ISSN: 2321-7782 (Online)
Volume 2, Issue 5, May 2014
International Journal of Advance Research in Computer Science and Management Studies
Research Article / Survey Paper / Case Study
Available online at: www.ijarcsms.com

Side view face authentication using wavelets and random forests with subsets

Shashank S. Lokhande[1]
Student M. Tech (E & TC)
Dr. Babasaheb Ambedkar Technological University, Lonere
Raigad – India

Narendra.S. Jadhav[2]
Assistant Professor, Department of Electronics & Tele
Dr. Babasaheb Ambedkar Technological University, Lonere
Raigad – India

Abstract: This paper presents a face authentication method using discrete wavelet transform and random forest. A subset selection method that increases the number of training samples and allow subset to preserve the information. The authentication method has various steps such as Profile extraction, wavelet decomposition, subset splitting and random forest verification. The new method takes advantage of wavelet localisation property in both frequency and spatial domains, while maintaing the generalised property of random forest. Random forest play a major role in thins authentication method which is a emerging method now a days. The implementation is computationally feasible and experiment results show that he performance is satisfactory.

Keywords: Side view face authentication, Discrete wavelet transform, subsets, Random forest.

I. INTRODUCTION

Face authentication has gained a considerable attention in last few decades due to its increasing applications of security surveillance system and guarded entrance. Face authentication plays a key role in verifying if the person is the one as he/she has claimed using stored images for that particular person. Since the no of images stored for particular person is small it is difficult to determine whether the person appears in all kinds of view, frontal or side views for example. A wide range of research has been carried out as far as frontal face authentication is concerned but side view faces have huge scope to go with.

Side-view profile is of great importance because of its potential in a wide scope of application including the following:

When the frontal view portrait is easily obtainable, the side-view profile can be used as a complementary feature for authentication to improve the accuracy; when the frontal view portrait is unavailable, the side-view profile can play the main role in authentication process. This kind of situation happens in all the guarded entrances.

The profile-based face authentication method can be categorized into two main categories: appearance-based methods and the silhouette base method the appearance-based method use the information of pixel value of the image. Virtual views are generated by shape modeling followed by texture synthesis. Compared to appearance based method silhouette method has advantage of computational simplicity and memory usage efficiency. There are two sub-categories in Silhouette based method namely featuring based method and curve based method. The feature based method extract some predefined points as features from the facial profile curve. On the other hand the curve based method extracts the representing pattern from the facial profile curve.

Our goal is to develop a robust approach which can be conveniently implemented. It is observed that no 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, a new silhouette based method is developed. The flow diagram is shown in figure 1 below.

 International Journal of Advance Research in Computer Science and Management Studies
Volume 2, Issue 5, May 2014 pg. 314-321

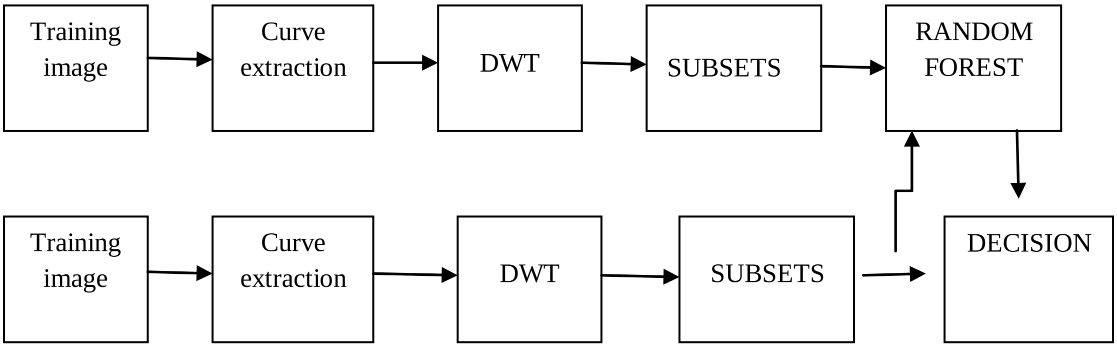

Figure 1 Block diagram of proposed approach

The outline curve of side view face is first extracted. Then discrete wavelet transform is applied to decompose the curve. Then the wavelet coefficients are split into several subsets from which random forest models are generated. The subsets that take 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 random forest model which has been trained off-line before the applications.

