EMOTIONAL FACIAL EXPRESSION RECOGNITION FROM TWO DIFFERENT FEATURE DOMAINS

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Keywords: Emotion recognition, Facial expression, Gabor wavelets, Human-computer interaction, Affective computing.

Abstract: There has been a significant amount of work on automatic facial expression recognition towards realizing affective interfaces in human-computer interaction (HCI). However, most previous works are based on specific users and dataset-specific methods and therefore the results should be strongly dependent on their lab settings. This makes it difficult to attain a generalized recognition system for different applications. In this paper, we present efficiency analysis results of two feature domains, Gabor wavelet-based feature space and geometric position-based feature space, by applying them to two facial expression datasets that are generated in quite different environmental settings.

1 INTRODUCTION

Recently numerous studies on automatic emotion recognition using audiovisual (facial expression, voice, speech and gestures) and physiological (electrocardiogram, skin conductivity, respiration, etc.) channels of emotion expression have been reported (Cowie et al., 2001) (Kim and André, 2008). Overall, most approaches achieved average recognition rates of over 70%, which seems to be acceptable for some restricted applications. However, it is true that the recognition rates should be strongly dependent on the datasets they used and the subjects. Moreover, most of the recognition results were achieved for specific users in specific contexts with the "forced" emotional states. All these make it difficult to attain a generalized recognition system for different applications. Particularly, due to the lack of a standard benchmark of emotional dataset and recognition method, it is almost impossible to objectively compare the efficiency of feature domains and the performance of classification algorithms.

For a comprehensive survey of previous works on the recognition of facial expression we refer the reader to (Fasel and Luettin, 2003) (Jain and Li, 2005). Generally the feature-based methods for facial emotion recognition in the literature can be divided into two general ideas with respect to feature coding spaces, i.e. transform-based feature coding by using such as Gabor wavelets (Zhan et al., 2007) and principle component analysis (PCA) and geometry-based distance coding by using extended fiducial points defined in the facial action coding system (FACS) (Pantic and Rothkrantz, 2004), for example. In the FACS, almost every visible movement of facial muscles is assigned to Action Units (AU) and a fine grained language is given to allow a human annotator the description of facial behavior.

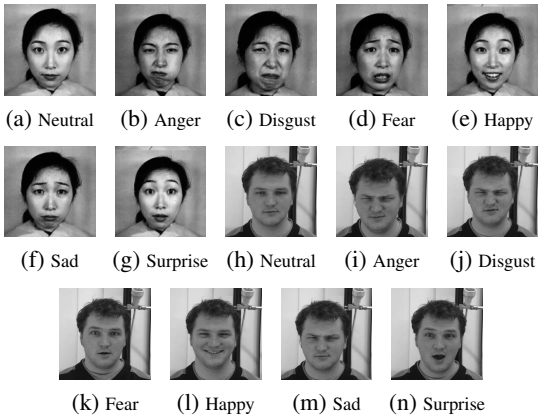
In this paper, we investigate the efficiency of two well-known feature domains, i.e. Gabor wavelet-based feature set and geometric position-based feature set, by using two emotional static image datasets that are generated in quite different environmental settings. Throughout the paper, we try to derive a specific characteristic of the feature domains, which can be generally accepted for designing an universal facial emotion recognition system.

2 USED DATASETS

Two different datasets are used for our experiment. The first one is the Japanese Female Facial Expression Database (*JAFFE*) (Lyons et al., 1998) consisting of 213 images of ten different subjects. The amount of samples is roughly equal for each of the seven emotion classes, i.e. neutral, happiness, sadness, surprise, anger, disgust and fear. The second dataset is the Facial Expressions and Emotion Database (Wallhoff, 2006) (*FEEDTUM*) of the Face and Gesture Recognition Research Network (FG-NET). Differently from

Kim J. and Jung F. (2010).
EMOTIONAL FACIAL EXPRESSION RECOGNITION FROM TWO DIFFERENT FEATURE DOMAINS.
In *Proceedings of the 2nd International Conference on Agents and Artificial Intelligence - Artificial Intelligence*, pages 631-634
DOI: 10.5220/0002737306310634

the JAFFE which is a set of photo images, FEEDTUM is generated by collecting images taken out of video streams and contains a bigger amount of images available, recorded in three sessions for each of the 18 subjects and each of the seven emotion classes. For testing, one image of each session has been selected picturing the subject in the apex phase of the facial deformation. Figure 1 shows some example images sampled from both datasets corresponding the seven emotional expressions.



