

# Face Recognition Using Fast Discrete Curvelet Transform via Wrapping and SVM Classifier

Raveendra K<sup>\*1</sup>, Ravi J<sup>\*2</sup>

<sup>1</sup>Dept. of ECE, GEC, K R Pet, Karnataka, India

<sup>2</sup>Dept. of ECE, GAT, Bangalore, Karnataka, India

*\*Corresponding Email and Author:*

<sup>\*1</sup>raveendrakit@gmail.com

<sup>\*2</sup>gnkereravi@gmail.com

## Abstract

The growth of automation in our daily life needs prime requirement of security. Biometric recognition or identification is one of the most important system for security and surveillance related activities compared to conventional techniques like ID cards, Personal Identification Number (PIN) and password. In this research work, we are proposing the Face Recognition using Curvelet Transform by Wrapping (FRCTW) technique for different face databases. The preprocessing has been carried out on all the images to extract the face region by removing the background and resizing to 100x100. The curvelet via wrapping technique is applied on the resized image to extract the feature coefficients. The SVM classifier is used to compare the database image features to test image features for recognition. The values of False Acceptance Rate (FAR), False Rejection Rate (FRR), Total Success Rate (TSR) and Equal Error Rate (EER) were measured for L space k, JAFFE and Near Infrared (NIR) Database. It is found that L space k database has the least equal error rate among the databases studied.

**Keywords:** Face recognition; FDCT; SVM; Voila Jones.

## 1. Introduction

The rapid growth in the internet technology of the modern world is more connected with the digital network. Every day, communication between each user and between several organizations is rapidly increasing through the digital devices. Since there is a massive communication network, each person or user is identified through unique Personal Identification Number (PIN) in order to establish a reliable communication. The Personal Identification Number (PIN) acts like an ID card of an individual for authentication but it fails to satisfy the security requirements as there is a chance of stealing or hacking the card details. Biometric is the term from the Greek word with meaning Bio for life and metrikos is to measure which means measurement life [1]. It authenticates the person or an individual based on their behavioral or physiological characteristics. Behavioral or physiological characteristics of any individual/human can be considered for biometric authentication until it obeys the following requirements such as Circumvention, Distinctiveness, Universality, Performance, Acceptability, Permanence and Collectability. Based on the number of Biometric traits, the Biometric system is classified as Unimodal and Multi modal biometric system. Unimodal biometric system uses only one biometric trait for authentication where as multimodal biometric system adopts more than one biometric trait simultaneously to authenticate a person.

Human Face recognition is a challenging task in Digital Image Processing and Computer Vision because a query face has to be compared with the gallery faces in an actual dataset to determine its identity. In recent years, many methods have been proposed for face recognition, most of them are based on Artificial neural network, feature extraction of skin color etc. Most of the research has been focused more on the accuracy for different varying conditions such as facial expression and face orientation. Feature extraction plays an important role in determining the recognition rate which could be substantially improved if a good feature with high discrimination ability is extracted. Many researchers have

proposed that feature extraction corresponds to good recognition performance because of robust nature of local features to illumination variation [2, 3, 4] and the histogram of local features is relatively more stable for different variation factors [5]. Multiscale methods will provide robust representation based on the expression changes. They are also capable of capturing significant features with least computational complexity in both time and frequency domain approaches

## 2. Literature Survey

Many research works have been proposed on face recognition. The dimensional reduction for face recognition through Principal Component Analysis (PCA) and Linear Discriminator Analysis (LDA) have been proposed by Firoz Mahmud et al., [6]. They reported that PCA will do more of data classification and LDA is more of feature classification. Yi-Kang Shen and Ching-Te Chiu [7] have presented a novel on Local Binary pattern (LBP) orientation based face recognition. Here LBP texture information is added to the Scale-Invariant Feature Transform (SIFT) orientation information to reduce the orientation number by half and also the computation time. Further, Region of Interest (ROI) has been considered by discarding the non interest points to improve the computation time there by maintaining the recognition rate. Jagadeesh H S et al., [8] have proposed a model of Directional Binary Codes (DBC) based Face Recognition using Discrete Wavelet Transform (DWT). They derived the LL sub band by applying DWT which is then divided into cells of fixed size. Further, the DBC has been applied for each cell to extract the desired features. They compared the features of test image with the image of database through Euclidean Distance measure. Rangaswamy Y et al., [9] have introduced the face recognition method in which the directional and shift invariant features of face image are obtained by Dual Tree Complex Wavelet Transform (DT-CWT). Further, they obtained the different pose, expression variation and illumination of face in frequency domain through Fast Fourier Transform (FFT). The obtained features from DTCWT and FFT are combined by means of arithmetic addition

to get the desired final features. Performance analysis of different data base has been carried out to show that the studied method is more effective for face recognition.

