IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 10, May 2016)

Side View Face Authentication using DWT and Neural Network

Archana Tiwari
archanatiwari.sgi@gmail.com

Dr. Pankaj Sharma
pankaj_sharma1@rediffmail.com

Abstract –**This paper provides a side-view face authentication method focused around discrete wavelet transform (DWT) and Neural Network. A subset determination strategy that expands the quantity of training samples and permits subsets to protect the global information is exhibited. The authentication technique could be summarized to have the accompanying steps: feature extraction, wavelet decomposition, subset splitting and Neural Network verification. This strategy exploits localization property of wavelet in both frequency and spatial domains, while keeping up the generalized properties of Neural Network. The implementation of the proposed strategy is computationally attainable and the simulation is performed with MATLAB 2010a which demonstrates that the performance is satisfactory.**

Keywords – **DWT, Neural Network.**

I. Introduction

Intelligent Face Recognition i.e. IFR can give profit in the diverse territories of: Law Enforcement, Access Control, Airport Security, Country Defence, and Customs & Immigration. Going with entries detail each of these subjects, thus Law Enforcement: Today's law implementation organizations are searching for imaginative advances to help them stay one stage in front of the world's continually propelling terrorists. Air terminal Security: IFR can upgrade security endeavours effectively underway at most airplane terminals and other significant transportation centre points (seaports, train stations, and so forth). This incorporates the identification of known terrorists before they get onto a plane or into a secured position [1]. Access Control: IFR can improve security exertions significantly step by step. Biometric identification for the most part guarantees that an individual is who they case to be is accurate or not furthermore taking out any stress of somebody who can acquire keys or access cards for unlawful reason. Driver's Licenses & Passports: IFR can power the current ID foundation by utilizing existing photograph databases and the current enrolment method (e.g. cams and catch stations); and coordinate with terrorist records, including national, provincial and global databases of "most needed". Country Defence: IFR can help in the war against assassination and improving security deliberations. This incorporates travellers scanning at the ports of entrance section; incorporating with CCTV cams for reconnaissance of structures and offices; and a lot of people more. Customs & Immigration: There are new laws require progressed accommodation of evident from planes and boats touching base from different nations; this ought to empower the security framework to help in distinguishing proof of persons who ought to, and ought not to be there [2-3].

The most common answer for this undertaking may be to gather different gallery images in all conceivable poses to cover the pose varieties in the captured images, which obliges a reasonably simple face recognition technique. In a lot of real time circumstances, it is repetitive and/or hard to gather these various gallery images in diverse stances and in this manner the capability of face recognition method to endure pose varieties is alluring. Case in point, if a passport size photograph for every individual was put away in the database, an effective face recognition technique ought to still have the capacity to perform the above air terminal reconnaissance assignment. In such sense, face recognition over pose alludes to perceiving face pictures whose poses are not the same as the display (known) images. On the off chance that a face recognition does not have a decent pose tolerance, given a frontal passport size photograph, the framework seems to oblige helpful subjects who look straightforwardly at the camera and face recognition is no more passive and non-meddlesome. Thus, pose invariance or tolerance is a key capability for face recognition to attain its preferences of being non-nosy over other biometric procedures obliging helpful subjects, for example, iris recognition and fingerprint recognition.

Because of the complex 3D structures and different surface reflectivity of human faces, on the other hand, pose varieties bring genuine difficulties to current face recognition frameworks. The image varieties of human faces under 3D changes are bigger than that routine face recognition can endure. Particularly, natural attributes of the faces, which recognize one face from an alternate, don't fluctuate incredibly from individual to individual, while

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 10, May 2016)

extents of picture varieties brought about by pose varieties are frequently bigger than sizes of the varieties of the inalienable qualities. The testing undertaking faced by pose invariant face recognition technique is to concentrate the inborn qualities free from pose varieties.

The aim of this paper is to implement a side-view face authentication method based on discrete wavelet transform and Neural Network classifier.

II. PROPOSED METHOD

Our goal is to develop a robust approach which can be conveniently implemented. Our observation is that the number of samples for extracting the features is always limited in application. Thus, a method which uses only a few samples for training is preferred to those which need many. Based on this philosophy, the proposed method is developed. The flow diagram of the proposed approach is shown in figure 1.

