

Image Enhancement using Adaptive and Gaussian Filters, DWT for Face Recognition

K.Mala^{#1}, T.Lavanya^{#2}

Department of Computer Application, S.A.Engineering College,
malamca7@gmail.com

Abstract—Automatic recognition of people is a challenging problem which has received much attention during recent year due to its many application in different fields .Face recognition is one of those challenging problems and up to date. There is no technique that provides a robust solution to all situations. This paper presents a new technique for human face recognition. This technique uses an image-based approach towards artificial intelligence by removing redundant data form face images through image compression using the two-dimensional discrete cosine transform (2D-DCT) It containing five subjects and each subject has 5 images with different facial expressions. the last recognition rate is valued by 81.36% for 10 consecutive trails. Image Enhancement using the Gaussian filters to compress image on any directional, cosine transform is processed by only few type of face reactions are observed. so, to overcome we using the DWT. It observed many type of face reactions. the main advantage of this technique is it is high-speed processing capability and low computational requirements in terms of both speed and memory utilization.

Keywords—Face recognition, discrete wavelet transform, self-organizing map, Neural network, Artificial intelligence.

1. Introduction

In today's networked world, the need to maintain the security of information or physical property is becoming both increasingly important and increasingly difficult. From time to time we hear about the crimes of credit card fraud, computer breakings by hackers or security breaches in a Company or government building .face recognition has becomes a very active area of research in recent years mainly due to increasing security demands and its potential commercial and enforcement applications.A block diagram of the proposed technique of the face recognition system is presented first, the DWT for each face recognition system is computed and feature vectors are formed from the discrete wavelet transform co-efficient. second, using the (som) with an unsupervised learning technique to classifies the vectors into group images on presented or not the data base the original image is presented result is displayed it doesn't the

subject the result is not displayed. Since skin color in humans varies by individual, research has revealed that intensity rather than chrominance is the main distinguishing characteristic.

2. Methodology

In many practical applications and especially in the application described in this report the signal of interest is sampled. In order to use the results we have achieved so far with a discrete signal we have to make our wavelet transform discrete too. Remember that our discrete wavelets are not time-discrete, only the translation- and the scale step are discrete. Simply implementing the wavelet filter bank as a digital filter bank intuitively seems to do the job. But intuitively is not good enough, we have to be sure. In (16) we stated that the scaling function could be expressed in wavelets from minus infinity up to a certain scale j . If we add a wavelet spectrum to the scaling function spectrum we will get a new scaling function, with a spectrum twice as wide as the first. The effect of this addition is that we can express the first scaling function in terms of the second, because all the information we need to do this is contained in the second scaling function. We can express this formally in the so-called multi resolution formulation [Bur98] or two-scale relation.

$$\varphi(2^j t) = \sum_k h_{j+1}(k) \varphi(2^{j+1} t - k).$$

The two-scale relation states that the scaling function at a certain scale can be expressed in terms of translated scaling functions at the next smaller scale. Do not get confused here: smaller scale means more detail. The first scaling function replaced a set of wavelets and therefore we can also express the wavelets in this set in terms of translated scaling functions at the next scale. More specifically we can write for the wavelet at level j :

$$\psi(2^j t) = \sum_k g_{j+1}(k) \varphi(2^{j+1} t - k),$$

which is the two-scale relation between the scaling function and the wavelet. Since our signal $f(t)$ could be expressed in

terms of dilated and translated wavelets up to a scale $j-1$, this leads to the result that $f(t)$ can also be expressed in terms of dilated and translated scaling functions at a scale j :

$$f(t) = \sum_k \lambda_j(k) \varphi(2^j t - k).$$

To be consistent in our notation we should in this case speak of discrete scaling functions since only discrete dilations and translations are allowed. If in this equation we step up a scale to $j-1$ (!), we have to add wavelets in order to keep the same level of detail. We can then express the signal $f(t)$ as

$$f(t) = \sum_k \lambda_{j-1}(k) \varphi(2^{j-1} t - k) + \sum_k \gamma_{j-1}(k) \psi(2^{j-1} t - k).$$

