing techniques. Recently all the modules were integrated in an Integrated System for Facial Expression Recognition (ISFER) workbench [3].

All the so far developed modules are based on analysis of a frontal view of the face. As we know from earlier research, person identification can be achieved using a lateral view of the face [4]. So it seems reasonable to develop a module based on a lateral view of the face also for our system. We suggest the analysis of a lateral view of the face to be based on the analysis of the facial silhouette in this view. We chose that approach because a silhouette is very characteristic for a lateral view of the face and finding the contour of the face profile is much simpler than tracing e.g. the contours of fuzzy regions as eyes, eyebrows or mouth.

For years the classification of facial emotional expressions is a dominant theme in psychological research. So, to test our model we used emotional facial expressions.

2 Related research

At this moment there are many researchers involved in projects concerning non-verbal communication. Recently R. Cipola and A. Pentland presented an overview of advances in ongoing research [5].

Researchers from MIT work currently not only on recognition of facial expressions but also on the project that aims at designing environments with which people can communicate (so called smart rooms). Several prototypes have already been developed [6],[7].

In the framework of a program around artificial life researchers from the University of Pavia developed a system to generate and to recognize facial expressions. The system is based on neural networks and genetic algorithms [8].

The most ambitious project on non-verbal communication is running at the University of Kyoto. The goal of the project is to explore basic technologies for realistic multimedia communication and to design hyper-realistic communication environments for better sharing thoughts and images between human and machines. A well-known

Table 1. Description of Ekman's basic emotions

Emotion	Facial Feature	Action Unit
Surprise	Eyebrows are raised	AU1, AU2
	Upper eyelid is raised slightly	AU5
	Jaws dropped; mouth opened	AU26
Fear	Eyebrows are raised high and pulled together	AU1, AU2, AU4
	Upper eyelid is raised; lower eyelid tightened	AU5, AU7
	Mouth dropped open, lips are stretched horizontally	AU20, AU26
Disgust	Nose is wrinkled so that lips are parted	AU9
	Upper lid is raised	AU10
	Lower lip is pulled down	AU16
	Tongue is moved forward in the mouth and can be put out	
Anger	Eyebrows are pulled together down	AU4
	Upper eyelid is raised	AU5
	Lower eyelid is tightened, but upper eyelid is kept raised	AU7
	Lips are tightened, pushed up and pressed together	AU23, AU24
Happiness	Cheeks are raised	AU6
	Corner of the lips are raised	AU12
Sadness	Inner corners of eyebrows are raised and pulled down	AU1, AU4
	Corners of the lips are pulled down	AU15
	Cheeks are raised; lip corners are pulled down	AU6, AU12

prototype is Neuro-Baby '95. This animated baby is able to recognize and to respond to emotional expressions and emotions in the voice and on the face of the communicator [9].

3 Theory on emotions

Facial expressions are generated by contraction or relaxation of facial muscles or by other physiological processes such as coloring of the skin, tears in the eyes or sweat on the skin. We restrict ourselves to the contraction or relaxation of the muscles category. In 1978 P. Ekman [10] developed a comprehensive system to describe and measure all possible visually distinguishable facial movements in any context. The contraction or relaxation of muscles can be described by a system of 43 Action Units (AUs). The activity of these AUs can be assessed in a direct way by measurements of the electrical activity in the muscles. A less invasive non-direct way is a measurement on the basis of changes in visible facial features. Possible features are e.g. the distance between the upper and lower lid of the eye, the position of the corners of the mouth or the curvature of the brows or wrinkles in the face. From these changes the activity of the underlying muscles can be concluded.

A key stone in the automatic recognition of facial expressions is the set of emotional facial expressions. In Ekman's study [11] six basic emotions are defined: surprise, fear, disgust, anger, happiness and sadness. It is an ongoing dispute between psychologists whether this set of emotions is universal or not. In Table 1 a description is given of the basic emotions in terms of facial features and activated AUs.

From the Table 1 we can conclude that the changing features are located in the regions around the mouth, eyes, and eyebrows. So an automated tool for classification of facial expressions should be based on the analysis of these parts of the face.

The Facial Action Coding System (FACS) of Ekman and Friesen is generally accepted. A lot of facial feature models have been developed [12],[13]. Although all these models are based on the frontal 2-D view of the face, the facial expressions involve in fact 3-D movements. So, a 3-D feature model is more appropriate. Especially movements along the axis perpendicular to the frontal plane result in minimal movements after projection on the view plane. The 3-D movements of the muscles do not imply the choice of the projection plane. Therefore, we set about to investigate the lateral view of the face.

