Coding Facial Expressions with Gabor Wavelets (IVC Special Issue)

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Abstract

We present a method for extracting information about facial expressions from digital images. The method codes facial expression images using a multi-orientation, multi-resolution set of Gabor filters that are topographically ordered and approximately aligned with the face. A similarity space derived from this code is compared with one derived from semantic ratings of the images by human observers. Interestingly, the low-dimensional structure of the image-derived similarity space shares organizational features with the circumplex model of affect, suggesting a bridge between categorical and dimensional representations of facial expression. Our results also indicate that it would be possible to construct a facial expression classifier based on a topographically-linked multi-orientation, multi-resolution Gabor coding of the facial images at the input stage. The significant degree of psychological plausibility exhibited by the proposed code may also be useful in the design of human-computer interfaces.

\textit{Key words:} Facial Expression; Gabor Wavelet; Affective Computing; Vision

1 Introduction

Processing of information related to social relationships in groups is an important computational task for primates. The recognition of kinship, identity,
sex and emotional or attentive state of an individual from the appearance of the face are all examples of this type of visual task (for a review see [2]). Whether or not we are explicitly conscious of it, such non-verbal information channels are a critical component of human communication. It would be desirable to make use of these modes for human-compute interaction or computer-mediated human-human interaction. The development of computational methods for handling face and gesture information is a critical step to achieve this goal.

The current paper concentrates on the representation of facial expressions. The face displays several classes of perceptual cues to emotional state: relative displacements of features (opening the mouth), quasi-textural changes in the skin surface (furrowing the brow), and changes in skin hue (blushing); and the time course of these signals. The methods presented in this paper treat feature displacements and quasi-textural cues. Motion is considered only implicitly through the comparison of images. We do not examine colour information.

Our general framework for representing facial expressions uses topographically ordered, spatially localized filters to code patterns in the images. The filters consist of a multi-resolution, multi-orientation bank of Gabor wavelet functions. A similar representation appears in the automatic face recognition system developed by the von der Malsburg group [8].

Previous work on automatic facial expression processing includes studies using representations based on optical flow estimation from image sequences [16,22,1]; principal components analysis of single images [3,1]; and physically-based models [6]. This paper describes the first study to use Gabor wavelets to code facial expressions. Our findings indicate that it is possible to build an automatic facial expression recognition system based on a Gabor wavelet code that has a significant level of psychological plausibility. The recently obtained results of Zhang et al. [23] support this by demonstrating expression classification using Gabor coding and a multi-layer perceptron.

This work is the first to use Gabor wavelets to code facial expressions. Our approach also differs from previous studies on expression recognition in that we test the “fidelity” of the facial expression representation scheme: if two facial expressions are perceived as being similar by human observers, they should be neighbours in the space of the representation. In addition to being a potentially important engineering criterion in the design of facial expression processing systems, fidelity is convenient in testing the utility of a representation because it allows the use of examples of expression images that are not pure (or even standard) facial expressions. Rather than assigning training examples to hard expression categories and testing the classification performance of a model, we examine the”fidelity” of our representation scheme.

2 Preliminary reports on the research were presented at the ARVO’97 conference in May 1997 [10], and at a workshop in Okinawa in June 1997 [11].

2
Fig. 1. Examples of Gabor filter responses to two facial expression images for three of the filters used.

we can examine the extent to which the representation model reflects human judgements on the expression content of the face.

2 Multi-Scale, Multi-Orientation Gabor Coding

To extract information about facial expression, each 256 by 256-pixel image, $I$, was convolved with a multiple spatial resolution, multiple orientation set of Gabor filters (Fig.1), $G_{\vec{k},+}$ and $G_{\vec{k},-}$. The sign subscript indicates filters of even and odd phase, while $\vec{k}$, the filter wave-vector, determines the spatial frequency and orientation tuning of the filter. A description of the complex-valued two dimensional Gabor transform is given by Daugman [4]. Responses of the filters to the image were combined into a vector, $\mathbf{R}$, with components given by:

$$R_{\vec{k}, \pm}(\vec{r}_0) = \int G_{\vec{k}, \pm}(\vec{r}_0, \vec{r})I(\vec{r})d\vec{r},$$  \hspace{1cm} (1)

