AAM based Continuous Facial Expression Recognition for Face Image Sequences

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***Abstract*—In this paper a method of automatic real-time capable continual facial expression recognition becomes described and compared with a similarly classification. Whereas the classification maps each image into one of the 7 basic emotions (neutral, happy, sad, disgust, surprise, fear, anger) and the regression maps each image into an one-dimensional emotion space. Both methods, the continual recognition and the classification based on *Active Appearance Models* (AAMs) and *Support Vector Machines* (SVMs). To reduce the influence of individual features an *Individual Mean Face* (MF) is estimated over time. The emotion regression will be used in service robotic by human-robotic interaction to analyze the continual change of humans emotional state to get a feedback for a gentler, more natural and adaptive dialog. This is needed for more acceptance and usability of service or health-care robotic in the household environment.**

***Index Terms*—Emotion Space Regression, Person Specific Mean Face, Facial Image Sequences, Active Appearance Models, Support Vector Machines**

I. Introduction

Nowadays, service systems like shopping robots, ticket machines or entertainment electronics are established in our society. Furthermore, service systems are getting more and more important in home environment. This range from robotic animals for amusement through to service robots which help with housework, scheduling, home health care and so on. Especially, for the acceptance of these systems they must be easy to use, since non-instructed users should be able to operate these systems. The most intuitive kind to interact with a technical system is the human like communication. Therefore, the system must generate and understand spoken words and gestures. To understand the correct sense of the spoken words and gestures it is important to interpret the emotion since the communication between humans is context sensitive. However, emotion recognition is needed to generate a natural dialog system. This work focus a feedback system which generate continual positivity values from the current facial expression. Certainly, an opportunity to get information about person's emotional state is to analyze the face. In this work the face becomes analyzed by using the parameters of facial *Active Appearance Models* (AAMs) for an emotion regression with the help of *Support Vector Regression* (SVR). The emotions are mapped into an one-dimensional emotion space which consist only in the positivity axes. This automatic continual emotion recognition system becomes compared with a similar classification to evaluate.

II. Emotion

Nowadays, it is not clearly defined what emotion is and how emotion becomes expressed. However, some works like [1], [2] or [3] discussed this problem not finally. Nevertheless, four kinds to estimate human emotions are known, interpretation of the facial expression [4], gestures [5], acoustic [6] and biomedical characteristics [7] like the heart rate or the conductivity of skin. The interpretation of gestures is seldom possible, because humans express his emotion seldom by gestures, also the interpretation of the acoustic is only possible when a person talks. To interpret the biomedical characteristics, it is needed to contact the people, but this is not possible in a natural human-robot interaction. For this reasons the interpretation of the facial expression is used in this work. There are two known possibilities to interpret facial features for an emotion estimation. On the one hand it is possible to map these features into discrete emotion classes and on the other hand it is possible to map into a continuous emotion space. In this work continuous values are used because this work focus to a continual feedback system for a dialog adaption. So the face images are mapped into an emotion space. The emotion space is known since Aristoteles described the one-dimensional emotion space [8]. In [9] an one-dimensional emotion space is used for automatic emotion generating. In psychology the 2D- and 3D-emotion space is mostly used, nowadays. In [10] the 2D-emotion space with its cultural variations are described. Certainly, the one-dimensional emotion space which are used in this work is based on the 3D-emotion space from Breazeal [11], which is shown in Fig. 1 with the entered 7 basic emotion classes[1].

There is a lot of space between the emotion classes which is not described by the 7 basis emotion classes, but the emotion regression is also able to interpret this areas. The system which are described in this work focus on a simple feedback value.

[1] neutral, happy, sad, disgust, surprise, fear, anger

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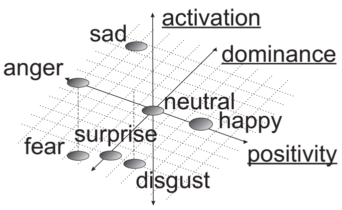

Fig. 1. **3D emotion space** The seven basis emotions are exemplary mapped into this emotion space. [11]

For that reason, only an one-dimensional emotion space is used, which only consist in the positivity axes.