II. Proposed Approach

A. Profile outline 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 Canny edge detector for our method since the nature of hysteresis thresholding of the detector is very suitable for detecting profile outline which ignoring the uninterested edges in the image is detected, profile alignment will be performed . One of the most widely used methods for Profile alignment is tangent-based normalization. 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 face verification or recognition. Once the nose tip is locate, 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 below. Then a point located on the profile above the nose tip is selected so that the Euclidian distance between this point and nose point equals the Euclidian distance between the chin and the nose tip.

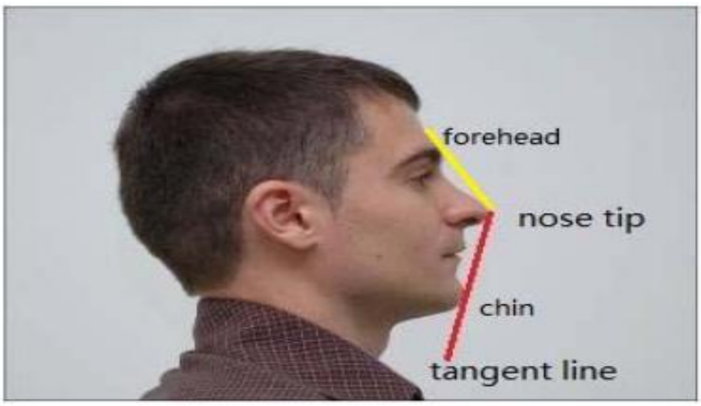

Figure 2. Curve extraction and alignment

Figure 2.1 Fiducial point detection

In our process, all the curves extracted from profile images are first rotated counter clockwise by $\pi/2$ rad assuming the person faces right. If the person faces left simply flip the image horizontally before the rotation. Then the profile is mapped to the complex plane for functional representation. This is illustrated in Figure 3. 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 of the line is the new origin, and theline connecting the nose tip to the origin is the imaginary axis. The curve profile from the forehead to the chin is used in later person as the side-view face curve. After the rotation, the curve should be normalized to a constant length, and then be mapped back to the real numbers. Now we have converted the profile curve into a one-dimensional real valued vector.

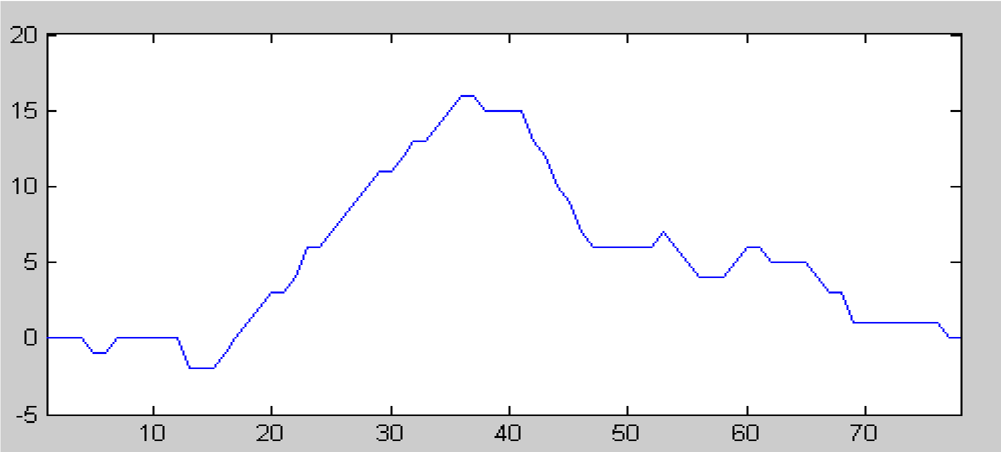

Figure 3. Curve conversion to vector representation

B. 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:

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

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 "mother wavelet" ψ (t) Є L_2can be described as follows:

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

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:

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

$$d_{k,n} = <\psi_{k,n}(t), x(t)> = \int_{-\infty}^{\infty}\psi_{k,n}^{*}(t)\,x(t)dt. \qquad \text{........................ (3)}$$

The set of wavelets with n Є 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.