4 Classification of emotional expressions by human

Human communication is mostly based on frontal communication. So, the classification of lateral views of facial expressions seems even for human an unusually difficult job. We guess that lateral views are mentally rotated to frontal views and then classified. There is some psychological evidence for that hypothesis [14].

In order to assess the rate of recognition of emotions by human observers from lateral views we confronted 50 students from Delft University of Technology with 49 pictures of emotional facial expressions. The respondents were requested to classify the expressions. Every picture should be labeled with one of the basic emotions or classified

Table 2. Rate of recognition by human observers

	Anger	Disgust	Fear	Happiness	Neutral	Surprise	Sadness	Unknown
Anger	67%	9%	8%	1%	-	3%	2%	10%
Disgust	11%	61%	5%	1%	-	5%	13%	4%
Fear	1%	2%	23%	0%	-	41%	5%	27%
Happiness	0%	0%	1%	83%	-	4%	1%	12%
Neutral	0%	0%	3%	6%	-	0%	17%	71%
Surprise	0%	0%	16%	1%	-	65%	0%	16%
Sadness	6%	1%	1%	0%	-	7%	65%	20%

as undefined. The results of this survey are reported in Table 2.

We conclude that the overall recognition of a lateral view is about 61%. We also know that the recognition of a frontal view is significantly higher and more than 75%. So, the results show that although the recognition rate of a lateral view is smaller than the frontal one, it is still high enough to make it interesting to develop a model for automated facial expression recognition in this view.

5 Automatic classification of emotional expressions

The aim of our research project is to design and implement an automated system for the recognition of facial expressions. To get an idea how to model such a system we observed the way human observers make an analysis of facial expressions. If we present a picture with a facial expression to a human observer, probably he recognized the expression and is able to classify the expression. During his education he is trained to label expressions in the appropriate way.

If the picture is ambiguous, the observer starts reasoning about it. From the thinking aloud protocols in our experiment we noticed that human observers have some memory or hypothesis about emotional expressions. On the basis of the most salient, dominate features they make a classification. To emulate the behavior of the human observer in our system we designed two modules.

In the first module neural networks are used. We have to train a neural network with labeled expressions in the same way as humans are educated to classify these expressions. In the second module expert systems are used. The face is reduced to the contours of essential features. We extract the parameters describing these contours. The changing contours correspond with different expressions. The correspondence between the parameters and the emotions can be described by "if-then" rules. We developed prototypes for both modules, which we describe now.

6 Automatic classification of emotional expressions using neural networks

From Table 2 based on human observations, we concluded that it is possible to classify emotional expressions from a lateral view. The question remains what should be extracted from the lateral view so that the classification could be done automatically. We decided for different reasons to use only the profile data (a silhouette of lateral view of the face). In the experiment, respondents reported that the information on eyes/brows in lateral views is very fuzzy, but the silhouette is very sharp.

The binarized image of a face was scanned horizontally in order to locate the profile of the face.

anger surprise sadness happiness

Figure 1. Pictures with emotional expressions

Table 3. Rate of recognition on the training set

	Anger	Disgust	Fear	Happiness	Neutral	Surprise	Sadness	Unknown
Anger	46%	15%	0%	0%	38%	0%	0%	0%
Disgust	0%	62%	0%	19%	19%	0%	0%	0%
Fear	0%	0%	64%	14%	14%	7%	0%	7%
Happiness	0%	13%	0%	73%	7%	7%	0%	0%
Neutral	7%	13%	0%	7%	67%	0%	7%	0%
Surprise	0%	0%	7%	7%	21%	64%	0%	0%
Sadness	8%	8%	0%	23%	8%	0%	54%	0%

Table 4. Rate of recognition of the test set

	Anger	Disgust	Fear	Happiness	Neutral	Surprise	Sadness	Unknown
Anger	20%	0%	0%	20%	40%	0%	20%	0%
Disgust	0%	50%	0%	0%	33%	17%	0%	0%
Fear	0%	20%	60%	0%	20%	60%	0%	0%
Happiness	0%	17%	0%	83%	0%	0%	0%	0%
Neutral	33%	0%	0%	17%	33%	0%	17%	0%
Surprise	0%	0%	17%	17%	0%	67%	0%	0%
Sadness	17%	0%	17%	0%	0%	0%	67%	0%

An extreme point of the profile was then taken as the tip of the nose and the profile was sampled in 40 points to provide input data for the network. To train the network we captured 140 pictures of a lateral view of the face. The pictures were taken using CCD camera on the black background with only head and shoulders within the picture (see Figure 1). From all this data we have chosen randomly 100 samples and used them for the training of the network. The remaining 40 samples were used as test data.