If the scaling function $\phi_{j,k}(t)$ and the wavelets $\psi_{j,k}(t)$ are orthonormal or a tight frame, then the coefficients found by taking the inner product.

$$\lambda_{j-1}(k) = \langle f(t), \phi_{j,k}(t) \rangle$$

$$\gamma_{j-1}(k) = \langle f(t), \psi_{j,k}(t) \rangle$$

These two equations state that the wavelet- and scaling function coefficients on a certain scale can be found by calculating a weighted sum of the scaling function coefficients from the previous scale. Now recall from the section on the scaling function that the scaling function coefficients came from a low-pass filter and recall from the section on subbandoding how we iterated a filter bank by repeatedly splitting the low-pass spectrum into a low-pass and a high-pass part. The filter bank iteration started with the signal spectrum, so if we imagine that the signal spectrum is the output of a low-pass filter at the previous (imaginary) scale, then we can regard our sampled signal as the scaling function coefficients from the previous (imaginary) scale. In other words, our sampled signal $f(k)$ is simply equal to (k) at the largest scale! But there is more. As we know from signal processing theory a discrete weighted sum like the ones in (23) and (24) is the same as a digital filter and since we know that the coefficients $j(k)$ come from the low-pass part of the spitted signal spectrum, the weighting factors $h(k)$ in (23) must form a low-pass filter. And since we know that the coefficients $j(k)$ come from the high-pass part of the spitted signal spectrum, the weighting factors $g(k)$ in (24) must form a high-pass filter.

3. Experimental Results

3.1 Image Database

A face image database was created for the purpose of benchmarking the face recognition system. The image database is divided into two subsets, for separate training and testing purposes. During SOM training, 25 images were used, containing five subjects and each subject having 5 images with different facial expressions. Fig. 7 shows the training and testing image database constructed. The face recognition system presented in this paper was developed, trained, and tested using MATLAB™ 7.2. The computer was a Windows XP machine with a 3.00 GHz Intel Pentium 4 processor and 1 GB of RAM

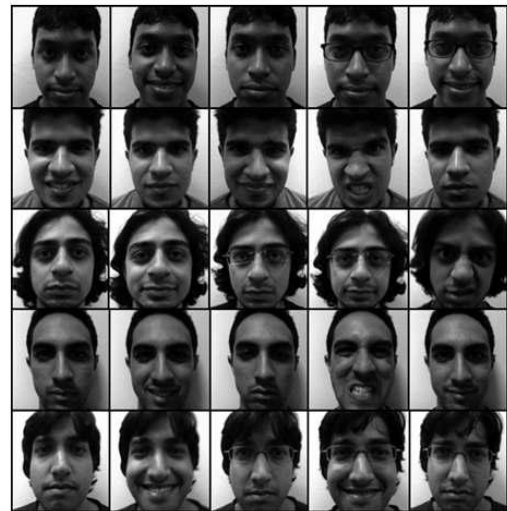


Fig.1: Image database for training



Fig.2: Training and testing image database. Untrained image is used for testing

3.2 Validation of Technique

The preprocessed grayscale images of size 8×8 pixels are reshaped in MATLAB to form a 64×1 array with 64 rows and 1 column for each image. This

technique is performed on all 5 test images to form the input data for testing the recognition system. Similarly, the image database for training uses 25 images and forms a matrix of 64×25 with 64 rows and 25 columns. The input vectors defined for the SOM are distributed over a 2D-input space varying over [0 255], which represents intensity levels of the grayscale pixels. These are used to train the SOM with dimensions [64 2], where 64 minimum and 64 maximum values of the pixel intensities are represented for each image sample. The resulting SOM created with these parameters is a single-layer feed forward SOM map with 128 weights and a competitive transfer function. The weight function of this network is the negative of the Euclidean distance[3]. This SOM network is used for all subsequent experiments. As many as 5 test images are used with the image database for performing the experiments. Training and testing sets were used without any overlapping. Fig.1.1 shows the result of the face recognition system simulated in MATLAB using the image database and test input image shown in Fig. 1.2.