(a) Neutral (b) Anger (c) Disgust (d) Fear (e) Happy

(f) Sad (g) Surprise (h) Neutral (i) Anger (j) Disgust

(k) Fear (l) Happy (m) Sad (n) Surprise

Figure 1: Examples of facial expression images. (a)-(g) are sampled from the JAFFE and (h)-(n) from the FEEDTUM.

3 METHODOLOGY

3.1 Feature Extraction in Gabor-filter Domain

A two-dimensional Gabor wavelet is a plane wave that is enveloped by a Gaussian, i.e.

$$\Psi(\mathbf{k},\mathbf{x}) = \frac{\mathbf{k}^2}{\sigma^2}\, e^{\left(-\frac{\mathbf{k}^2\mathbf{x}^2}{2\sigma^2}\right)} \left(e^{(i\mathbf{kx})} - e^{\left(-\frac{\sigma^2}{2}\right)} \right) \tag{1}$$

where $\mathbf{k}$ is the frequency of the plane wave, and σ is the relative width of a Gaussian envelope function. Field (Field, 1987) pointed out that most cells in the visual cortex of mammals come in pairs with even and odd symmetry, similar to the real and imaginary part of Gabor wavelets. Following this we used Gabor filter with the elliptic Gaussian which approximates even more exactly the neurons in the visual cortex,

$$\Psi(x,y) = \frac{\alpha\beta}{\pi}\, e^{-\left(\alpha^2 x'^2 + \beta^2 y'^2\right)} e^{j2\pi f_0 x'} \tag{2}$$

$$x' = x\cos\theta + y\sin\theta \tag{3}$$

$$y' = -x\sin\theta + y\cos\theta \tag{4}$$

where f_0 is the frequency, θ the orientation and α and β the scaling factors for the elliptic Gaussian envelope. The orientation of the Gaussian rotates together with the orientation of the filter. To get the same number of waves over all scales the ratio between the frequency and the Gaussian is fixed. The ratios that approximate the cells in the visual cortex are:

$$\gamma = \frac{f_0}{\alpha} = \frac{1}{\sqrt{0.9025\pi}},\ \eta = \frac{f_0}{\beta} = \frac{1}{\sqrt{0.58695\pi}} \tag{5}$$

The normalized filter in the spatial domain is then:

$$\Psi(x,y) = \frac{f_0^2}{\pi\gamma\eta}\, e^{-\left(\frac{f_0^2}{\gamma^2}x'^2 + \frac{f_0^2}{\eta^2}y'^2\right)} e^{j2\pi f_0 x'} \tag{6}$$

For the design of Gabor filter bank in our experiment, we used the following parameters: the relative width σ has been set to π and six orientations and three spatial frequencies have been used. The orientations ϕ range from $\frac{\pi}{6}$ to π in an equidistant manner. The maximal frequency is $\frac{\pi}{4}$ and the different scales are separated by the factor two which results in three scales with $k = \frac{\pi}{4}, \frac{\pi}{8}, \frac{\pi}{16}$. For normalization the interocular distance is 60 pixels and if the three-point-method is employed the distance between mouth middle point and the straight line between the eye centers is as well 60 pixels.

3.1.1 Points of Interest

Since we apply the Gabor filter to each fiducial point, instead of whole image, it is necessary to identify the points of interest (POI) that are relevant to affective facial expressions. For this, focusing on wrinkles and bulges is a rather poor choice. This makes sense when one considers that the appearance and visibility of such are highly influenced by illumination, age and even contexts like tiredness of an individual. They can be altered by make-up, even completely covered by facial hair and are highly dependent on the individual. Considering the issues above and the common evidence that the mouth area holds most information related to facial expression recognition, followed by eyes and then eyebrows, we identified 26 POIs as shown in figure 2, where the points 14, 15 and 23-25 are for image normalization, not for filtering purposes.

