Real-Time Facial Expression Recognition Using a Fuzzy Emotion Model

Natascha Esau, Evgenija Wetzel, Lisa Kleinjohann and Bernd Kleinjohann

Abstract— **This paper presents the fuzzy video based emotion recognition system VISBER, that allows to analyze facial expressions in video sequences. In order to process images in real-time a tracking mechanism is used for face localization. The fuzzy classification itself analyzes the deformation of a face separately in each image. In contrast to most existing approaches, also blended emotions with varying intensities as proposed by psychologists can be handled. For this purpose we propose a fuzzy emotion model which is generally applicable for also for other emotion recognition solutions. Furthermore, VISBER supports the automatic adaptation to the characteristics of individual human faces by a short training phase that can be done before the emotion recognition starts.**

I. Introduction

Emotions are an evident part of interactions between human beings. But also for interactions of humans with computer systems emotions play a major role, since humans can never entirely switch off their emotions. During the last years interest in emotions increased considerably in various domains of computer based systems. Examples are robots or virtual agents that show emotions or human-computer interfaces that consider human emotions in their interaction capabilities. In Japan an entire stream called KANSEI information processing [12] deals with subjective human feelings when interacting with IT systems. These few examples already reveal two major tasks of emotion processing in IT systems, the *recognition of human emotions* and the *(re)production of artificial emotions*. This paper focuses on recognition of human emotions from facial expressions.

For emotion recognition two major types of emotion models can be distinguished (also mixtures of these types are found): models that rely on basic emotions and emotion models that classify emotions according to different dimensions like valence, potency, arousal or intensity. The first one has a major advantage for automatic emotion recognition, since it considerably decreases recognition complexity due to a small number of basic emotions to which the recognition can be restricted. Therefore we selected it for our emotion recognition system VISBER (VIdeo Based Emotion Recognition).

VISBER uses a fuzzy rule based approach for emotion recognition from facial expressions. It classifies an image from a video sequence into a set of basic emotions (happiness, sadness, anger, fear) with corresponding intensity as it is proposed by many psychologists. An overview of psychological work on basic emotions can for instance be found in [19]. In VISBER the classification results are represented by means of a fuzzy emotion model that also allows to handle blending of emotions. This solution is integrated into our robot head MEXI [8] in order to support emotional communication with humans. Hence, a major challenge was its real-time capability and low resource-consumption. These requirements motivated our rule based approach that uses single images taken from a video sequence to classify emotions. However, since we have video sequences as input we use a tracking mechanism for face localization to reduce the time needed for analysis of a single image.

After a presentation of related work, we give an overview of VISBER in Section III. Sections IV and VI concentrate on the fuzzy emotion model and the fuzzy rule based classification of emotions, while Section V illustrates the representation of facial data. Section VIII describes implementation and results and Section IX concludes the paper with a summary and outlook.

II. Related Work

Systems for classification of facial expressions can be characterized whether they analyze movements or differences of facial expressions in an image sequence ([3], [4], [5], [9], [17], [23]) or with respect to a reference image of the neutral expression ([22], [24]) or whether they analyze the "deformation" of a single facial expression ([6], [13], [16], [25]). Many systems belonging to the first group of systems [3], [4], [5], [9], [17], [23] rely on the Facial Action Coding System (FACS) [7] developed by Ekman and Friesen. It allows to analyze facial movements in terms of 44 so called Action Units (AU). An AU corresponds to an atomic muscle action like the raising of one corner of the mouth. Optical flow ([9], [24]), feature point tracking ([5], [17], [22]) or difference images [10] are used to analyze the movements within the face. Only the approaches described in [3], [17], [22], [23] use rule based mechanisms for classification like the work described in this paper.

However, our approach belongs to the second group of approaches that analyze the deformation from single images. Also that group often relies on the findings of Ekman and Friesen to characterize typical deformations for certain emotions. For classification often statistical methods are used. However, earlier approaches relying on Linear Discriminant Analysis ([6], [16]) are not real-time capable. Recent results using Support Vector Machines (SVM) for facial expression classification already work in real-time ([15], [1]) but they

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analyze face motions. Also neural nets or a combination of neural nets and fuzzy rules [13] are described.

We realized a fuzzy rule based approach, since we already successfully applied it for emotion classification on the basis of natural speech [2]. Our approach uses a feature based representation of facial data for classification like [5], [17], [25] in contrast to holistic face models that often rely on Gabor filters [16] which are very time consuming in computation. It classifies single images taken from an image sequence with respect to four basic emotions anger, fear, happiness, sadness and the neutral state. However, in contrast to most existing approaches it also allows to represent a blend of these emotions.