The concept of face recognition using DT-CWT and LBP has been proposed by Ravi et al., [10]. The coefficients of DT-CWT have been determined using 5 level DT-CWT. Further, the obtained coefficients were organized into 3x3 matrix. The final features of the face have been obtained using LBP on this 3 x 3 matrix. The test image features are compared with the image of the database through Euclidean Distance. Mohammad Da'san et al., [11] have presented a multi stage model for face detection based on the integration of Viola and Jones algorithm, Gabor Filters, PCA and Artificial Neural Networks (ANN). This model has been tested with the Carnegie Mellon University (CMU) data set which results in an enhanced performance for face detection rate.

Gordon Stein et al., [12] have proposed an algorithm for improving the accuracy and efficiency of LBP method by creating sub-grids by using tree based data structure. They allowed for novel patterns for face recognition rather than uniform grids used in LBP method of face recognition. Ganapathi V Sagar et al., [13] have introduced a technique for compressing unique features of face images for improving the speed of recognition during matching process. Here the LL band features obtained by the application of 2D-DWT were normalized to scale the magnitude values. These normalized values are convolved with the original face samples for getting unique features. The feature vector of several images of each individual person are compressed to single column unique vector which results in minimizing the feature vector and maximizing the matching speed. Ivanna K. Timotius et al., [14] developed a model on face recognition technique on generalized discriminant analysis for feature extraction and dimensionality reduction of the data. The classification of test image features with the image of database has been carried out using Support Vector Machine (SVM) with better accuracy. Min Yao and The extraction of features using the concept of fast PCA has been proposed by Changming Zhu [15]. The extracted features are classified by using Adaboost learning algorithm and SVM classifier for various face condition to compare the recognition rate of two classifiers.

### 3. Model

#### A Proposed Model

The proposed model uses Fast Discrete Curvelet Transform via wrapping to extract the facial image features. The obtained features are thus classified using multi SVM classifier. The block diagram showing the proposed model is depicted in Fig. 1.

#### B Training Face Database:

##### Near Infrared Database (NIR):

The complex variations in intensity, illumination, blurring effect, different facial expressions and different pose variations of NIR database has been considered for the analysis. The database has total number of 115 persons with 14 images per person. The training data has been organized for first 20 persons out of 115 persons by considering 6 images per person. The FRR and TSR are evaluated based on the seventh image of the 20 persons as test image. On the other hand, the remaining 95 persons from the database of 115 were treated as out of database for evaluating FAR of the proposed face recognition system.

#### L-Space k Database:

The L-space k database is considered to develop an algorithm because of its variation in expression, image lightning large head scale variation. The database has been created for first 113 persons from 152 by considering 20 images per person. The training data has been created for first 63 persons from the database of 113 by considering first 10 images per person for recognition. The FRR and TSR are evaluated based on the eleventh image of the same 63 persons as test image. The FAR has been evaluated based on the remaining 50 persons out of 113 as out of data base.

#### JAFFE Database:

The JAFFE Database is considered because of its identical/similar face images of all the persons. The database has been created for 10 persons with 22 images per person. The training data has been organized for first 6 persons out of 10 with first 10 images per person. The FRR and TSR are evaluated based on the thirteenth image of the same 6 persons as a test image. The FAR has been evaluated based on the remaining 4 persons from 10 as out of database.

### C Preprocessing:

The preprocessing has been carried out for all the three databases to extract the region of interest (face) from the complex background by eliminating the surrounding background which increases the recognition rate. In the proposed method, Viola Jones algorithm [16] is adopted to detect the face from the complex background. This method uses Haar like features to extract features of both face and non-face regions. Any redundancies of the obtained features were eliminated using Adaboost learning algorithm and finally the remaining features are cascaded to detect the face in the given image. This method is accurate in detecting the face for a given set of images. The obtained face images for NIR, L-space k and JAFFE database are non-uniform in dimensions. Uniformity is achieved by resizing the detected image of a face for a fixed size of 100 x100.