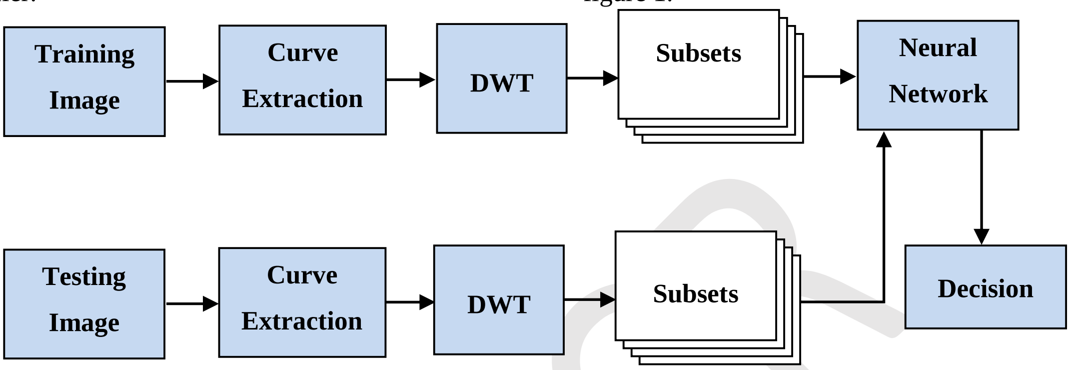

Figure 1: Block diagram of the proposed approach

The outline curve of the side-view face is first extracted. Then discrete wavelet transform (DWT) is applied to decompose the curve. Then the wavelet coefficients are split into several subsets from which Neural Network models are generated. The subsets that take the advantage of the coarse-to-fine structure of DWT allow us to address the problem of limited training samples. The testing images go through the same process and the decision is made by the Neural Network model which has been trained off-line before the applications.
Methodology consists of following steps:

Curve Extraction

The silhouette of the face profile needs to be extracted for further analysis. First, edge detection is performed to the profile images. We choose the Sobel edge detector for our method since the nature of hysteresis thresholding of the detector is very suitable for detecting profile outline while ignoring the uninterested edges in the images. After the edge is detected, profile alignment will be performed. The basic idea of the method is that the nose tip is the most stable and easily obtained fiducial point in human face profile for verification or recognition. Once the nose tip is located, a line can be drawn from the nose tip to the lower-jaw such that the line is tangent to the chin, as shown in Figure 2. Then a point located on the profile above the nose tip is selected so that the Euclidian distance between this point and the nose tip equals the Euclidian distance between the chin point and the nose tip.

Figure 2: Curve extraction and alignment

In this process, all the curves extracted from profile images are first rotated counter clockwise by assuming the person faces right. If the person faces left simply horizontally flip the image before the rotation. Then the profile is mapped to the complex plane for functional representation. Representing the curves by complex numbers allows us rotating the whole curve conveniently by multiplying all the points on the curve by a complex number, which represents the rotation. The rotation alignment is performed such that the line connecting the forehead and chin points is the real axis, the center point of the line is the new origin, and the line connecting the

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 10, May 2016)

nose tip to the origin is the imaginary axis. The curve profile from the forehead to the chin is used in the later process as the side-view face curve. After the rotation, the curve should be normalized to a constant length, and then be mapped back to real numbers. Now we have converted the profile curve into a one dimensional real valued vector.

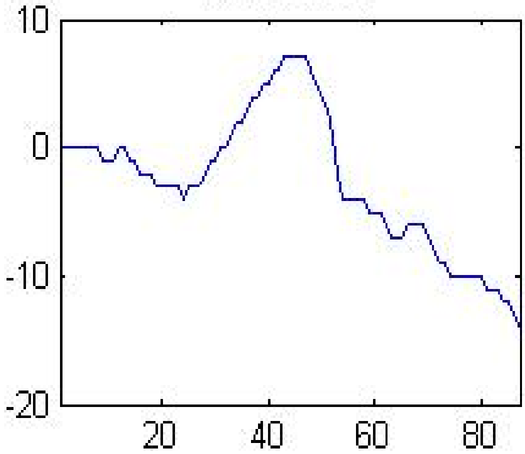

Figure 3: Converting curve to vector representation

Feature Representation Using DWT

The wavelet coefficient is used as the curve descriptor here. The curves of face profiles are regard as different one-dimensional signals. Discrete wavelet transform (DWT) is applied to the signal, which can be described by the following equation:

$$x(t) = \sum_{n=-\infty}^{\infty} C_{0,n}\varphi_{0,n}(t) + \sum_{k=0}^{\infty}\sum_{n=-\infty}^{\infty} d_{k,n}\psi_{k,n}(t) \quad (1)$$