We trained a feed-forward neural network using the error back propagation algorithm. The experiments were done using the well known SNNS (Stuttgart Neural Network Simulator) tool. In Table 3 and Table 4 we report the results of training and testing.

It is worth noticing that a lot of emotions were recognized as a neutral face. It results from the fact that people, who were asked to play emotions, were not professional actors. Sometimes they had problems with showing expressive emotions (especially anger). And in such cases the network reacted as for neutral face. When none of the outputs of the network was sufficiently high the emotion was classified as unknown.

It proved that the recognition rate of the training set was about 61% while for the test set it scored about 54%. As expected human observers score better. But taken into account that human observers have used more information, the score of automatic recognition isn't too bad. From the above results we can conclude that using just information from the face profile is enough to base on it an automated system for facial expression recognition.

7 Model

Our model of a lateral view of the face has to fulfill some requirements:

anger disgust fear happiness sadness surprise

Figure 2. Silhouette with emotional expressions

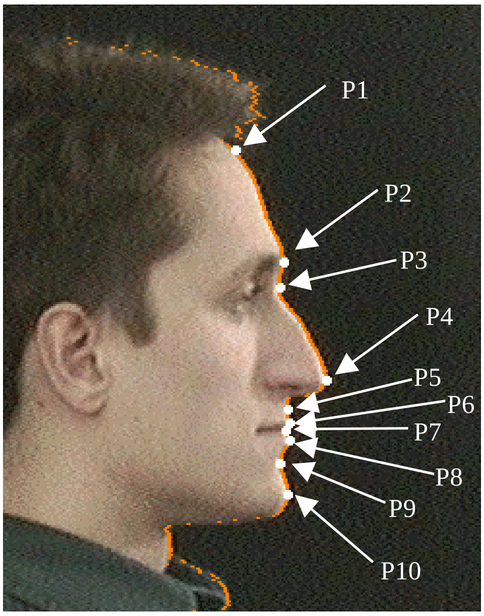

Figure 3. The characteristic points on the silhouette contour

- it should be a basis for automatic extraction of specific features,
- it should be a basis for the classification of emotional facial expressions.

In order to develop a model for lateral views of the face we analyzed a set of 140 pictures of emotional expressions. We compared lateral emotional expressions against the neutral expression of the corresponding person (see Figure 2). We found that different emotions can be classified by tracing changes of contours of the eyes, eyebrows, chin and cheek line [15].

As we presented in the previous section the automated recognition of facial expressions can be done using only the silhouette of lateral view of the face. So we defined points on specific locations of this contour. We noticed that if we rotate the graph of the contour to some fixed position, the points correspond to the peaks and the valleys in the graph. It offers the possibility to use mathematical tools (e.g. Matlab) to locate maximum and minimum points or points of extreme curvature in an automated way. In this way the points P2 - P10 can be found. Point P1 ? Algorithm for finding these characteristic points on the silhouette is described in the section “Extreme searching algorithm”. The co-ordinates of those points can then be used to classify an emotional expression and to characterize a general expression.

Our model of the lateral facial view is presented in Figure 3. The characteristic points are defined as follows:

P1: *Top of forehead* - the beginning of the forehead line. This point corresponds to the point where the hair started.

P2: *Eyebrow* - the point where the eyebrow contacts the profile.
P3: *Valley below the eyebrow* - the point with maximum curvature in front of the eye.
P4: *Tip of the nose* - the point with maximum curvature on the top of the nose.
P5: *Valley bellow the nose* - the point of maximal curvature of the line below the nostrils.
P6: *Upper lip* - the point with maximum curvature of the upper lip.
P7: *Valley between lips* - the point with maximum curvature between the upper and lower lips.
P8: *Lower lip* - the point with maximum curvature of the lower lip.
P9: *Valley below the lower lip* - the point in the valley with maximum curvature.
P10: *Tip of the chin* - the point with maximum curvature in the chin.

If the contour is changing the points P1-P10 are changing too. But it is important to note that the points P1-P10 are changing points along the contour. So if we mark the location of these points in the neutral position with stickers on the skin, the sticker doesn’t necessarily correspond with the points P1-P10 in pictures of different emotions.