where,

$$G_{\vec{k},+}(\vec{r}) = \frac{k^2}{\sigma^2}e^{-k^2||\vec{r}-\vec{r}_0||^2/2\sigma^2}\cos(\vec{k} \cdot (\vec{r} - \vec{r}_0)) - e^{-\sigma^2/2},$$ \hspace{1cm} (2)

$$G_{\vec{k},-}(\vec{r}) = \frac{k^2}{\sigma^2}e^{-k^2||\vec{r}-\vec{r}_0||^2/2\sigma^2}\sin(\vec{k} \cdot (\vec{r} - \vec{r}_0)).$$ \hspace{1cm} (3)
The integral of the cosine Gabor filter, $e^{-\sigma^2/2}$, is subtracted from the filter to render it insensitive to the absolute level of illumination. The sine filter does not depend on the absolute illumination level. Three spatial frequencies were used with wave-numbers:

$$k = \{ \frac{\pi}{2}, \frac{\pi}{4}, \frac{\pi}{8} \}$$

measured in inverse pixels. The highest frequency is set at half the Nyquist sampling frequency, with frequency levels spaced at octaves; $\sigma = \pi$ was used in all calculations, giving a filter bandwidth of about an octave, independent of the frequency level. Six wave-vector orientations were used, with angles equally spaced at intervals of $\frac{\pi}{6}$ from 0 to $\pi$.

The components of the Gabor vector, $R_k$, are defined as the amplitude of the combined even and odd filter responses:

$$R_k = \sqrt{R_{k,+}^2 + R_{k,-}^2}$$

The response amplitude is less sensitive to position changes than are the linear filter responses. To study the similarity space of Gabor coded facial images, we compared responses of filters having the same spatial frequency and orientation preference at corresponding points in the two facial images. We use the normalized dot product to quantify the similarity of two Gabor response vectors. We calculate the similarity of two facial images as the average of the Gabor vector similarity over all corresponding facial points. Since Gabor vectors at neighbouring pixels are strongly correlated, it is sufficient to carry out this calculation at points on a sparse grid covering the face (Fig. 2). The automatic face recognition system developed by the von der Malsburg group [8] uses a related similarity measure. However, the filter parameters used here differ from those used in that work. Previous work has demonstrated automatic systems for scaling the face and registering a graph approximately with the features of the face [8]. For this reference study, the highest precision positioning was desirable. Therefore grids were positioned manually on facial images scaled to a standard size.

3 Facial Expression Dataset

A dataset of facial expression images was collected. Ten expressers posed 3 or 4 examples of each of the six basic facial expressions (happiness, sadness, surprise, anger, disgust, fear) [5] and a neutral face for a total of 219 images.
Fig. 2. The 34 node grid used to represent facial geometry.

of facial expressions. To simplify the experimental design, only Japanese female expressers and subjects were employed. Figure 3 shows the apparatus used to photograph the expressers. Each expresser took pictures of herself while looking through a semi-reflective plastic sheet towards the camera. Hair was tied away from the face to expose all expressive zones of the face. We positioned tungsten lights to illuminate the face evenly. A box enclosed the region between the camera and plastic sheet to reduce back-reflection. The images were printed as monochrome photographs and digitized using a flatbed scanner. Figure 4 shows sample images.

4 Semantic rating of facial expression images.

To provide a basis for testing the fidelity of the Gabor representation, we directly compare the similarities as measured from the Gabor coded images and derived from human judgements. With this procedure, we do not have to use the expression labels attached to each image (the emotion posed by that the expresser) when comparing the model with the data. Instead, viewers rate the emotional content of each image using emotion adjectives. This approach
captures variations in intensity and blends of mixed facial expressions and reduces the epistemological difficulties of working with photographs of the Ekman standard basic facial expressions in a different cultural context.

Experimental subjects rated pictures for the degree of each component basic expression on a five-point Likert scale. A total of 92 Japanese female undergraduates took part in the study. The subject pool was divided into four groups: 1.A, 1.B, 2.A, and 2.B. Group 1.A (31 subjects) rated 108 pictures on six basic facial expressions (happiness, sadness, surprise, anger, disgust and fear). Group 1.B (31 subjects) rated the complementary set of 111 pictures (out of the 219 total) on the six basic expressions. Both Group 1.A and 1.B saw images of all seven expression categories (including fear images). Group 2.A (15 subjects) rated 94 pictures on five of the six basic facial expressions (fear was excluded). Group 2.B (15 subjects) rated a different set of 93 images on the five basic facial expressions (fear excluded). The images presented to
Table 1
Rank correlation between model and semantic rating similarities.