III. Related Work

Different authors focused on examining different methods to classify emotions using AAMs. The different classifiers used for that task range from *Support Vector Machines* [12], [13] and *Neural Networks* (NN) [14] to *Hidden Markov Models* (HMMs) [15]. The similarity of these approaches is that they try to map the users emotion onto discrete basis emotions. Through, using the discrete emotion classes is not the only way to explain human emotions. Breazeal and Scassellati show in [11] that emotions can also be arranged in a continuous 3D-emotion space. Whereas one dimension of the continuous emotion space is the positivity of the emotion. Certainly, in [16] a 2D-emotion space is used for an automatic emotion classification. This work also use AAMs and SVMs to map the facial emotions into the emotions positivity and intensity. Through, Beszedes used a SVM-Classification to map into positivity and intensity classes and compared the systems result with humans evaluation. As long ago as 1993 Morishima [17] present a method to generate *facial muscle Action Units* (AUs) from a 2D-emotion space to facilitate artificial emotions.

In a related work that discusses systems with online ability, Valsatar and Pantic [18] reported some progress of building a system that enables fully automated fast and robust facial expression recognition from face video. They analyzed subtle changes in facial expression by recognizing AUs and analyzing their temporal behavior. The AUs displayed in the input video and their temporal segments are recognized finally by *Support Vector Machines* trained on a subset of highly informative spatio-temporal features selected by AdaBoost. However, like all geometric-based methods, their work demands labeling of the first frame as reference. Bartlett et.al. [19] proposed a system that automatically detects frontal faces in the video stream and also classifies them into the seven basic emotions. The face detector which is based on Viola & Jones detector is used to convey an image patch containing the face to a Gabor-wavelet-based facial feature extractor. Gabor representation of the conveyed patch is formed and processed by a bank of SVM classifiers.

In the most works which focus a facial emotion estimation, the emotions are classified. However, to the best of our knowledge there is no approach which tries to automatically map emotional face image sequences onto a linear positivity scale with the help of AAMs.

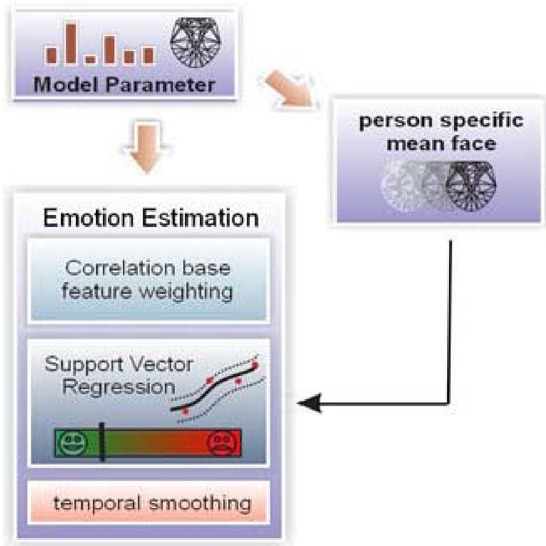

Fig. 2. **System Architecture** The 1D positivity measure is realized by applying SVR. Therefore, the AAM parameters are scaled and the person specific mean is removed. Temporal smoothing is applied to reduce input noise.

IV. System Architecture

This system based on the parameters of a good fitting AAM. Unfortunately, there are two main problems when analyzing the facial expression in 2D images: On the one hand there are the individual features of a person and on the other hand the human interpretation of an emotion may differ.

One way to handle these person specific features is to eliminate them from input vector. Here a *Person Specific Mean Face* is used to reduce this input noise by eliminating them from the actual AAM parameters. So the *Person Specific Mean Face*, which is described in section IV-B, is used to improve the automatic emotion estimation.

Afterwards, the resulted parameter vector is mapped into a 1D-emotion space using a SVM. In order to be able to handle different interpretations of emotions, it is favorable to map the facial expression in an emotion space instead of classification, to reduce the interpretation error. In many applications, like the mentioned feedback system it is not necessary to know the current emotion class. Furthermore, in process controlling a continuous result is often easier to handle. Here, it is sufficient to know the orientation of the facial expression. It is of large interest whether the facial expression is positive or negative for the receiver. Hence, the facial expression are mapped into a 1D-emotion space using *Support Vector Machines* since these emotion space coding the positivity of the users emotion.

An overview of this architecture is shown in Fig. 2. This system is applicable in real-time, running at a rate of 30Hz on a 2GHz PC.