Here in our application, $x(t)$ represents the profile, $\psi_{k,n}(t)$ represents the family of wavelets obtained by shifting, which is represented by n, and stretching, which is represented by k. The relationship between $\psi_{k,n}(t)$ and the "mother wavelet" $\psi(t) \in \mathcal{L}_2$ can be described as follows:

$$\psi_{k,n}(t) = 2^{-\frac{k}{2}}\psi(2^{-k}t - n), \quad k, n \in Z \quad (2)$$

In (1) and (2), $C_{0,n}$ and $d_{k,n}$ represent the wavelet coefficients of approximate and detail description of the signal, respectively which can be expressed as:

$$C_{0,n} =< \varphi_{0,n}(t), x(t) \geq \int_{-\infty}^{\infty} \varphi_{0,n}(t), x(t)dt,$$

$$d_{k,n} =< \psi_{k,n}(t), x(t) \geq \int_{-\infty}^{\infty} \psi_{k,n}^{*}(t), x(t)dt \quad (3)$$

The set of wavelets with $n \in Z$ at some fixed scale k describes a particular level of "detail" in the profile curve. The wavelets describe more "detailed" information as k becomes smaller. The DWT thus can produce a multi-resolution description of a profile curve. The proposed approach takes the advantage of such property.

The benefits of representing the profile by wavelet coefficients are as follows: a. we can represent the profile by a much smaller volume of data; b. the wavelet has localization ability in both frequency and spatial domains while the traditional frequency representation using Fourier transform can only be accurate in one domain, but spreads in the other. The powerful time-frequency localized property entitles the wavelet coefficients to localize the profile curve in the spatial domain so that we know which coefficient represents which part of the profile curve. This localization ability will enable us to select the relevant subsets in a more rational way than using other transformation methods.

Figure 4 shows the wavelet coefficients of a particular individual in our database. We use Daubechies 4 (D4) wavelet for DWT. Each profile curve is decomposed and represented by 154 wavelet coefficients, of which the first 14 coefficients are at the approximate level, followed by 4 detail levels with 14, 22, 37 and 67 coefficients, respectively. The levels are in sequence from rough to fine. Each detail level contains sequentially a more detailed part of the signal, i.e. the side-view profile, than the previous level. When we take a closer look at the coefficients we can see that the last 67 coefficients are all nearly zero. Thus we can ignore them without degrading the performance during the authentication process.

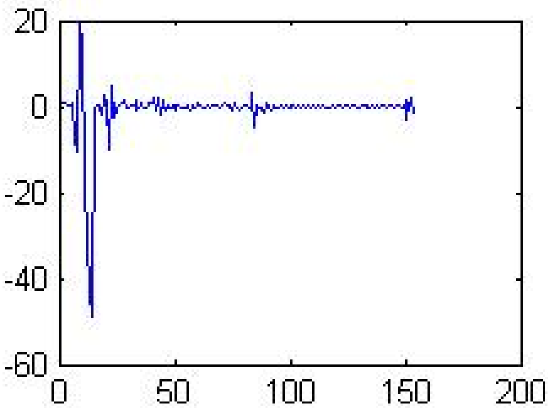

Figure 4. Wavelet coefficients of one profile curve

Subsets Selection and Evaluation by Neural Network

Using the wavelet coefficients, gathered from the previous step, face profiles can be grouped by a certain criterion. Traditional distance-based methods are not suitable for this task because one cannot expect the curves to be aligned exactly the same. As a result, wavelet coefficients of a profile

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 10, May 2016)

may appear at locations different from that of the model along the horizontal axis shown in Figure 3. We therefore use Neural Network (NN) to perform feature evaluation instead of other distance based methods.

In our approach, the wavelet coefficients are used as input feature vectors. Due to the nature of wavelet, we do not simply plug in all the wavelet coefficients as one feature vector. Instead, we use some subsets of them to build feature vectors for each side face image.