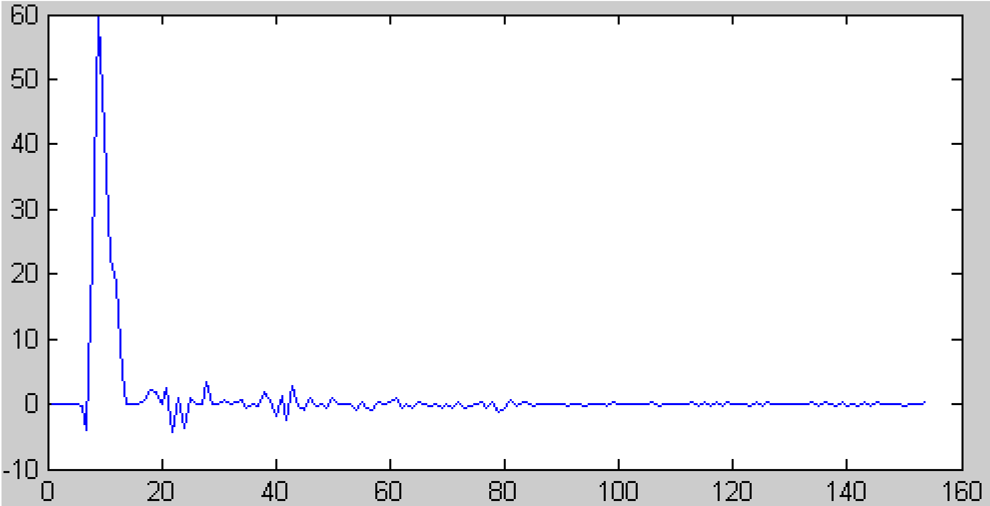

Figure 4. Wavelet coefficient of one profile curve

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 course 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.

C. Subsets Selection and Evaluation by Random Forest :

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 may appear at locations different from that of the model along the horizontal axis shown in Figure 3. We therefore use random forest (RF) to perform feature evaluation instead of the K-Nearest Neighbor Algorithm (KNN) or other distance based methods.

Random forest is an ensemble classifier that consists of many decision trees and puts out the class that is the mode of the classes produced by individual trees. Ensemble methods have been proven to improve existing learning algorithms, and random forest is one of them. However the split threshold at each node of the decision trees is selected totally at random and no score measurement is needed in the process. Thus it is fast and generalized. 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 random forest 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:

ISSN: 2321-7782 (Online)

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

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. Following the description in part B, here in our approach M equals to 4 (notice that we have already ignored the last 67 coefficients which are all close to zero). 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. However, this will not result in repeating the same coefficients in all the subsets because the variable that random forest utilizes at each node is completely chosen randomly. Some of the coefficients maybe selected while others are not. What such subset splitting structure really leads to is that the coefficients at coarser levels have more chances to be chosen at each node. In fact the ratio of the chances of each level from coarse to fine in the overall forest is approximately 4:3:2:1. This ratio gives different weights to the coefficients at different levels.

One random forest which is corresponding to one subset is composed by multiple random trees. At each node of the tree, one of the variables in the input vector will be selected by the split function. The split function usually works as binary decision maker whose decision is made by comparing the selected variable with a randomly chosen threshold. By constructing the subsets of different levels, we can preserve the global information in each subset while giving higher weight to the coarser level coefficients, i.e. more changes to be selected as the variable of split function in random forest. The random forests will produce some decisions that are based on lower levels of subsets only and other decisions that need both lower and higher resolution.

The diagram in Figure 5 shows how we split each example into subsets and train their corresponding tree and forests:

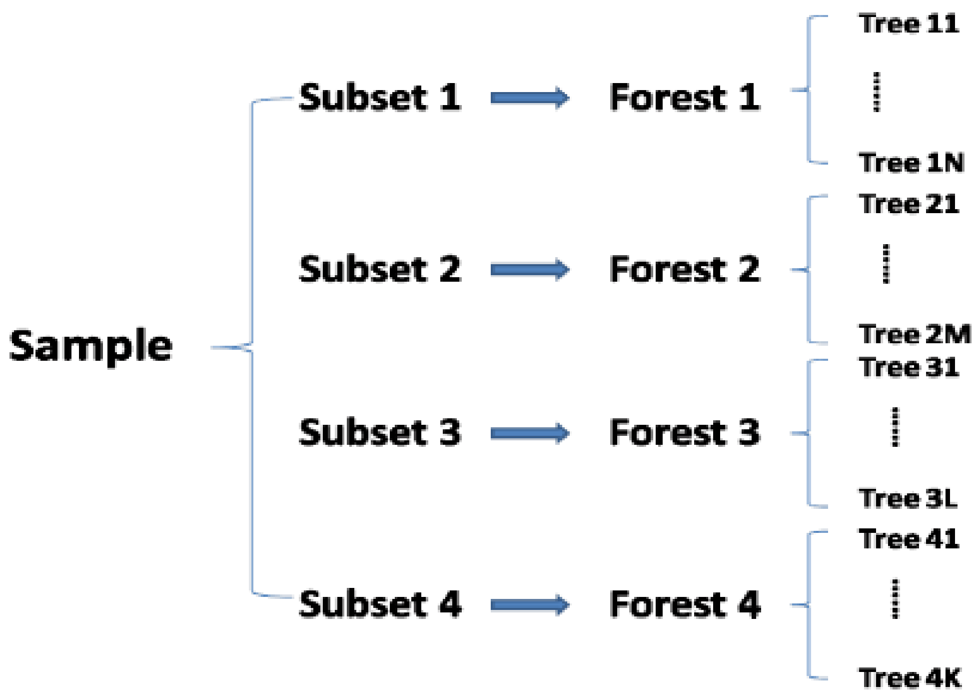

Figure 5. Subset splitting

ISSN: 2321-7782 (Online)

During the training process, a set of wavelet coefficient of each training profile will be given. They will be split into four subsets described earlier. A forest which contains of multiple random trees grows for each subset. The number of trees in each forest can be different and is selected case by case. Typically the more trees are used; the better results as well as longer training and testing time are expected. So there's a tradeoff between performance and computational efficiency. Once the increasing of the numb in little or no increasing of better performance, the trees 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 method as described above, and put them into the corresponding random forest. In each forest, each tree will cast a vote to the result label this tree obtains. Finally, a decision is made by gathering and summing up the votes casted by each tree in each forest. The results will be used to make the authentication.

III. RESULTS

A. Database:

The database used for evaluating the proposed method is GTAV face database. The database includes 10 different individuals and each contributes 6 side-view images. The size of the images in the database is 316× 236 pixels in each of the examples of the side-view face images in each of the RGB channels. Some examples are displayed in Figure 6 (for same individuals) and figure 8 for (different individuals):

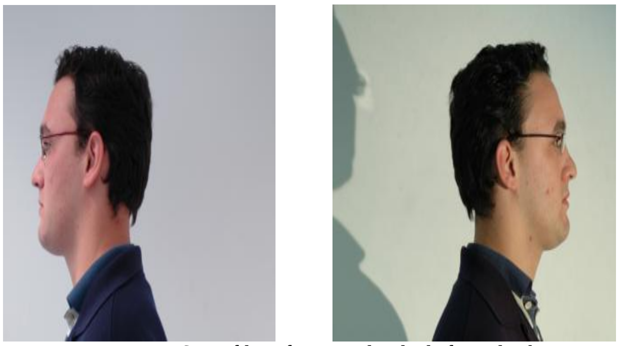
Figure 6. Profiles of same individuals from database

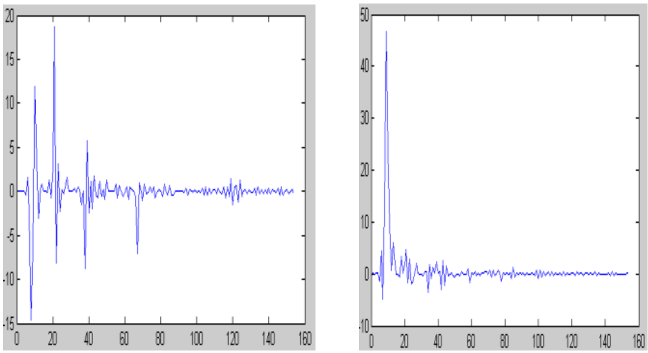

Figure 7. Wavelet coefficients of faces in fig. 6

It can be observed from Figure 6 that for the same individuals, the profile images are taken under different conditions and different distances. During the experiments, all the side-views towards left are flipped to right in the training and testing process for all the images. A set of experiments were performed of side view face authentication in order to measure the effectiveness of the proposed method and compare it with some of the classical methods. All the experimental results are evaluated by the leave-one-out criterion.