As we mentioned before, a similar model was developed by Harmon [4]. He used face profiles in a face recognition system. In his model from the characteristic points a set of features were calculated, such as distances between the points, angles between them and areas of some triangles formed by some of these points. But we note that face recognition and recognition of facial expressions are different tasks. Personal characteristics such as the length of the nose can be considered as noise in the recognition of facial expressions and in the other way around facial expressions can be considered as noise in person identification.

8 Qualitative assessment

As we noted already most researchers in the field of facial expressions use the FACS system. To apply the results of their research we have to find a relation between the characteristic points P1-P10 and the Action Units. In a neutral face no AU is activated. If one of the AUs is activated we might expect that one or more points are moving from their default position. To find the requested relations we analyzed a set of pictures of facial expressions with only one AU activated. Next a comparison was made by analyzing the position of each of the characteristic points in relation to the original position of the neutral picture. Pictures were overlapped so by visual inspection it could be observed if a characteristic point was going up, down, back or in front, comparing to the neutral position. In Table 5, the results of the comparison study are presented.

Table 5. Relation between the activated AUs and position of the characteristic points

AU1	Inner Brow Raiser	P2	Up
AU2	Outer Brow Raiser	P2	Up
AU4	Brow Lowerer	P2	In Front
AU5	Upper Eye Lid Raiser	?	
AU6	Cheek Raiser	P7	Up
AU7	Lid Tighter	?	
AU9	Nose Wrinkler	P2,P5	In Front
AU10	Upper Lip Raiser	P6	Up
AU12	Lip Corner Pulled	P7	Back
AU15	Lip Corner Depressor	P7	Down
AU16	Lower Lip Depressor	P8	Back/Down
AU20	Lip Stretcher	P7	Back
AU23	Lip Tighter	P6/P8	Down/Up
AU24	Lip Presser	P6/P8	Down/Up
AU26	Jaw Drop	P7/P10	back/Down

From Table 5 can be concluded that activation of AUs related to the eyes does not result in changing positions of one of the characteristic points. The eyes and as a consequence the movements of the eyes are not tractable in a silhouette contour. But in the case of an emotional facial expression, we can say that AUs are activated with a redundancy. For one emotion a few AUs are involved. Thanks to this redundancy for example the information about the movements of the eyes can be omitted and yet the emotional facial expression can still be recognized. Therefore, we expect that classification on the basis of chosen characteristic points is possible at least to some extent.

9 Automatic classification of emotional expressions using expert systems

We mentioned already that facial expressions could be fully described by Action Units. The set of AUs is a universal set of parameters. So if we know which AUs are activated we can derive by reasoning which emotions are involved by applying the expert system. In our group such an expert system for the automatic recognition of emotions from frontal view based on AUs was already developed [13].
The AUs are related to the activation and relaxation of muscles. So the activation of AUs can not be assessed from visual inspection. From the changing positions of characteristic points we have to conclude which AUs are activated. So the next step is to find a relation between the position of the characteristic points and the activation of AUs.
In Table 5 we reported some of the results of our study on the relation between AUs and profile characteristic points. Next we transformed this knowledge in “if-then”-rules. We compute the distance of the changing positions of some characteristic point from a neutral expression to an emotional expression. If this distance surpassed a certain threshold then we conclude that the corresponding facial feature is activated.

We developed a prototype of an expert system using (Fuzzy) CLIPS. The expert system was based on an extended model of the characteristic points. The model includes characteristic points around the contours of eyes and mouth. The input of the system is information about the positions of the characteristic points and the output of the system is one of 6 of the Ekman’s emotions.
In the theory of Ekman only full emotions are analyzed, i.e. an AU can be activated or not. In reality there is a gradual change in the activation of the AUs. The distance between the changing positions of the characteristic points is a metric parameter too. The next step is to develop an expert system based on continuous change of the characteristic points and strength of activation of the AUs. To develop a fully functional fuzzy expert system for the relations between characteristic points and AUs we need a lot of data to set the parameters. We will report about the results in next future.

10 Extreme searching algorithm

As we mention in section 7, in order to fully automate the emotional facial expression recognition we developed an algorithm to locate the characteristic points. We mentioned already the advantages of the face profile processing such as moving from image- to vector-processing. All algorithms have to deal with considerably reduced amount of information, which obviously leads to a faster system response.
The algorithm was firstly implemented in the Matlab framework and secondly in the ISFER workbench. That last framework allows the module developer to choose between writing modules in C, C++ or Java languages. This flexibility is achieved using Java Native Interface (JNI) which allows calling programs native to an operating system on which the framework works from a Java-based GUI. Modules written in C or in C++ execute usually much faster than Java modules but writing them requires the use of intermediate classes and structures according to JNI specification. In our case we decided to profit from the simplicity of integrating Java-based modules in the framework and chose Java as a programming language.
We describe here the algorithm shortly. For further details we refer to [16].