Typically the Neural Network algorithm requires a large amount of data as training samples in order to achieve high accuracy. Unfortunately for profile verification, the number of available training images is usually small. To obtain more feature vectors using a fixed number of training samples, extracting subsets from the original set is an applicable effective method.

While we want more feature vectors from splitting the original set into subsets, we also need to make sure that the subsets contain global information of the samples. As we explained earlier, wavelet coefficients can be classified into several levels and each level contains information at different resolution levels. The wavelet theory implies that the coarser level has more important information for face representation and authentication than the finer level because coarser levels build up the main shape of the face side-view. The finer level, on the other hand, specifies some small scale differences between individuals which are crucial when the overall shapes are similar. Using different wavelet levels, we construct the coefficient subsets for each sample as follows:

$$\begin{aligned} &Subset\ 1: approximate \\ &Subset\ 2: approximate + detail\ 1 \\ &Subset\ 3: approximate + detail\ 1 + detail\ 2 \\ &\ldots\ldots \qquad \ldots\ldots \qquad \ldots\ldots \\ &Subset\ M: approximate + detail\ 1 + detail\ 2 + \\ &\qquad \cdots \ldots \ldots .\ detail\ (M-1) \end{aligned} \tag{4}$$

There are M subsets for each sample and M is determined by the length of the profile curves and how many levels the wavelet transform is performed and used. Here in our approach M equals to 4. In the above, approximate represents the coarsest level of a wavelet decomposition of a curve in the image, while detail m represents different levels of details. As M increases, more details are added to a subset, which produces a higher resolution representation of the side-view. In each subset we use the same coarser level coefficients from the previous subsets.

Figure 5 shows how we split each sample into subsets and train their corresponding outputs.

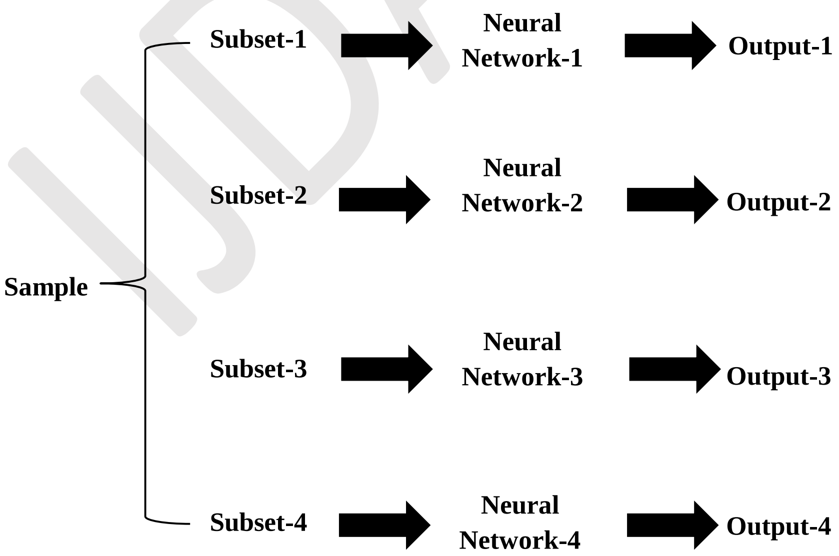

Figure 5: Subsets splitting

During the training process, a set of wavelet coefficients of each training profile will be given. They will be split into four subsets described earlier. A Neural Network which consists of multiple outputs grows for each subset. The number of outputs in each Neural Network can be different and is selected case by case. Typically the more outputs are used, the better results as well as longer training and testing time are expected. So there is a trade-off between performance and computational efficiency. Once the increasing of the number of outputs results

IJDACR
ISSN: 2319-4863
IJDACR
International Journal Of Digital Application & Contemporary Research
International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 10, May 2016)

in little or no increasing of better performance, Neural Network outputs are considered sufficient.

During the testing process, we perform exactly the same operation to the testing sample: extract the side face curve, compute the wavelet coefficients by DWT, split the coefficient vector into four subsets by the same criterion described above, and put them into the corresponding Neural Network. In each Neural Network, the corresponding output will cast a vote to the result label. Finally, a decision is made by gathering and summing up the votes casted by each output in each Neural Network. The result will be used for the final decision making on authentication.

III. SIMULATION AND RESULTS

The performance of proposed algorithms has been studied by means of MATLAB simulation.