The result obtained from this simulation identifies that the subject in the input image Fig. 1.2(a) is “present” in the image database. The best match image displayed in Fig. 1.1(b) illustrates that subjects with different facial expressions in the image database can be easily identified.

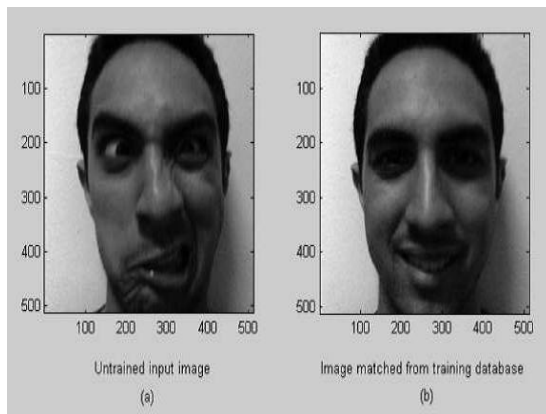


Fig.3: Result of face recognition system. (a) Untrained input image for testing. (b) Best match image of subject found in training database

4. Conclusion

This paper has presented a novel face recognition technique that uses features derived from DWT coefficients,

along with a SOM-based classifier. The system was evaluated in MATLAB using an image database of 25 face images, containing five subjects and each subject having 5 images with different facial expressions. After training for approximately 850 epochs the system achieved a recognition rate of 89.36% for 10 consecutive trials. A reduced feature space, described for experiment 2 above, dramatically reduces the computational requirements of the method as compared with standard DWT feature methods.

References

- [1] B. Abboud, F. Davoine, and M. Dang. Facial expression recognition and synthesis based on an appearance model. *Signal Processing: Image Communication*, 19(8):723–740, 2004
- [2] B. Abboud and F. Davoine. Bilinear factorisation for facial expression analysis and synthesis. *IEEE Proceedings of the Vision Image and Signal Processing*, 152(3):327–333, 2005
- [3] V. Blanz, C. Basso, T. Poggio, and T. Vetter. Reanimating faces in images and video. *Computer Graphics Forum*, 22(3):641–650, 2003
- [4] V. Blanz, K. Scherbaum, T. Vetter, and H.-P. Seidel. Exchanging faces in images. *Computer Graphics Forum*, 23(3):669–676, 2004
- [5] F. Bookstein. Principal warps: Thin-plate splines and the decomposition of deformations. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 11(6):567–585, 1989
- [6] C. Bregler, M. Covell, and M. Slaney. Video rewrite: Driving visual speech with audio. In *Proceedings of SIGGRAPH*, pages 353–360, 1997.
- [7] N.P. Chandrasiri, T. Naemura, and H. Harashima. Interactive analysis and synthesis of facial expressions based on personal facial expression space. In *Proceedings of IEEE International Conference on Automatic Face and Gesture Recognition*, pages 105–110, 2004
- [8] K. Chang, K. Bowyer, and P. Flynn. A survey of approaches and challenges in 3D and multi-modal 2D+3D face recognition. *Computer Vision and Image Understanding*, 101(1):1–15, 2006.
- [9] H. Chen, Y.-Q. Xu, H.-Y. Shum, S.-C. Zhu, and N.-N. Zheng. Example-based facial sketch generation with non-parametric sampling. In *Proceedings of International Conference on Computer Vision*, volume 2, pages 433–438, 2001
- [10] P.-Y. Chiang, W.-H. Liao, and T.-Y. Li. Automatic caricature generation by analyzing facial features. In *Proceedings of Asian Conference on Computer Vision*, 2004

K.Mala is holding under graduation in Bachelor of Computer Application at Kamban Arts and Science college for women, Thiruvanamalai. And pursuing Master of computer Application at S.A Engineering college, Chennai. This paper is a part of curriculum covered under in (MC7413) Technical Seminar & Report Writing.

T.Lavanya is holding a under graduation in Bachelor of Computer Application at Sindhi Arts and Science college. And pursuing Master of computer Application at S.A Engineering College, Chennai This paper is a part of curriculum covered under in (MC7413) Technical Seminar & Report Writing.