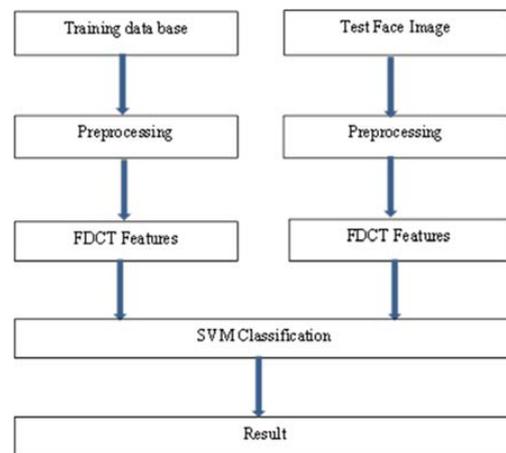


Fig. 1 Block Diagram of FRCTW and SVM

#### D Curvelet Transform by Wrapping :

The resized image obtained after preprocessing is used to extract facial features using curvelet transforms. The Curvelets via wrapping technique [17] has been used in the proposed work as

this technique is simple, faster and less redundant than first generation curvelet transform. The curvelet via wrapping technique is applied on resized images to obtain the coefficients at each wedge. The curvelet coefficients obtained at each wedge is a function of two windows namely radial window  $W$  and the angular window  $V$ .

The Cartesian window  $\tilde{U}_{j,l}$  isolates frequencies near the wedges  $(\omega_1, \omega_2)$  is given by

$$\tilde{U}_{j,l} = W_j(\omega)V_j(\omega),$$

Where

$$W_j(\omega) = \sqrt{\varphi_{j+1}^2(\omega) - \varphi_j^2(\omega)}, j \geq 0, (1)$$

$$\varphi_j(\omega_1, \omega_2) = \phi(2^{-j}\omega_1)\phi(2^{-j}\omega_2), 0 \leq \phi \leq 1.$$

$$V_j(\omega) = V(2^{j/2}\omega_1/\omega_2) (2)$$

Curvelet via wrapping technique algorithm is developed by considering  $f(t_1, t_2)$  as an input Cartesian array and  $\hat{f}(n_1, n_2)$  as 2D Discrete Fourier Transform as follows:

- 2D Fast Fourier Transform (FFT) is applied for input Cartesian array  $f(t_1, t_2)$  to obtain  $f(n_1, n_2)$ .
- For each angle  $l$  and scale  $j$ , the product  $\tilde{U}_{j,l}(n_1, n_2) * \hat{f}(n_1, n_2)$  is calculated, where  $\tilde{U}_{j,l}(n_1, n_2)$  is discrete localizing Cartesian window.
- This product is wrapped around origin to obtain  $\hat{f}_{j,l}(n_1, n_2) = W(\tilde{U}_{j,l}\hat{f})(n_1, n_2)$ , where  $0 \leq n_1 < L_{1,j}$  and  $0 \leq n_2 < L_{2,j}$  and  $L_{1,j} \sim 2^j$  and  $L_{2,j} \sim 2^{j/2}$ .
- Apply 2D inverse FFT to each  $\hat{f}_{j,l}$ , to obtain the discrete curvelet coefficients.

The input face image of size 100 x 100 with different intensity maps are considered. The different intensity images are thus obtained by quantizing the image pixels with quantization parameter like 1, 16 and 64. Then curvelet is applied for each quantized image for different scales till scale = 5. This results in 5 (scales) x 3 (quantized images) = 15 (feature vectors) and these features are considered as final features. Fig. 2 shows the curvelet via wrapping technique for L-space k face image with scale = 5.

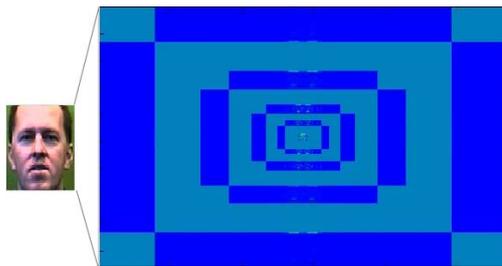


Fig. 2 Curvelet via wrapping technique for face image with scale = 5

**E SVM Classification for matching:**

The set of data consists of  $N$  samples called training set  $\{x_i, y_i\}_{i=1}^N$ , where  $x_i$  are the input samples,  $x_i \in \mathcal{R}^n$  belongs to one of two classes labeled by  $y_i = \pm 1$ . The SVM classifier outputs based on the decision surface of the form  $sign[f(x; w)]$ , where  $f(x; w) = w^T \phi(x) + b$  with an approximation to the mapping function  $y$ . The following optimization problem [18] is obtained in order to derive  $w$  and  $b$ .

$$\min_{w,b,\xi} \phi(w, b, \xi) = \frac{1}{2} (w^T w) + C \sum_{i=1}^N \xi_i,$$

Subject to  $y_i [w^T \phi(x) + b] \geq 1 - \xi_i, \xi_i \geq 0,$

$i = 0, 1, \dots, N$ , Where  $C$  represents the trade-off parameter reflecting the relative significance of model's complexity compared to training error and  $\xi_i$  indicates the training error for  $i^{th}$  sample.