III. Overview

The fuzzy facial expression recognition system VISBER is able to classify facial expressions from image sequences sampled with a frame rate of 30 fps (frames per second) by a usual web camera in real-time. As input it receives images with the size of 320 x 240 pixels in the YUV 4:2:2 format, which are processed by the steps as depicted in Figure 1. When developing VISBER a major challenge was its real-time processing capability on resource bounded hardware. Therefore, VISBER uses a tracking mechanism for face localization if the face position in the actual image does not deviate too much from the previous one. However, the fuzzy classification of facial expressions is independently done for each image.

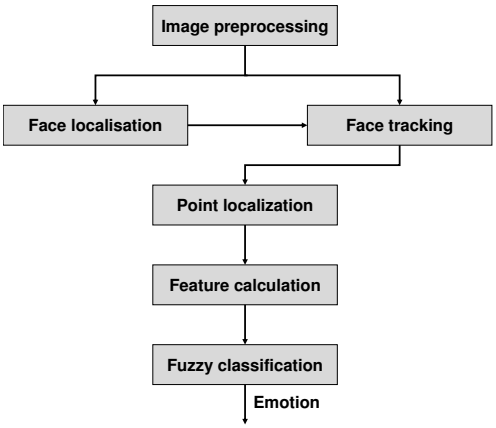

Fig. 1. Architecture of Fuzzy Facial Expression Recognition

As a first step *image preprocessing* takes place. After normalization of contrast and luminance, color segmentation and region analysis are done. Since color-segmentation has to process the huge amount of 76800 pixels per image, we use a real-time capable algorithm based on moments of up to second order for region representation [21]. Afterwards the color of each region is compared to the skin color to detect potential face regions. The largest detected skin colored region is then processed by the *face localization*, to verify whether it really contains a face. For face localization we rely on a template based approach described in [20]. We extended it by supporting three experimentally determined scaling factors for the template in order to localize faces with different size. The localization determines the position and the scaling factor of the matched template.

Since this step is very time-consuming we use the fact that VISBER works on image sequences to substitute it by a *face tracking* based on the pupils of the eyes whenever some prerequisites described below are fulfilled. We use the pupils for face tracking since they can be easily determined with high accuracy. Since the positions of a face differ only a few pixels between subsequent images, also the search regions to be analyzed for tracking of the pupils are very small. We use search regions of 12x12 pixels. Hence after a face has been successfully localized, for subsequent images at first fiducial points for the pupils, and depending on these for the nose tip and the corners of the mouth are determined. As prerequisites for face tracking we check whether the fiducial points for pupils and nose tips have certain color characteristics, both pupils are not located near the image borders, their relative positions are correct and the mouth region lies within the face region. These conditions were experimentally determined.

Afterwards the *point localization* determines the positions of the remaining fiducial face points for eye brows and lips (see Figure 2). In total we use twelve fiducial points that are needed by the *feature calculation* step to calculate the geometrical features used by the *fuzzy classification*.

Fig. 2. Fiducial Face Points

For classification of facial expressions we developed a fuzzy rule base that classifies facial expressions based on typical angles between fiducial points. The choice of angles for classification provides a size invariant classification and saves the effort for normalization. Our approach allows an easy adaptation to facial characteristics of a certain person by an automatic training phase of less than five minutes. Before describing the feature based face representation and fuzzy classification realized by VISBER in more detail, we present a general overview and the fuzzy emotion model developed for representing classification results.

IV. Fuzzy Emotion Representation and Calculation

VISBER uses an independent fuzzy rule system for each classified emotion (anger, fear, happiness, sadness). Each rule system determines to which degree the actual facial expression belongs to the corresponding emotion. Figure 3 shows the principle structure of the fuzzy classification.

For this purpose each fuzzy rule system receives the geometrical features (angles) determined for the current

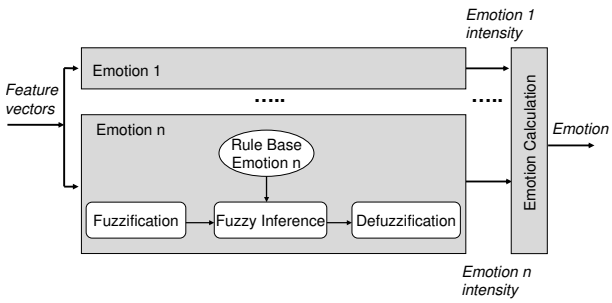

Fig. 3. Principle structure of fuzzy classification

image. First these features are fuzzified and then evaluated by means of fuzzy rules. Afterwards, the output for each emotion is defuzzified using the center of gravity (COG) method. By projecting the COG to the x-axis we calculate the corresponding emotion intensity. These emotion intensities are combined to an emotional state in the fuzzy emotion model, that also allows to represent blends of emotions as described in the next section.