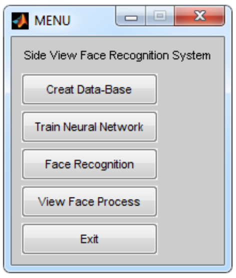

Figure 6: Menu function interface for proposed system

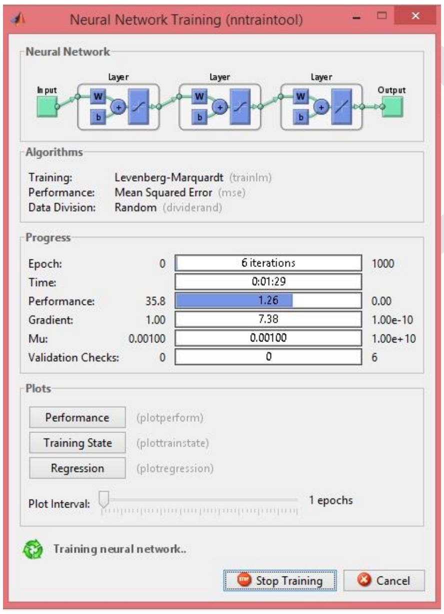

Figure 7: Neural Network training

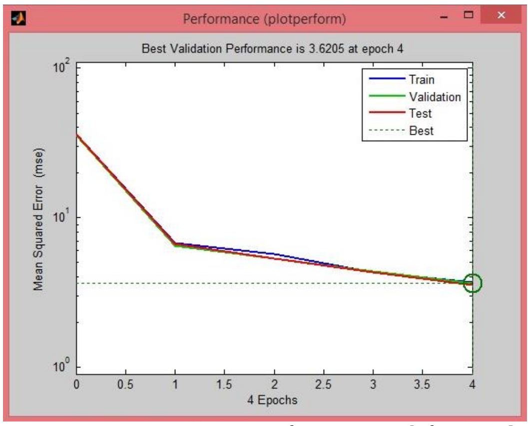

Figure 8: Mean square error performance graph for Neural Network

Figure 8 shows the MSE performance graph for trained Neural Network. It is clear the performance goal was archived when the ephoch value for training and test data reaches 4.

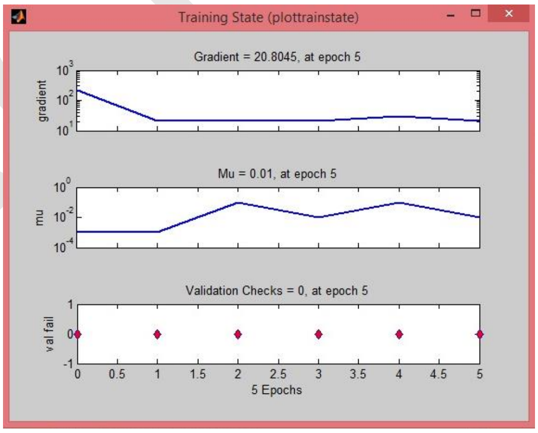

Figure 9: Training State plot

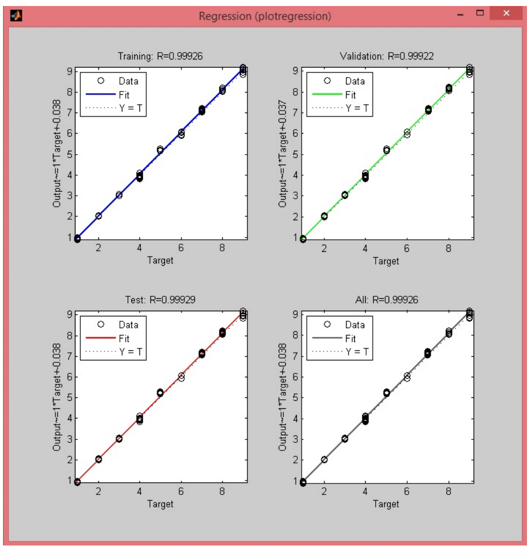

Figure 10: Regression plot

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 10, May 2016)