3.1.2 Normalization and Feature Calculation

Images are converted to gray scale in order to avoid problems with filtering in different planes and application of feature reduction algorithms. It is clear that

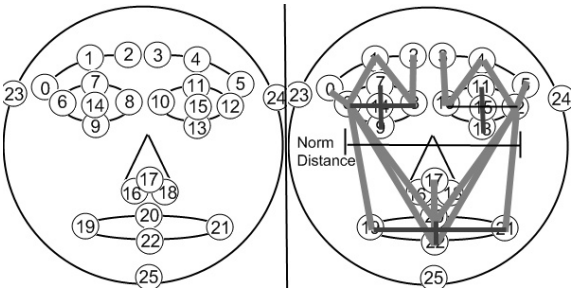


Figure 2: Left: the 26 points of interest identified in a frontal face. Right: considered minimal set of distances.

the Gabor filters are anisotropic and estimating of frequency parameter depends on the face sizes in pixels. Since the images in the datasets are generated by using single camera positioned at front of face, a pertinent normalization has to be conducted to address in-plane rotations and face size. Two methods based on a three-point-normalization via transformation matrices are employed. The first one uses three fixed points, where two are located in the eye centers and the third in the middle of the mouth determined by the cutting lines through opposing mouth points. It maps simply the points onto three predefined points to determine transform matrix. The second method preserves the relation between the inter-ocular distance and the perpendicular line distance of the mouth middle point to that line. Therefore the "natural appearance" of the face is more preserved, since the face shape is respected.

After the normalization, the Gabor filters are applied to the sample at each POI. As a result, we obtained feature vector containing 18 complex coefficients for each POI and reduced the size of the feature vector by considering only magnitude of real and imaginary parts.

3.2 Feature Extraction in Geometric Domain

To provide a unit system for the intra-face measurements that are comparable across individuals, we need certain anchor points that have to lie in areas with sufficient textural information (for easy detection), be present in a consistent manner across different samples/models, be at locations that do not move due to facial deformations and be not located at points with transient information (e.g. wrinkles, bulges). Among different candidates illustrated in the Figure 2 the outer points of the left and the right eye turned out to be the best options. The points at the temples would be a good choice, too, but can vanish due to even small out-of-plane rotations or be hard to detect because of hair. All measured distances will be divided by this span for conversion into the unit system. As facial landmarks, we used a subset of the points in the Figure 2, except for point 6, 8, 10, 12, 16-18 and 23-25 which are anchor points.

We calculated geometry-based features by measuring distances of anchor-to-landmark, landmark-to-landmark points and dividing them by the base unit. Furthermore, *div*- and *med*-features are obtained by considering two intersecting lines between the corresponding points, for example, the lines of point 20 to 22 and 19 to 21. We then calculated the ratio and median values based on the lines. Consequently, these features represent the change of the eye- or mouth-form. Figure 2 right shows a possible minimal set of distances. Light gray lines are the spans between anchor-to-landmark and the dark lines indicate distances that were used to calculate div- and med-features.

3.3 Classification

We tested the recognition efficiency of the two feature sets by employing two well-known statistical classifiers, k-nearest neighbor (k-NN) and support vector machines (SVM). For k-NN, Euclidean distance measure is used with $k = 3$. We used the C-SVM (RBF kernel) with a fixed γ and high cost factor c by building binary classifiers in terms of one-vs-one as well as one-vs-all.

4 RESULTS

Figure 3 illustrates the Fisher projection of the feature sets in order to get an preview of the distinguishability according to the seven expression classes. The distributions in the figures show that the class related sample density for the Gabor approach seems satisfying, even though some classes (e.g. disgust and anger) intersect each other.

