FACE REPRESENTATION AND TRACKING USING GABOR WAVELET NETWORKS

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ABSTRACT

This work presents a new method for a human face representation and tracking in video sequences. A discrete face template is represented by linear combination of the continuous 2D odd-Gabor wavelet functions (Gabor Wavelet Network). The weights and 2D parameters (position, scale and orientation) of each wavelet are determined optimally. Using this representation, an effective face tracking method is achieved that is robust to illumination changes and deformations of the face image such as eye blinking and smile.

1 INTRODUCTION

The automatic face and facial features tracking in video sequence is a fundamental problem of gesture recognition. A new method for face tracking based on the approach of *Krüger* [1] is introduced. The potential of a Gabor Wavelet Networks (GWNs) for face template representation is also shown. This tracking method is quite robust and it is insensitive to homogeneous illumination changes and affine deformations of the face image. The face template is represented by continuous 2D odd-Gabor wavelets. A model of a discrete face image is obtained by linear combination of wavelets. With respect to earlier defined approaches to object representation, it could be said that GWN combines *template-based* and *feature-based* approaches. Each wavelet represents a model of some image feature. On the other side, the overall face geometry is presented in this model as well.

2 WAVELET NETWORKS

This concept was inspired by wavelet decomposition and neural networks. It is well known that any function f may be expressed as a linear combination of wavelets obtained by dilating and translating a single mother wavelet function ψ. The number of the wavelets is elective and parameters are optimized by a learning process. The more wavelets are used, the more precise approximation is achieved. As the number decreases, the representation becomes more general; thus, it is possible to suppress effect of different individuals' faces. Figure 1 shows the typical architecture of the wavelet network.

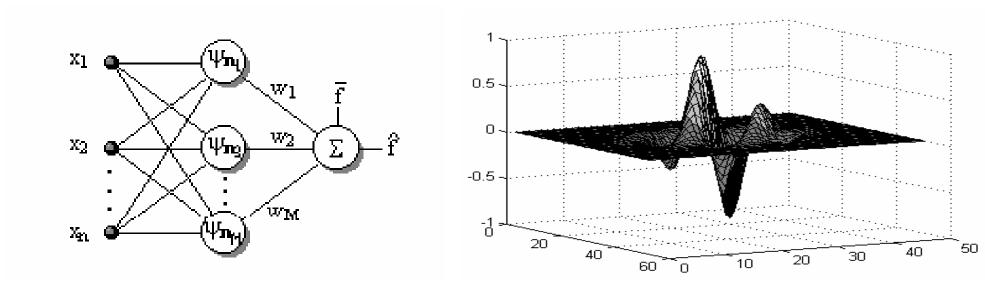

Fig. 1: *Wavelet network (left), used mother wavelet (right)*

3 GABOR WAVELET NETWORKS (GWN)

In this case, the face template is represented by a wavelet network where the mother wavelet is an 2D odd-Gabor function. Figure 1 also illustrates used mother function. An important part of this method is parameters and weights optimization. The family of wavelets $\psi=\{\psi_{n1},\dots\psi_{nm}\}$ is optimized with respect to parameters $\boldsymbol{n}_i=\{c_x,c_y,\theta,s_x,s_y\}$ that modify the shape of the mother wavelet, c_x, c_y are the translation (position), s_x, s_y denote the dilatation, and θ denotes orientation of wavelet. For image f an energy function E is specified which is minimized by the means of learning process regarding the desired wavelet network parameters.

$$E = \min_{\vec{n}_i, w_i \forall i} \left\| f - \left(\sum_i w_i \psi_{\vec{n}_i} + \bar{f}\right) \right\|_2^2$$

It can be said that the two optimized vectors ψ and $\boldsymbol{w}$ constitute an optimized Gabor Wavelet Network (GWN) for the specific face image f. The energy minimization problem is useful to solve e.g. by the *Levenberg-Marquardt* gradient descent method.

Fig. 2: *Optimized GWN_{52}* as the face template

4 GWN REPOSITIONING

Now assume face motion in a new image. The face position is changed. In the repositioning process, all the wavelets are positioned correctly on the same facial features in the new image. It is important to note that GWN repositioning process may cover any affine transformation (translation, dilatation, rotation, etc.) applied to the original face region. The GWN repositioning consists in determination of correct parameters of this transformation. First it is necessary to define the so-called Gabor superwavelet Ψ_n. *GSW* is defined as a linear combination of the wavelets ψ_{ni} such that:

$$\Psi_n(x) = \sum_i w_i \psi_{\vec{n}_i}(SR(x-C)+C+T)$$

where parameters of the superwavelet Ψ_n determines the dilatation matrix $\boldsymbol{S}$, the rotation matrix $\boldsymbol{R}$ and the translation vector $\boldsymbol{T}$. The vector $\boldsymbol{C}$ contains coordinates of the face center. In order to find the optimal parameters, the difference of the new image and repositioned GWN must be minimized using previously declared *LM* method.

5 FACE TRACKING USING GWN

The principle of GWN repositioning may be also applied to a video sequence providing the way to solve face tracking problem. In this approach, the face is considered as planar object that is viewed under an orthographic projection. After the initialization (face localization in the first frame), the wavelet representation for face region is obtained using a GWN. This template is then affinely repositioned in the next frame as described above. Face tracking is then performed applying the found transformations to the selected points. This tracking method includes the overall geometry of face as well.

Fig. 3: *Face tracking using the GWN*

6 CONCLUSION

The GWN approach for face representation and tracking was presented. This representation may be face specific or generic, depending on the number of used wavelets. The face specific representation can be used for face recognition while the generic representation can be used for facial expression detection. The face tracking algorithm was implemented by repositioning of the superwavelet. GWN approach appears to be quite perspective, insensitive to certain deformations and iconic changes in face region (smile, eye blinking), insensitive to homogenous illumination changes, and also generally very robust. It is worth mentioning that the GWN technique has been also used to face detection, recognition and face position estimation.

REFERENCES

[1] Volker Kruger: *Gabor Wavelet Networks for Object Representation*. Kiel, 2000.

[2] Rogério S. Feris, Roberto M. Cesar Junior: *Tracking Facial Features Using Gabor Wavelet Networks*. Brasil, 2001.