| Expresser Initials | Gabor | Geometry |
|--------------------|-------|----------|
| KA                 | 0.593 | 0.467    |
| KL                 | 0.465 | 0.472    |
| KM                 | 0.616 | 0.527    |
| KR                 | 0.636 | 0.368    |
| MK                 | 0.472 | 0.287    |
| NA                 | 0.725 | 0.358    |
| NM                 | 0.368 | 0.099    |
| TM                 | 0.423 | 0.282    |
| UY                 | 0.648 | 0.074    |
| YM                 | 0.538 | 0.455    |
| **Average**        | 0.568 | 0.366    |

Group 2.A and 2.B excluded fear expressions. Each image was thus labelled with a 5 or 6 component vector with ratings averaged over all subjects. Similarities between these semantic vectors were calculated using the Euclidean distance.

In pilot experiments, we found that fear ratings showed greater variability than ratings for the other expression categories. For this reason, we also ran a set of experiments that excluded pictures of fear expressions and fear ratings.

5 Results

Facial expression image similarity computed using the Gabor coding and semantic similarity computed from human ratings were compared by rank correlation. It is convenient to compare similarity spaces rather than categorization performance as this avoids the problem that posed expressions are not necessarily pure examples of a single expression category.

As a control, geometric similarity was also rank correlated with the semantic ratings similarity values. The distance of each grid point (Fig. 2) from the point at the nose tip formed the components of a 33 dimensional shape vector. Dissimilarity between two grid configurations were calculated using the Euclidean distance. For the experiments in which all facial expressions were included (i.e. comparison with data from subject groups 1.A and 1.B) the rank
Table 2
Rank correlations between model and semantic rating similarities for experiments which excluded fear stimuli and ratings.

correlation between Gabol model and human data ranged from 0.42 (expresser TM) to 0.725 (expresser NA) with an average value of 0.568. For the geometry based control, rank correlation between model and data ranged from 0.074 (expresser UY) to 0.527 (expresser KM) with an average value of 0.366. Correlation results for all expressers are listed in Table 1. With fear stimuli and ratings excluded (data from subject groups 2.A and 2.B) the rank correlation between Gabor model and data ranged from 0.624 (expresser TM) to 0.782 (expresser KA), with an average value of 0.679. For the geometry based control, rank correlations between model and data ranged from 0.206 (expresser UY) to 0.619 (expresser KM) with an average value of 0.462. Correlation results for all expressers are listed in Table 2. Expresser NM was considered to be an outlier and excluded from the above quoted averages and ranges. On closer inspection NM’s expressions appeared to be difficult to interpret.

All rank correlations quoted were calculated using Spearman’s method. The two sided significance of all of the deviation of all rank correlations calculated indicated a high level of significance. In all cases the correlation coefficient was greater for the Gabor model than for the model based solely on geometric displacement of feature points. Gabor and human similarity data was analyzed using non-metric multidimensional scaling (nMDS) using the ALSCAL algorithm [21]. nMDS embeds points in a Euclidean space in such a way that the distances between points preserves the rank order of the dissimilarity values between those points. “Stress” and “Rsq” respectively measure the residual misfit of the Euclidean distance to the dissimilarities and the squared correla-

| Expresser Initials | Gabor  | Geometry |
|-------------------|--------|----------|
| KA                | 0.782  | 0.574    |
| KL                | 0.634  | 0.500    |
| KM                | 0.744  | 0.619    |
| KR                | 0.684  | 0.401    |
| MK                | 0.644  | 0.512    |
| NA                | 0.696  | 0.420    |
| NM                | 0.458  | 0.207    |
| TM                | 0.624  | 0.425    |
| UY                | 0.653  | 0.206    |
| YM                | 0.650  | 0.506    |
| Average           | 0.679  | 0.462    |
tion between distances and dissimilarities. By monitoring these parameters as the number of nMDS dimensions was increased, it was found that two dimensions provide an adequate embedding of the similarity data. Figs. 5, 6, and 7 show sample nMDS solutions for human ratings similarity values and Gabor code derived similarity values. In figs. 6 and 7, the following abbreviations are used: NE - Neutral, HA - Happiness, SA - Sadness, SU - Surprise, AN - Anger, DI - Disgust. Fig. 5 shows sample nMDS solution in which images have been positioned at their coordinates in the Euclidean space. nMDS solutions are arbitrary up to rotation, translation and reflection of the configuration of points. In Fig. 5 the points have been rotated, translated, and reflected to show the agreement between model and data. Figs. 6 and 7 have not been treated in this way. The most salient aspect of these plots is the relative positioning of the facial expression clusters.