A. Fuzzy Emotion Model

According to psychologists like Plutchik humans do not only feel a single basic or primary emotion but have more complex emotional states, where more than one basic emotion is involved with varying strength or intensity. Plutchik describes that the primary emotions may be mixed in order to synthesize complex emotions. A mixture or blend of any two primaries may be called a dyad, of any three primaries, a triad. For instance, the emotion mixture of anger and joy according to Plutchik's investigations is pride and forms a dyad $anger + joy = pride$ [18]. Based on these results we defined a fuzzy emotion model that does not only support the representation of basic emotions but also allows to represent blends of emotions as result of the emotion classification. Different sets of basic emotions can easily be mapped to this emotion model, which allows its use for various emotion recognition applications relying on basic emotions.

We propose a fuzzy classification of emotional states using fuzzy hypercubes [14]. We assume that the intensity of an emotion can be mapped to the interval $[0, 1]$. First we define a fuzzy set corresponding to an emotional state and then show how it is represented in a fuzzy emotion hypercube.

Fuzzy set for emotional state. Let BE be a finite base set of n basic emotions $e_1, e_2, \ldots e_n$ and $\{\mu_{FE_j} : BE \rightarrow [0, 1], j = 1, 2, \ldots\}$ an infinite set of fuzzy membership functions. Then each $FE_j := \{(e_i, \mu_{FE_j}(e_i) \mid e_i \in BE\}, j = 1, 2, \ldots$ defines a fuzzy set corresponding to an emotional state ES_j.

Fuzzy emotion hypercube. If BE, μ_{FE_j} and FE_j are defined as described above, we shall use the membership vector $(\mu_{FE_j}(e_1), \mu_{FE_j}(e_2), \ldots, \mu_{FE_j}(e_n)) =: (\mu_{FE_j}(e_i))$ to denote a point in an n-dimensional hypercube.

Each axis of the hypercube corresponds to one basic emotion e_i. Thus a membership vector $(\mu_{FE_j}(e_i))$ denotes the hypercube point E_j corresponding to an emotional state ES_j and can be interpreted psychologically as vector of emotion intensities $(I_{e_i}) := (I_{e_1}, I_{e_2}, \ldots, I_{e_n})$.

The number of distinguished emotions depends on the psychological theory or in the case of computer based emotion recognition on the intended application. If for instance the three basic emotions happiness h, anger a and surprise s shall be distinguished, a three dimensional unit cube as depicted in Figure 4 is needed for modelling emotional states.

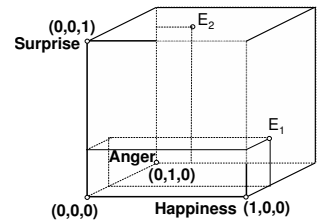

Fig. 4. Fuzzy unit cube for three emotions happiness, surprise and anger

The corners in the unit cube describe dual memberships (0 or 1) for all emotions, vertices desribe dual memberships for two emotions where the third one varies from 0 to 1. For example, the point $E_1 = (1.0, 0.2, 0.3)$ corresponding to the fuzzy set $FE_1 = \{(happiness, 1.0), (anger, 0.2), (surprise, 0.3)\}$ represents a happy emotional state. The point $E_2 = (0.2, 1.0, 0.9)$ corresponding to $FE_2 = \{(happiness, 0.2), (anger, 1.0), (surprise, 0.9)\}$ certainly represents an emotional state for an emotion blend. from anger and suprise. An interpretation of emotion blends is for instance described in [18]. This generic emotion model does not only support the recognition of variable application dependent sets of basic emotions but also allows the handling of derived emotions.

B. Emotion Calculation

Each fuzzy rule system calculates the intensity of the corresponding basic emotion. For an emotion e_i its intensity I_{e_i} is represented by two triangular membership functions $weak$ and $strong$ as depicted in Figure 5.