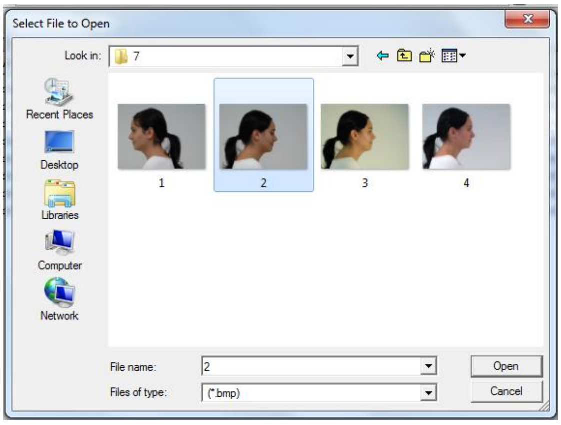

Figure 11: Selection face profile ID 7

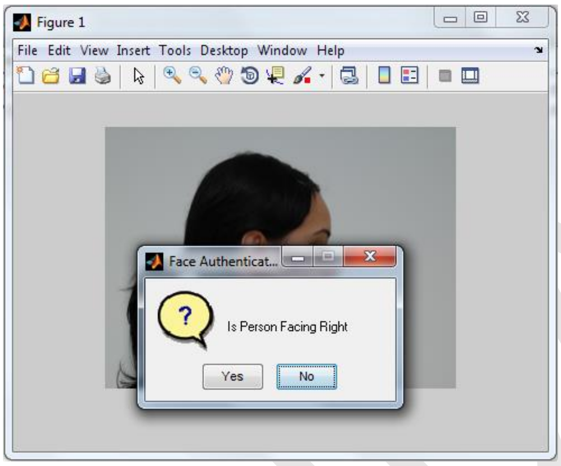

Figure 12: Is person facing right?

Figure 12 acknowledge whether the selected profile person is facing the right direction.

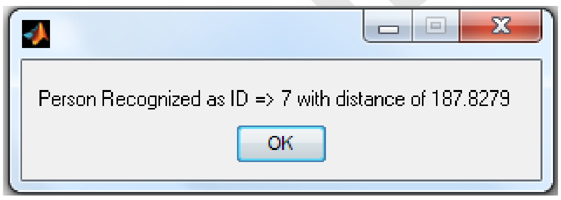

Figure 13: Recognition of person as ID

Figure 14: Face with nose-tip, chin and forehead for profile ID 7

Figure 14 is taken for edge detection using 3 points; nose-tip, chin and forehead which is presented in the Figure 15.

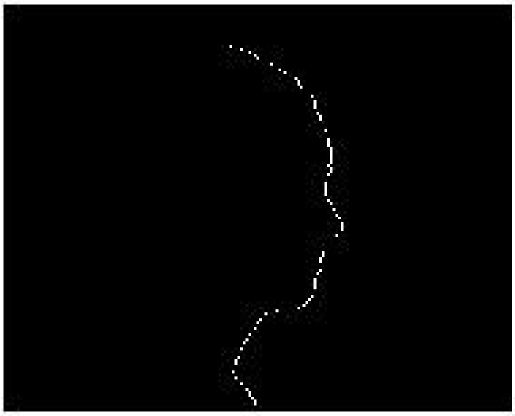

Figure 15: Extracted Face Edge for profile ID 7

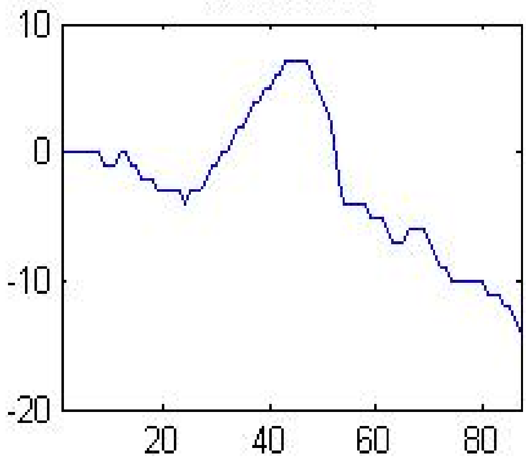

Figure 16: Face profile for profile ID 7

Forehead point and chin point are joined by a single line then it is rotated and we get the face profile as

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 10, May 2016)

shown in Figure 16. The line which joints nose-tip and chin is called base line. Total distance of the edge is called face profile.