Fig. 5. nMDS solutions for Gabor and semantic rating similarities.

Fig. 6. nMDS solution spaces for Gabor and semantic rating similarities (Subject KA). See text for key to expression abbreviations.
6 Discussion

Similarity values calculated using the Gabor coding and semantic ratings showed a highly significant degree of correlation, with no parameter fitting. Non-metric multidimensional scaling uncovered a low-dimensional space within which Gabor-coded images cluster into the known basic categories of facial expressions. Together, these findings show that this representation scheme extracts adequate image information to code facial expressions. Using this image coding method and a multilayer perceptron classifier a facial expression recognition system has been built [23].

Two sets of experiments were run, one excluding fear expressions. The agreement between the model and data is higher when we exclude fear from the comparison. Fear ratings are more variable than for the other expression categories, suggesting that fear is either more difficult for our expressers to pose, or for the viewers to recognize.

Interestingly, the low-dimensional spaces for ratings data and Gabor-coded image data are similar. One axis (nearly horizontal in Fig. 5) corresponds to the degree of pleasantness (happy vs. anger and disgust) in the expression. A roughly orthogonal dimension corresponds to the level of arousal shown by the face (surprised vs. sad). We observed this configuration for all of the expressers studied (except NM, where the data is erratic). Deviations from this general arrangement visible in Figs. 6 and 7 are typical of other nMDS results that we do not show here.

The Gabor similarity showed a higher degree of correlation with the data than did a geometry-based control. Feature geometry, an explicit and precise function of facial deformation due to expression, does not capture any textural changes. The addition of more grid points could increase the performance of

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3 Not long after these results were published, we demonstrated similar performance using a more constrained analysis based on linear discriminant analysis applied to the Gabor coded images [13].
the geometry measure but at the cost of increased computational complexity. Locating the grid points is the most expensive part of a fully automatic system [8]. Moreover, the Gabor measure puts less stringent demands on the precision of the grid position because the similarity calculation does not use the phase of the filter response. A combined Gabor+Geometry system could have even higher performance, but the results of [23] indicate the improvements are minor.

Previous studies on automatic facial expression processing classify images into facial expression or facial action categories. The facial images used in training or testing such systems should preferably be pictures of pure expressions posed by trained experts. A novel aspect of our work is that we compare the representation with differential ratings on emotion adjectives. This procedure avoids a requirement for pure expressions. By comparing the system with human semantic rating data, we relax the relevance of expression label categories.

Why is there any agreement with psychology? Facial expressions are distinguished by fine changes in the shape and texture of the face. From the standpoint of neurobiology, such changes are best represented using the spatially localized receptive fields typical of primary visual cortex (V1) cells. The neural systems processing facial expressions in higher vision require access to such spatially localized information. Gabor wavelet functions approximately model V1 simple cell while the amplitude of the complex Gabor transform models complex cells [4,7,17]. Hence a Gabor wavelet code of facial expression may partially model expression coding by the brain. Previous work by Lyons et al. [9] found that the Gabor measure predicts aspects of facial similarity perception.

Finally, it is interesting that the low-dimensional structure of the emotion adjective semantic rating data similarity space resembles that of the Gabor measure. Many studies in the psychological literature (beginning with Schlossberg [20], but more recently studied by Russell [18,19]) suggest a “circumplex” arrangement of the basic facial expressions in a two-dimensional space with dimensions of pleasantness and arousal. We conjecture that high-level (even semantic level) processing of facial expressions may preserve some of the topographical organizational aspects of the low-level processing by the early visual system.

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4 A more detailed account of this work was finally published in [14].
References

[1] M. Bartlett, P. Viola, T. Sejnowski, J. Larsen, J. Hager, P. Ekman, Classifying Facial Action, in: D. Touretzky et al. eds., Advances in Neural Information Processing Systems 8, MIT Press, Cambridge, MA, 1996.

[2] V. Bruce, A. Young, In the Eye of the Beholder - The Science of Face Perception, Oxford University Press, Oxford, UK, 1998.