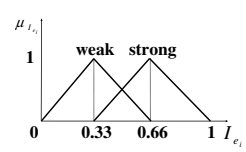

Fig. 5. Fuzzification of emotion intensities

For defuzzification of fuzzy emotion values the center of gravity (COG) method is used. By projecting the COG to the x-axis the corresponding emotion intensity I_{e_i} is calculated.

Since VISBER distinguishes the four basic emotions happiness h, sadness s, anger a and fear f, a four dimensional vector is generated:

$(I_h, I_s, I_a, I_f) = (\mu_{FE}(h), \mu_{FE}(s), \mu_{FE}(a), \mu_{FE}(f))$

This vector represents the membership values for each basic emotion and serves as input for the *emotion calculation*, which is described by the following rules:

$$ES = \begin{cases} neutral, & \text{if } \forall i, i = 1, ...4,\ I_{e_i} \leq 0.5, \\ \text{primary } e_i, & \text{if } I_{e_i} > 0.5 \text{ and} \\ & \forall j, j \neq i, I_{e_j} \leq 0.5, \\ \text{dyad } e_i + e_j, & \text{if } I_{e_i} > 0.5 \text{ and } I_{e_j} > 0.5 \\ & \forall k, k \neq i \neq j, I_{e_k} \leq 0.5, \\ \text{triad } e_i + e_j + e_k, & \text{if } I_{e_i} > 0.5, I_{e_j} > 0.5, \\ & I_{e_k} > 0.5 \text{ and } I_{e_m} \leq 0.5, \\ \text{quad } e_1 + \ldots + e_4, & \text{otherwise} \end{cases}$$

The result ES decides into which category the facial expression of the actual image is classified. This can be the neutral face ($ES = neutral$), a single basic emotion e_i ($ES =$ primary e_i), a blend of two emotions e_i and e_j ($ES =$ dyad $e_i + e_j$) or a blend of three emotions (triad) or four emotions (quad). According to these calculation rules a blend of e.g. two emotions is recognized when the corresponding two rule systems recognized that emotion with an intensity over 0.5.

V. Feature based face representation

When selecting the features for classification of facial expressions we relied on psychological results of Ekman and Friesen, who characterized typical facial expressions for basic emotions using a set of Action Units (AU) that describe atomic muscle actions. The facial deformations analyzed by VISBER are seen as the result of a combination of those AUs, which correspond to a certain emotion. The deformations can be described in terms of angles or distances between certain fiducial face points. In order to support a size invariant representation of facial data VISBER relies on a set of angles. This saves the effort for face normalization that is necessary for distance based features. Furthermore our investigations showed that typical angles show a large coincidence between different persons whereas typical distances vary considerably between different persons. Therefore the angle based classification produces better results also for unknown persons, for whom no specific training (see Section VII) is performed.

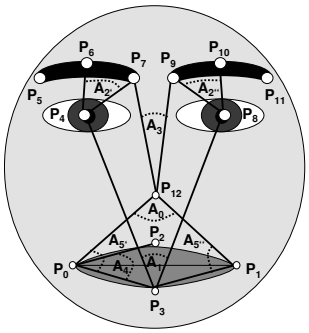

Fig. 6. Angles for facial feature representation

We determined six angles that can be calculated from the twelve fiducial points already mentioned (see Figure 6). The angles are separated into two groups: A_2, A_3 belong to the upper part of the face and A_0, A_4 and A_5 belong to the lower part of the face, A_1 is not clearly mapped to one of the groups. According to Ekman and Friesen the lower-part angles A_0, A_4 and A_5 are involved for expressing happiness (corners of the mouth are raised - A_0), sadness (corners of the mouth are lowered - A_0) or fear (mouth is opened widely A_4 and A_5). The upper-part angles A_2, A_3 are deformed when expressing anger (A_2 is larger, A_3 is smaller) or fear (A_2 is smaller). The angle A_1 is considerably decreased when the mouth is open, which may indicate fear or happiness. The exact values of the angles between 0 and 180 degrees are calculated by the cosine lemma. They build a six dimensional feature vector that is the input for the fuzzy classification described in the next section.

VI. Fuzzy classification

First the fuzzification of the angles and then the fuzzy rule systems used for classification are described. The defuzzification is done by the COG method as already mentioned above.

A. Fuzzification of Angles

For each angle a linguistic variable with three linguistic terms $small, medium$ and $large$ is defined, that correspond to the degrees of AU-intensity distinguished by Ekman and Friesen. The typical values of the angles $A_j, j = 0, ..., 5$ for the neutral facial expression are represented by the linguistic term $medium$. In relation to this $medium$ angles the linguistic terms $large$ and $small$ are defined.