Image preprocessing

In our approach we didn't use any noise removal techniques. Those are usually time-consuming and therefore not suited for our task. Instead more effort was put on developing noise-independent tools in further preprocessing steps.

Segmentation of the head

The input image must be first binarized to simplify further processing. We solve this task by simple thresholding. In the developed framework of the

Table 6. Frequency of searched extreme points with and without use of a-priori knowledge

Number of extremes found	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
search without knowledge	3					6		6		6			15		15	30			12		6
search with knowledge	4	29	23	20	13	10	3	1													

modules the threshold value is fixed but it may also vary according to the actual image histogram. In the ISFER workbench there is already a module available for image processing with a more complex background This module is based on a-priori knowledge about the skin color and head position [17].

Nose localization

The nose is the most important referential point in our model so its proper localization is a matter of fundamental importance. As we know that the head on the input image is turned to the right we search the nose as the most right part of the image. To exclude the hairy part of the head from processing we limit the nose-searching algorithm only to the lower part of the head.

Chin localization

The bottom of the chin is another important point in the face profile. From following image analysis can be seen that the chin is the first from the bottom distinct minimum in the vector of summed background pixels. The algorithm for chin localization is performed on the sub-image clipped from the segmented head image.

Extraction of face profiles

To extract the face profile we have to solve the problem of face rotation. In the Matlab algorithm we have solved this problem using the convex hull. Later on we replaced the convex hull by the line between two distinct points. We used the line between the tip of the nose and the chin points as the *x*-axis of the new coordinate system. Although for some emotions tip of the chin changes position e.g. when opening mouth in surprise, it doesn't influence the algorithm significantly. The number and the relative positions of peaks and valleys in the graph of the contour remain the same. This approach considerably speeded up the process of region extraction.

Contour extraction

To obtain a contour from a binary image we simply count the number of background pixels between the right edge of an image and the first foreground pixel. In this way we obtain a vector which represents a sampling of a contour curve. The contour description obtained in this way from the image contains a lot of noise, which could complicate further processing. To remove this noise we perform an average procedure with use of a three-pixel wide window, which is slided along the vector.

Searching of extremes

The zero crossing of the first derivative of the face profile function defines extremes. We usually find many extremes that correspond to local profile changes. From Table 6 can be seen that the most frequent is the number of 20 extremes. We used a-priori knowledge about extreme alternation to remove redundant information. Each minimum must be preceded and followed by a maximum. We started the rejection algorithm for the global maximum and not from the fuzzy terminal extremes. The list of extremes is processed in both directions from it. The decision about particular extreme rejection is made using two consecutive records in the list. In such a way we get the list of extremes which are expected to reflect the most distinct peaks in the face profile. From Table 6 we can see that there are usually six or more extremes. The points P3, P4, P5, P6, P7 (if the mouth is open) P8, P9 are almost always included. The region around the chin and above the brows shows one or many extremes. There can be more than one wrinkle above the brows and the region of the chin can have some local extremes. Using the a-priori global position of the points P1 to P10 we come to an exact localization of those points. If the points P1 to P10 are defined not as extreme points but as points with extreme curvature we proceed in a similar way.

11 Conclusion

In order to develop an automatic classification system for 3-D data of facial expressions we analyzed lateral views of facial expressions. We developed two prototypes for the automatic classification of emotional expressions and one prototype for preprocessing the data.

The first prototype was based on neural networks. The basic emotions could be recognized up to 60% on the basis of a face profile. The second prototype was an expert system based on the changing positions of some specific points. Both prototypes can be used for almost real time classification of emotional facial expressions. The main advantage of the profile analysis is that that we can move from image to vector processing. The main idea in the profile analysis is to use mathematical characteristics of the face profile.

In the paper [18] we combine the results of research on frontal and lateral view. We expect that the data extracted from the frontal and lateral view will complement each other. And the redundancy in both data sets can be used to improve the reliability of the extracted data. The results of analysis will also be used to develop a system to generate 3-D facial expressions. Both systems will be used in the development of multi-modal user interfaces.

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