A. Active Appearance Model

Active Appearance Models (AAMs) are very popular to model human faces. Although facial analysis has been well studied in computer vision literature [20], [21] these approaches have mostly been designed for the still image context and rarely for continuous processing [22]. Here Strickers approximation [23] is used to be real-time capable and accurate enough for the facial expression regression. This approximation use the requirement of continuous image sequences to speed up the model fitting. Furthermore, this approximation is able to reduce the influence of several illuminations.
In this approximation the shape parameters are divided into two parts. Four of these shape parameters are direct determined by a face detector. These so called global shape parameters describes only the face position into the image. Each used AAM consist in this parameters. Further shape parameters which describes the individual form of a face are so called local shape parameters.
First tests of the estimator have shown that the AAM parameters can be mapped to their positivity value. However, these tests expose a major problem: For a good fitting, an AAM parameter vector has a typical dimension between 50 and 100 to allow a sufficient description of a face. The used AAM consists in 50 texture and 20 local shape parameters, but a lot of these parameters are noise for the positivity estimator. Furthermore, the training data are typically limited to a few hundred samples. To reduce the problems arising from the high dimensional parameter vector only the relevant parameters are selected with the help of the computed mutual information between each parameter and the emotional positivity values of all images in the used face image database [24]. Furthermore, the mutual information between all parameters became calculated. Thereby, an input vector is defined, which containing 10 selected relevant local shape parameters and 20 selected relevant texture parameters of a face image which are rectified by the *Person Specific Mean Face* which is declared in the next paragraph. In this work, the relevant local shape and texture components are the first which are selected by the PCA. For further reduction of the problems arising from the high dimensional parameter vector, a weighting of the single feature dimensions became applied. Therefore, the correlation values cv of every dimension i with the positivity values is computed to obtain the weighted parameters $\widehat{p_i}$.

$$\widehat{p_i} = p_i \cdot cv(p_i). \tag{1}$$

B. Person Specific Mean Face

A further problem, which are founded by the first tests is caused by the different characteristic of each face and is solved by using the *Person Specific Mean Face*. In Section V the system errors with or without using the *Person Specific Mean Face* becomes compared.
For face image interpretation, it is necessary to extract features from face images which vary in each state. Unfortunately, these features also vary often for each person. Fig. 3 illustrates this issue, both images are neutral, since the bottom image shows more down corner of the mouth than the upper image.

Fig. 3. **Person specific variance**, exemplary shown by two persons which looks neutral

In some scenarios like the facial expression recognition, it is troublesome to handle these person specific variance of the features since these features are sometimes similar for different stats between different persons. Furthermore, much more training data are needed to learn the generalized mapping function. To handle this problem the person specific features are eliminated from input images. More exact the *Person Specific Mean Face* becomes subtracted from the actual selected and weighted AAM parameter vector P_t. This *Person Specific Mean Face* M_{indiv} is a parameter set like the weighted AAM parameters which describe the neutral face of the current person.

$$I_0 = P_0. \tag{2}$$

$$I_t = P_t - M_{indiv}. \tag{3}$$

So the individual input vector I_i contains all information about the facial expression without the deranging individual features. In this work these person specific features are estimated over time by calculating the mean of each feature. Hence, these person specific features describe the *Person Specific Mean Face*. The used timescale can be variable

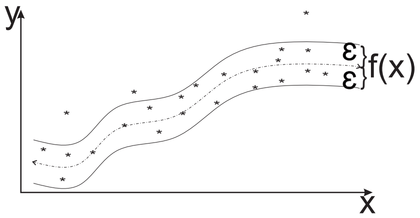

Fig. 4. **1D regression by *Support Vector Machines*** ϵ defines an array around the function $f(x)$ which is described by the support vectors. Points within this array are flawless in training. In this training the positions of the support vectors are learned with the help of a training set.

depending on the specific requirements. For an actual state, a short timescale of some seconds is needed. When the global mean face of a person is needed, the timescale should span some hours to few days. In this work a predefined *Person Specific Mean Face* is used. In some further experiments the *Person Specific Mean Face* becomes endless calculated by using the adaptive mean of Grießbach [25].

$$M_{indiv_{t+1}} = M_{indiv_t} + \alpha * (M_{indiv_{t+1}} - M_{indiv_t}). \quad (4)$$

The adaption constant α range from 0 to 1. Using a large adaption constant α the *Person Specific Mean Face* varies fast, so the current facial expression variance can be calculated. By using a small α the *Person Specific Mean Face* varies slower, so a global *Person Specific Mean Face* can be created. To handle the change of interaction partner a SIFT-approximation which work at the warped AAM input image is used.