Figure 7 depicts the principle form of the membership functions for $small, medium$ and $large$ angles. The membership functions for $small$ and $large$ have a trapezoid form, $medium$ has a triangular shape. This representation is simple enough to support real-time emotion recognition, yet allows to distinguish degrees to which a feature is present in the current input image. In order to adapt the classification to the facial characteristics of a certain person the exact shape is calculated in a short training phase as described in Section VII.

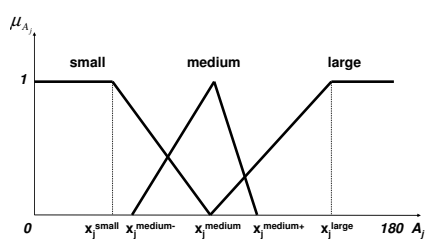

Fig. 7. Fuzzification of angles

B. Fuzzy Rule Systems for Classification

For each basic emotion $e_i, i = 1, ..., 4$, (happiness, sadness, anger, fear) a separate rule set was generated based on psychological results and own analysis of facial expressions. Each rule takes the fuzzified angles $A_j, j = 0, ..., 5$ as input and produces a fuzzy emotion value I_{e_i} which is either $strong$ or $weak$ as output. A rule set for the emotion e_i contains four rules that describe which typical facial deformation

indicates that e_i is $strong$. They are schematically shown in the respective part of Table I. Furthermore 12 rules are added to describe when e_i is $weak$. Their premesis correspond to the typical deformations of the other emotions (see Table I).

TABLE I
FUZZY RULES FOR EMOTION CLASSIFICATION

	A_0	A_1	A_2	A_3	A_4	A_5
hap.	large	medium	medium	medium	small	large
	large	medium	medium	medium	medium	large
	large	medium	medium	medium	medium	medium
	large	medium	medium	medium	small	medium
sad.	medium	medium	medium	medium	small	medium
	medium	medium	medium	medium	small	small
	medium	large	medium	medium	small	medium
	medium	large	medium	medium	small	small
ang.	medium	medium	medium	small	small	small
	medium	medium	medium	small	small	medium
	medium	medium	large	small	small	medium
	medium	medium	large	small	small	small
fear	small	medium	small	medium	large	large
	small	small	small	medium	large	large
	small	medium	small	large	large	large
	small	small	small	large	large	large

For instance, the first rules where the intensity of happiness is $strong$ or $weak$, respectively, have the following form: IF A_0 IS $large$ AND A_1 IS $medium$ AND $\ldots$ A_4 IS $small$ AND A_5 IS $large$ THEN $I_{happiness}$ IS $strong$
IF A_0 is $medium$ AND $\ldots A_3$ IS $medium$ AND A_4 IS $small$ AND A_5 IS $medium$ THEN $I_{happiness}$ IS $weak$

VII. TRAINING

As already mentioned an automatic training phase allows to adapt the classification to a certain person's facial characteristics. This is done by determining the exact shape of the membership functions for $small, medium$ and $large$ emotion specific angles from those angle values (0 to 180 degrees) present in a person's face when showing the respective emotion. For this purpose, about 200 high quality frames are needed for each emotion and the neutral facial expression of a person. Hence, less than five minutes will suffice for the automatic training. For each frame $F^{i_k}, k = 1 \ldots N_i$ (N is about 200) belonging to a specific emotion $e_i, i = 1, \ldots 4$ the corresponding angles $A_j^{i_k}, j = 0, ...5$, of the actual person are calculated from the fiducial points that are determined by the *point localization* (see Section III). They lie in the range between 0 and 180 degrees.

The exact shape of the trapezoidal membership functions μ_j^{small} and μ_j^{large} for an angle $A_j, j = 0, \ldots 5$ is characterized by the ending point $(x_j^{small+}, 0)$ of μ_j^{small}, the starting point $(x_j^{large-}, 0)$ of μ_j^{large} and the bending points $(x_j^{small}, 1)$ and $(x_j^{large}, 1)$ (see Figure 7). The x-coordinates of the bending points $(x_j^{small}, 1)$ and $(x_j^{large}, 1)$ are calculated from the angles determined from the test frames $F^{i_k}, k = 1, \ldots N_i$ of the four emotions $e_i, i = 1, \ldots 4$ as follows