Figure 8. Profiles of different individuals in database

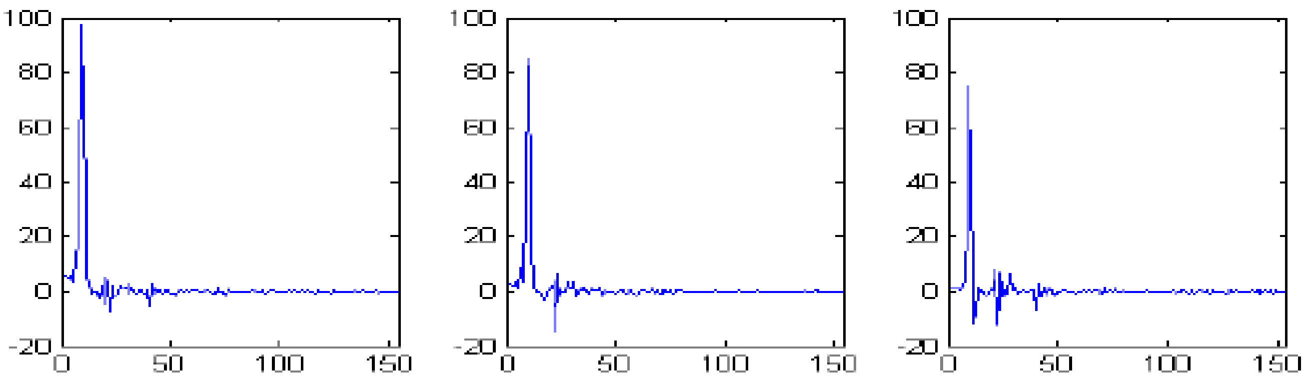

Figure 9. wavelet coefficients of faces in figure 8.

The other options we tested include DWT feature representation classified by k-nearest neighbour (DWT+KNN), Fourier transform feature representation classified by k-nearest neighbor (FT+KNN), fourier transform feature representation classified by random forest (FT+RF) and wavelet transform feature representation classified by random forest without splitting into subsets (DWT+RF). The proposed method is named as DWT+RF with Subsets.

The test Results of different methods are listed in Table 1.

Method	Accuracy
FT + KNN	62.50%
FT + RF	73.33%
DWT + KNN	42.92%
DWT+RF	84.17%
DWT + RF with Subsets	92.50%

As mentioned earlier that the accuracy of RF methods are averaged due to the randomness of RF. Hence the stability of the method, which can be measured by the standard deviation of accuracy, should also be examined. We observed during the experiments that the proposed method i.e. DWT+RF with subset achieves not only higher accuracy but also a smaller standard deviation of accuracy (4.25% on average) than DWT+RF without subsets (6.03% on average), which implies that the utilization of subsets improves the stability of the authentication. All the images of the individuals in the database are taken under various distances and illuminations, so it is fair to conclude that this method is robust to scale and illumination variations.

IV. Conclusion

In this paper we present a new side-view based face authentication method. 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 random forest, 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 composing the subsets, the coefficients at the coarser level are given higher weights. Then random forest is applied to the subsets. Our experimental results show that the proposed method has better performance than traditional distance-based methods, being more robust to scale and illumination variations. Furthermore the verification process can be done in real time since no score measurement is involved at each node once the random forests are trained. Even in the training process, the method requires only a few samples and is computationally feasible. This is possible since wavelet transform can identify facial features through its property of space-frequency localization. Our future work also includes integrating this method with frontal-face based authentication algorithm to achieve even higher robustness and accuracy.

References

1. I.A. Kakadiaris, H. Abdelmunim, W. Yang, and T. Theoharis, "Profile-Based Face Recognition," in Proc. IEEE International Conference on Automatic Face & Gesture Recognition, 2008, pp. 1-8.
2. H. Wu, P. Zhou and Z. Gao, "An algorithm for automatic side face portrait recognition based on Fourier descriptor," in Proc. Information Science and Engineering, ISISE '08. 2008, vol. 2, pp. 767-772.
3. Xiaozheng Zhang and Yongsheng Gao. Face recognition across pose: A review. Pattern Recognition, 42(11):2876–2896, November 2009.
4. V. Kruger, S. Bruns, and G. Sommer. "Efficient head pose estimation with gabor wavelet networks". In British Ma- chine Vision Conference, 2000.
5. P.Santemiz, L.J.Spreeuwers, and R.N.J. Veldhuis, "Side-View Face Recognition," in Proc. 32nd Symposium on Information Theory in the Benelux, 10-11 May 2011, Brussels, Belgium.

AUTHOR(S) PROFILE

Mr. Shashank S. Lokhande received B.Tech degree in Electronics & Telecommunication from Department of Technology, Shivaji University, Kolhapur.

Presently he is pursuing his M. Tech in Dr. Babasaheb Ambedkar Technological University, Lonere, Raigad.

Narendra Jadhav received B.Tech. and M.Tech degree from the Dr. BATU Lonere, Raigad Maharashtra, INDIA, in 2004, in Electronics and Telecommunication engineering. His research interests include gesture recognition, artificial intelligence, and FPGA System in Signal Processing

Presently he is working as Assistant Professor in Electronics and Telecommunication at Dr. Babasaheb Ambedkar Technology, Lonere Dist. Raigad, Maharashtra, India.