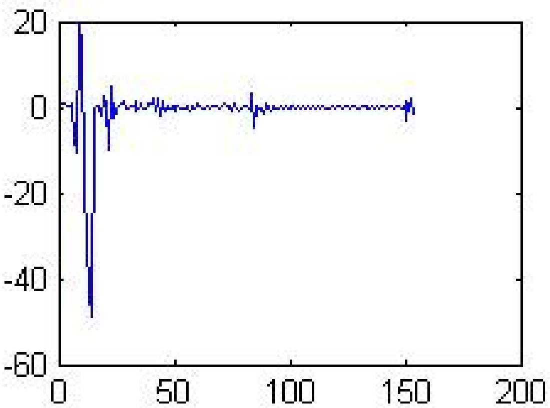

Figure 17: DWT coefficients for profile ID 7

Since, the length of face profile is 128, so here we have applied the DWT of the length of 128 using DB4 wavelets. If the length of face profile is less than 128 then the frequency domain interpolation is used to make it 128. Figure 17 shows the DWT coefficients for the profile ID 7. Then the Neural Network classifier is trained on the basis of DWT coefficients.

IV. Conclusion

This paper proposed a novel side-view based face authentication technique using DWT and Neural Network. The side-view face contours are first extracted from the profile image. After that we apply DWT to the extracted features. Then we use the corresponding wavelet coefficients as the feature vector for each face. For effective authentication by Neural Network, we split the vector into several subsets each of which contains some global information which is represented by the coarsest wavelet coefficients plus some finer and local information of the face. In comprising the subsets, the coefficients at the coarser level are given higher weights. Then Neural Network is applied to the subsets. Simulation results delineate that the proposed strategy has the best performance regarding the accuracy. Furthermore the verification process can be done in real time since no score measurement is involved at each node once the Neural Networks are trained. Even in the training process, the method requires only a few samples and is computationally feasible. In the experiment, the proposed method reached the highest accuracy of 96%.

Reference

[1] Newman, R. (2009). Security and Access Control Using Biometric Technologies. Information Security Professionals.
[2] Blackburn, D. M. (2001). Face Recognition: The Technology and Its Applications.
[3] Zhao, W., Chellappa, R., Rosenfeld, A., & Phillips, P. J. (2003). Face Recognition: A Literature Survey. ACM Computing Surveys, 35, 399-458.
[4] Bruner, J. S. & Tagiuri, R. (1954). The Perception of People. Handbook of Social Psychology, Cambridge, Mass.: Addison-Wesley, 2.
[5] Xiaozheng, Z. & Yongsheng, G. (2009). Face recognition across pose: A review. Elsevier, Pattern Recognition, 42, 2876-2896.
[6] Tsai, G. S.-Y. & Tang, A.C.-W. (2009). Two-View Face Recognition Using Bayesian Fusion. IEEE International Conference on Systems, Man and Cybernetics (SMC), 157-162.
[7] Santemiz, P., Spreeuwers, L. J. & Veldhuis, R. N. J. (2010). Side-View Face Recognition. University of Twente.
[8] Kakarwal, S. and Deshmukh, R. (2010). Wavelet Transform based Feature Extraction for Face Recognition. International Journal of Computer Science and Application, 7, 100-104.
[9] Dantcheva, A. & Dugelay, J. L. (2011). Frontal–to–side face re–identification based on hair, skin and clothes patches. IEEE, 8th International Conference on Advanced Video and Signal-Based Surveillance (AVSS), 309-313.
[10] Kan, M., Shan, S., Xu, D. & Chen, X. (2011). Side-Information based Linear Discriminant Analysis for Face Recognition. Proceedings of the British Machine Vision Conference, University of Dundee, 1-12.
[11] Imtiaz, H. & Fattah, S. A. (2011). A Face Recognition Scheme using Wavelet based Dominant Features. Signal & Image Processing: An International Journal (SIPIJ), 2, 69-80.
[12] Patel, R., Rathod, N. & Shah, A. (2012). Comparative Analysis of Face Recognition Approaches: A Survey. International Journal of Computer Applications, 57, 50-61.
[13] Ding, S., Zhai, Q., Zheng, Y. F. & Xuan, D. (2013). Side-view face authentication based on wavelet and random forest with subsets. IEEE International Conference on Intelligence and Security Informatics (ISI), 76-81.
[14] Tarres F., Rama, A. GTAV Face Database. Online available at http://gpstsc.upc.es/GTAV/ResearchAreas/UPCFaceDatabase/GTAVFaceDatabase.htm.