$$x_j^{small} = \min_{\substack{i=1,\ldots,4 \\ k=1,\ldots,N}} \{A_j^{i_k}\}$$

$$x_j^{large} = \max_{\substack{i=1,\ldots,4 \\ k=1,\ldots,N}} \{A_j^{i_k}\}$$

The x-coordinates of the ending points $(x_j^{small+}, 0)$ and the starting points $(x_j^{large-}, 0)$ correspond to the x-coordinates of the points $(x_j^{medium}, 1)$ where the triagonal fuzzy membership functions μ_j^{medium} have their maxima for the respective angle A_j. The x-coordinates of these points are calculated on the basis of the frames $F^{neutral_k}, k = 1, \ldots N_{neutral}$ taken for the neutral facial expression and the angles $A_j^{neutral_k}$ determined for these frames as follows:

$$x_j^{medium} = \frac{1}{N} \sum_{k=1}^{N} A_j^{neutral_k}$$

The x-coordinates of the starting points $(x_j^{medium-}, 0)$ and the ending points $(x_j^{medium+}, 0)$ of the membership functions $\mu_j^{medium}, j = 0, \ldots 5$ are also calculated on the basis of the frames for the neutral face:

$$x_j^{medium-} = \min_{k=1,\ldots,N} \{A_j^{neutral_k}\}$$

$$x_j^{medium+} = \max_{k=1,\ldots,N} \{A_j^{neutral_k}\}$$

The training on individual characteristics may also be omitted, but the emotion recognition would become worse in that case.

VIII. IMPLEMENTATION AND RESULTS

VISBER was implemented in $C++$ under Linux but can easily be ported to Windows. The fuzzy classification was realized using the Free Fuzzy Logic Library $FFLL$, which is optimized for time critical applications. The fuzzy models were defined in the standardized language FCL ([11]).

VISBER processes video sequences taken by a Philips webcam in the JPEG format with a frame rate of 30 frames per second. Images have a size of 320x240 pixels and contain one face in a frontal pose. We assume a homogeneous illumination for the video sequence but the background of the face may change.

For test of the fuzzy classification at least three video sequences with a minimum of 100 frames were used for each emotion. However, we had no professional actors and did no tests on images labeled with a blend of emotions. Since correctly extracted fiducial face points are a prerequisite for a successful classification, we selected only video sequences where they were relatively correctly localized. The results are shown in Table II.

The average recognition rate was 72%. The recognition rates for the emotions happiness and sadness are lower (63% and 53%) than those for anger (72%) and fear (90%).

TABLE II

CONFUSION-MATRIX FOR EMOTION RECOGNITION

Emotion	hap.	sad.	ang.	fear	neut.	ang.+ sad.	ang.+ sad.+hap.
hap.	63%				31%		
sad.		58%	13%		23%	6%	
ang.			72%		28%		
fear				90%	10%		
neut.	1%	2%			96%		1%

This may be due to inaccuracies in the localization of the corners of the mouth which are needed for angles in the lower face part mainly responsible for expressing happiness or fear. In contrast the emotions anger and sadness are mainly characterized by the upper part of the face (eye brows lifted or knitted and lowered). The confusion of anger and sadness may be due to their similar facial expressions in the upper face part. In some cases the fuzzy classification calculated a dyad $anger + sadness$ and in one case a triad $anger+sadness+happiness$, since the intensities of two or more basic emotions after defuzzification were higher than 0.5. In the majority of false classifications the intensities of all basic emotions were less than 0.5 resulting in a neutral classification. These confusions are presumably caused by imprecisely localized fiducial points. We assume that this is also the reason why the average recognition rate is lower than reported for other approaches where typical recognition rates for action units and facial expressions between 80% and 90% and in a few cases also over 90% are described. For improving the results of VISBER without giving up its real-time capability a revised set of features minimizing the effect of fiducial points seems promising.

IX. CONCLUSION

In this paper we presented a fuzzy system for video based emotion recognition in real-time called VISBER. It does not only use fuzzy rules for emotion classification but also uses a fuzzy emotion model for representing the recognized emotion. VISBER supports the recognition of four basic emotions and the neutral facial expression like many other systems. In addition VISBER's emotion model also supports the recognition of blended emotions which are a mixture of two or more basic emotions. For design and realization the real-time capabilities and resource efficiency were a major objective, since VISBER shall be used within the robot head MEXI for real-time communication with humans. Via combination with a prosody based emotion recognition [2] we hope to improve the average recognition rate considerably.

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