C. Support Vector Regression

In most cases the facial expression is mapped onto the seven common emotion classes. A more natural way to interpret facial expression is to map the facial expression into an emotion space. However, for most technical systems it is sufficient to know if a persons facial expression condition is positive or negative. Hence, in this work only a 1D emotion space is used to map the facial expression at its positivity. Now, the systems task is to realize a function which maps the AAM parameters onto the corresponding positivity value. To realize this, *SVM-Regression* (SVR) which is similar to SVM-Classification is used. In *SVM-Regression* support vectors describes a hyperplane in space which represent the approximation of the mapping from input (AAM parameters) to output (positivity of the facial expression). There is a small area ϵ around the hyperplane in which the training data are flawless. This is necessary for the capability of generalization. Some types of input can not mapped linear to the desired output. To solve this problem, a kernel function is used to increase the input dimensionality. Here, the *Radial-Basis-Function* (RBF) $e^{(-\gamma \cdot |u-v|^2)}$ is used to enable a linear mapping of the input onto the output.

To implement *SVM-Regression* the method of *Epsilon Support Vector Regression* which is provided by the software library LibSVM [26] is integrate in the presented system.

Finally, the result of the *SVM-Regression* is smoothed to eliminate momentary errors on the supposition that the positivity of a facial expression does not change so fast.

V. Experimental Results

This section presents experimental results which are achieved by using the described approach. Here, the presented system with or without using the *Person Specific Mean Face* is compared. Furthermore, the regression system is compared with a similar classification.

A. Database

The developed emotion-space-based regression is evaluated on the publicly available FG-Net database [24], which consists of image sequences of 18 people, 9 female and 9 male, showing the basic emotions. The database is quite challenging and realistic as authors of the database tried to capture realistic emotions. The images in this database have a resolution of 320x240 dots and are all colored. Few example images are shown in Fig. 5

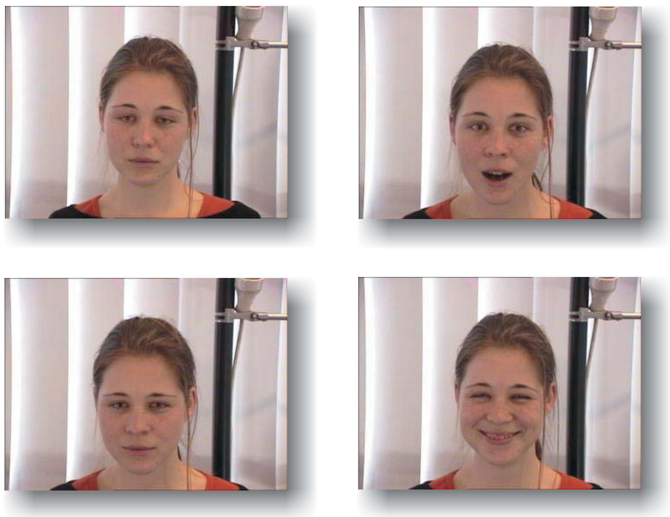

Fig. 5. **FG-Net database:** (a) sad (b) surprise (c) anger (d) happy

This database became divided into two parts, the first part is used for SVM training and to create the used AAM and the second part is used for the system evaluation. For that reason, sequences of 14 people, regularly divided in female and male, are used for the training. The remaining sequences are used to evaluate the system. Since all of the sequences of the FG-Net database start with a neutral facial expression, only clearly expressed emotion images of the training set have to be identified and labeled with the corresponding positivity values by several people. To generate the ground truth facial expression values for evaluating, each frame in the evaluation sequence are labeled with the corresponding positivity values by several people, too. After this, the *Support Vector Regression* can be trained using cross validation applying the leave one out strategy for every single person in the training set. As the neutral face for every person in the database is known, the

TABLE I

THE RESULTS PROVIDED BY THE EMOTION-SPACE-BASED FACIAL EXPRESSION ANALYSIS SYSTEM. EACH CLASSES REPRESENT THE WHOLE SEQUENCES, WHICH RANGE FROM NEUTRAL TO THE MARKED FACIAL EXPRESSION. TO COMPARE THE SYSTEMS PERFORMANCE THE RESULTS OF A SIMILARLY CLASSIFICATION ARE ALSO SHOWN IN THIS TABLE.