[3] C. Padgett, G. Cottrell, Identifying Emotion in Static Face Images, in: Proceedings of the 2nd Joint Symposium on Neural Computation, vol. 5, (La Jolla, CA, 1995) 91-101.

[4] J.G. Daugman, Uncertainty Relation for Resolution in Space, Spatial frequency, and Orientation Optimized by Two-dimensional Visual Cortical Filters, Journal of the Optical Society of America A 2 (1985) 1160-1169.

[5] P. Ekman, W. V. Friesen, Unmasking the Face. A guide to recognizing emotions from facial clues, Consulting Psychologists Press, Palo Alto, CA, 1975.

[6] I. Essa, A. Pentland, Facial Expression Recognition using Visually Extracted Facial Action Parameters, in: M. Bichsel, ed., Proceedings of the International Workshop on Automatic Face and Gesture Recognition (Zurich, Switzerland, 1995) 35-40.

[7] J.P. Jones, L.A. Palmer, An Evaluation of the Two-dimensional Gabor Filter Model of Simple Receptive Fields in Cat Striate Cortex, Journal of Neurophysiology 58 (1987) 1233-1258.

[8] M. Lades, J. C. Vorbruggen, J. Buhmann, J. Lange, C. von der Malsburg, R. P. Wurtz, W. Konen, Distortion Invariant Object Recognition in the Dynamic Link Architecture, IEEE Transactions on Computers, 42 (1993) 300-311.

[9] M. J. Lyons, K. Morikawa, A model based on V1 cell responses predicts human perception of facial similarity, Investigative Ophthalmology and Visual Science, 37:910 (1996).

[10] M. J. Lyons, M. Kamachi, P. Tran, J. Gyoba, V1 Similarity Measure Recovers Dimensions of Facial Expression Perception, Investigative Ophthalmology and Visual Science, 38:4 (1997).

[11] M. J. Lyons, M. Kamachi, J. Gyoba, Gabor Wavelet Representation of Facial Expression, Technical report of IEICE. HIP, The Institute of Electronics, Information and Communication Engineers, 97:117 (Okinawa,1997) 9-15.

[12] M. J. Lyons, S. Akamastu, M. Kamachi, J. Gyoba, Coding Facial Expressions with Gabor Wavelets, in: Proceedings of the Third International Conference on Automatic Face and Gesture Recognition (Nara, Japan, 1998) 200-205.
[13] M. J. Lyons, J. Budynek, S. Akamastu, Automatic classification of single facial images human perception of facial similarity, IEEE Transactions on Pattern Analysis and Machine Intelligence, 21:12 (1999) 1357-1362.

[14] M. J. Lyons, K. Morikawa, A linked aggregate code for processing faces, Pragmatics & Cognition, 8:1 (2000) 63-81.

[15] C. von der Malsburg, The Correlation Theory of Brain Function, Internal Report 81-2, Max Planck Institute for Biophysical Chemistry, Göttingen, 1981.

[16] K. Mase, Recognition of facial expression from optical flow, IEICE Transactions, 74 (1991) 3474-3483.

[17] D. A. Pollen, S. F. Ronner, Phase Relationships Between Adjacent Simple Cells in the Visual Cortex, Science 212 (1981) 1409-1411.

[18] J. A. Russell, A circumplex model of affect, Journal of Personality and Social Psychology, 39 (1980) 1161-1178.

[19] J.A. Russell, B. Fehr, Relativity in the Perception of Emotion in Facial Expressions, Journal of Experimental Psychology: General, 116 (1987) 223-237.

[20] H. Schlosberg, The description of facial expressions in terms of two dimensions, Journal of Experimental Psychology 44 (1952) 229-237.

[21] Y. Takane, F. W. Young, J. de Leeuw, Nonmetric individual differences multidimensional scaling: An alternating least squares method with optimal scaling features, Psychometrika 42 (1977) 7-67.

[22] Y. Yacoob, L. Davis, Recognizing Human Facial Expressions from Long Image Sequences using Optical Flow, IEEE Transactions on Pattern Analysis and Machine Intelligence, 18 (1996) 636-642.

[23] Z. Zhang, M. Lyons, M. Schuster, S. Akamastu, Comparison between Geometry-based and Gabor-wavelets-based Facial Expression Recognition using Multi-layer Perceptron, in: Proceedings of the Third International Conference on Automatic Face and Gesture Recognition (Nara, Japan, 1998) 454-459.