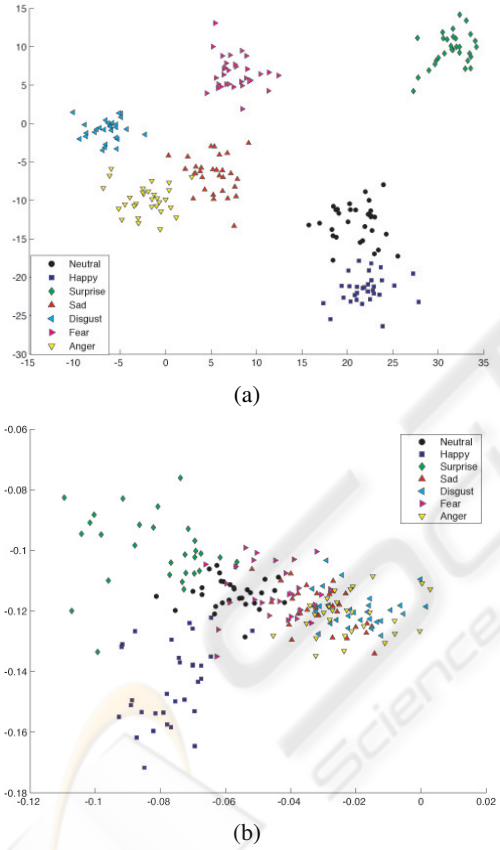
Table 1 and 2 summarize the recognition results. Through all tests it turned out that the JAFFE dataset could be easily classified, compared to the FEEDTUM dataset, regardless which feature set is used. This should be due to the high consistency of the samples and the feature extraction favorable setup of the JAFFE dataset, while the slightly more "real world" oriented FEEDTUM samples allowed therefore inferior results.

Table 1: Recognition results (accuracy rates in %) by using the Gabor-filter features. Validation method: leave-one-out.

	JAFFE	FEEDTUM	MIXED
3-NN	87.79	51.78	50.44
C-SVM 1-1	95.31	78.22	**65.56**
C-SVM 1-all	**96.24**	**80.22**	64.67

Table 2: Recognition results (accuracy rates in %) by using the distance features. Validation method: leave-one-out.

	JAFFE	FEEDTUM	MIXED
3-NN	77.46	35.02	55.78
C-SVM 1-1	**79.81**	**55.70**	**62.89**
C-SVM 1-all	78.87	48.10	54.67



(a)

(b)

Figure 3: Distribution of the Gabor-filter features (a) and the distance features (b) by using Fisher projection. Dataset: JAFFE.

5 CONCLUSIONS

In this paper we developed two feature domains, Gabor wavelet-based and geometry-based feature space, and investigated the efficiency of the feature sets by applying them to two facial expression image datasets that are quite differently characterized due to distinct recording settings. SVM and k-NN are employed to classify the seven expression classes, i.e. neutral, happiness, sadness, surprise, anger, disgust and fear, by using the obtained feature vectors.

The results showed that the Gabor filter approach outperformed the distance approach in all experiments. On the other hand, we note that the distance approach provided relatively consistent performance for the mixed dataset, compared to Gabor-filter approach. This finding should be considered for designing a facial expression recognition system, because it is one of well-known issues that most systems suffer from low accuracy of subject-independent recognition.

ACKNOWLEDGEMENTS

The work described in this paper is partially funded by the EU under research grant IST-34800-CALLAS and ICT-216270-METABO.

REFERENCES

Cowie, R., Douglas-Cowie, E., Tsapatsoulis, N., Votsis, G., Kollias, S., Fellenz, W., and Taylor, J. G. (2001). Emotion recognition in human-computer interaction. *IEEE Signal Processing Mag.*, 18:32–80.

Fasel, B. and Luettin, J. (2003). Automatic facial expression analysis: A survey. *Pattern Recognition*, 36(1):259–275.

Field, D. J. (1987). Relations between the statistics of natural images and the response properties of cortical cells. *Journal of the Optical Society of America A*, 4:2379–2394.

Jain, A. K. and Li, S. Z. (2005). *Handbook of Face Recognition*. Springer-Verlag New York, Inc., Secaucus, NJ, USA.

Kim, J. and André, E. (2008). Emotion recognition based on physiological changes in music listening. *IEEE Trans. Pattern Anal. Mach. Intell.*, 30(12):2067–2083.

Lyons, M., Akamatsu, S., Kamachi, M., and Gyoba, J. (1998). Coding facial expressions with gabor wavelets. In *FG '98: Proceedings of the 3rd. International Conference on Face & Gesture Recognition*, pages 200–205, Washington, DC, USA.

Pantic, M. and Rothkrantz, L. (2004). Facial Action Recognition for Facial Expression Analysis from Static Face Images. *IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics*, 34(3):1449–1461.

Wallhoff, F. (2006). Facial expressions and emotion database. Universitaet Muenchen.

Zhan, C., Li, W., Safaei, F., and Ogunbona, P. (2007). Face to face communications in multiplayer online games: A real-time system. In *HCI (4)*, pages 401–410.