	RMS error	RMS error MF	class. error	class. error
Anger	0.148	0.102	0.187	0.094
Fear			0	
Sadness	0.238	0.156	0.071	0.071
Disgust	0.314	0.187	0.381	0.381
Neutral	0.594	0.124	0.362	0.278
Surprise			0.194	
Happiness	0.66	0.142	0	0
Average	**0.376**	**0.132**	**0.171**	**0.165**

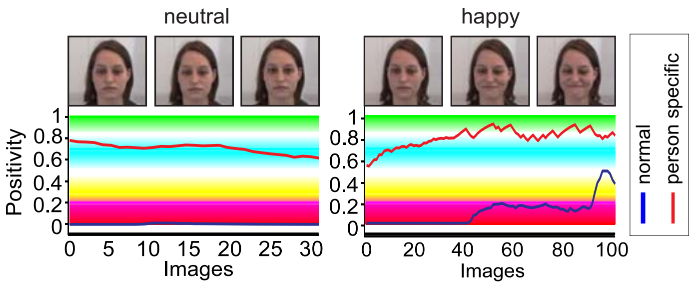

Fig. 6. **Comparison between evaluation with or without the *Person Specific Mean Face* (MF)** For the neutral sequence the evaluation without the MF fails to detect the persons facial expression while the modified version is able to adapt to the neutral face. The same results are presented for a sequence starting with a neutral facial expression and ending with a happy facial expression.

average mean face can be easily computed, by estimating the weighted AAM Parameters which describe this neutral facial image.

B. Facial Expression Regression

In this section the result of a facial expression classification becomes compared with the facial expression regression with or without using the *Person Specific Mean Face*. The classification system is similar to the regression, with the difference of the used SVM. In classification a classical multiclass SVM is used with the one-versus-one method which consist in $c\,(c-1)\,/2$ binary SVM-Classifier, where c is the number of classes. To decree which classifier is right the max-win policy is used. To handle the large input vector the RBF-kernel is used, too.

The RMS error between the ground truth facial expression value and the obtained value can be computed as an indicator of system performance. To show the usefulness of the proposed extensions, namely the mapping into an emotion space and the usage of the presented *Person Specific Mean Face* (MF), Table I shows different RMS errors obtained for the FG-Net database. First the regression is compared with or without the MF and second the regression is compared with a classical classification. For a better comparison, the regression results and the classical classification error rate is shown in the same table. Furthermore, the regression results is divided into 5 classes for a better comparability with the classification. This classes represent the whole sequences, which range from nearly neutral to the full evolved marked facial expression. In classification, 7 classes are used and only 5 classes are used in the regression since anger and fear as well as neutral and surprise are similar into the facial expression positivity. In this reason, the classification results of anger and fear as well as neutral and surprise are combined with the help of arithmetic averaging.

Table I shows that the use of the *Person Specific Mean Face* comes to smaller errors, so the positivity difference to the certain emotions averages 0.132. The proposed extensions like the *Person Specific Mean Face* lead to a more robust estimation. Therefore, the positivity regression result is similar to the classification result with an error rate of 16.5%. Nevertheless, the system can still give a good hint on person positivity for the challenging FG-Net database.

Particularly, if the neutral face of a person is quite different from the mean neutral face, the proposed integration of the *Person Specific Mean Face* can lead to a great improvement. Fig. 6 shows exemplary the varying system properties with or without the MF by two sequences, one sequence for neutral and one for happy. Without the use of the *Person Specific Mean Face* the neutral facial expression is nearly mapped onto the positivity value 0, so this image sequence is interpreted as anger or fear. This effect based on the individual features. Certainly, with the help of the feature correction named *Person Specific Mean Face* the positivity values ranged correct nearly 0.7. The same effect is shown by the selected happy sequence. This sequence starts with neutral and picks up to fully happy, so the positivity values for the sequence starts by 0.7 and increase up to nearly 0.9 by the use of the MF. As opposed to this the positivity starts by 0 and increase only up to 0.5 without the use of the MF.

VI. CONCLUSION

In this paper a way to extract positivity values of a facial expression utilizing the shape and texture parameters from an *Active Appearance Model* (AAM) became presented. By means of the presented system configuration, an automatic real-time capable continual facial expression recognition is achieved. Furthermore, to improve the facial expression regression, we suggest using a correlation based weighting of the AAM parameters and a person specific reference. In combination with the applied *Support Vector Regression* the proposed system is tested on the FG-Net database showing promising results for determining facial expression positivity over time. The comparison of the regression and the classification shows that the regression precision is similar to a classification. Now, the facial expression regression can be used to get continual values for a feedback system, which need informations about the continual facial expression state changes. However, the experiments elucidated the requirement of the used *Person Specific Mean Face* in the facial expression regression, to achieve an acceptable RMS error by 0.132. Furthermore, a combination of an attention and a head gesture estimation [27] and the presented system is used in a service robotic system [28]. A further work to increase the accuracy of the presented system could be a prior classification in male and female as well as into age groups, which is discussed in [29].

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