**4. Algorithm**

**Input:** Image of Face.

**Output:** Recognized Face of Person.

- Step 1:** Face image has been selected from the database for reading.
- Step 2:** Face region is detected from the input image using Viola Jones Algorithm.
- Step 3:** The detected face image is resized for 100 X 100 dimensions.
- Step 4:** Curvelet via wrapping is applied on detected face to extract final feature coefficients.
- Step 5:** Repeat the above procedure for test image from step 1 to 4
- Step 6:** Test image features were compared with Database image features through multi class SVM Classifier for matching.
- Step 7:** Image with more matching features were recognized as matching image otherwise not matching for the different threshold values.

**5. Results And Discussions**

The performance of proposed face recognition system has been evaluated on L-Space k, JAFFE and NIR databases. The performance is evaluated by computing FRR, FAR, TSR and EER for different threshold values.

From the Table 1, it is found that by varying the threshold values from 8 to 25, the FRR has been decreased from 100% to 0% with increase in total success rate to 100%. Furthermore, FAR increases with decrease in threshold value.

**Table 1 The Variation Of Frr, Far And Tsr With Threshold Values Of L Space- K Database**

| ►► TSR | FRR | FAR   | Threshold |
|--------|-----|-------|-----------|
| 0      | 100 | 0     | 25        |
| 0      | 100 | 0     | 24        |
| 0      | 100 | 0     | 23        |
| 0      | 100 | 0     | 22        |
| 100    | 0   | 12.50 | 21        |
| 100    | 0   | 12.50 | 20        |
| 100    | 0   | 16.66 | 19        |
| 100    | 0   | 20.83 | 18        |
| 100    | 0   | 29.16 | 17        |
| 100    | 0   | 41.66 | 16        |
| 100    | 0   | 50.00 | 15        |
| 100    | 0   | 58.33 | 14        |
| 100    | 0   | 70.83 | 13        |
| 100    | 0   | 70.83 | 12        |
| 100    | 0   | 79.16 | 11        |
| 100    | 0   | 91.66 | 10        |
| 100    | 0   | 91.66 | 9         |
| 100    | 0   | 100.0 | 8         |

The FAR and FRR as a function of threshold values is shown in the Fig. 3 for the data base L space k. It is found from the figure that FAR is very minimal with a value of 12.5% and FRR is 0. Further, the equal error rate is 11% at a threshold value of 21. Hence, the threshold value 21 is considered as optimum value.

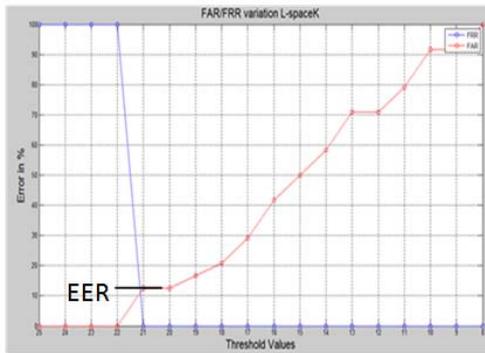


Fig. 3 FAR and FRR as a function of threshold value for the database L space k

It has been observed from the Table 2 that the value of FRR decreases from 100% to zero whereas TSR increases to 100%. Further, it is observed that FAR tends to zero till the threshold value was up to 22 and later it increases with decrease in threshold values.

Table 2 The Variation Of Frr, Far And Tsr With Threshold Values Of Jaffe Database

| ►► TSR | FRR   | FAR   | Threshold |
|--------|-------|-------|-----------|
| 0      | 100   | 0     | 25        |
| 0      | 100   | 0     | 24        |
| 0      | 100   | 0     | 23        |
| 0      | 100   | 0     | 22        |
| 0      | 100   | 0     | 21        |
| 38.89  | 61.11 | 0.50  | 21        |
| 52.78  | 47.22 | 10.50 | 20        |
| 58.34  | 41.66 | 22.50 | 19        |
| 88.89  | 11.11 | 40.50 | 18        |
| 97.23  | 2.77  | 47.50 | 17        |
| 97.23  | 2.77  | 54.50 | 16        |
| 100    | 0     | 62.50 | 15        |
| 100    | 0     | 70.00 | 14        |
| 100    | 0     | 82.50 | 13        |
| 100    | 0     | 82.50 | 12        |
| 100    | 0     | 90.00 | 11        |
| 100    | 0     | 92.50 | 10        |
| 100    | 0     | 92.50 | 9         |
| 100    | 0     | 97.50 | 8         |

The TSR and FAR values are zero and FRR is 100% up to a value of 21. After the threshold value of 21, the TSR has been increased to 95.84% with decrease in FRR to 4.16%. Further, FAR increases to 100% for a threshold value of 8.

The variation of FRR and FAR as a function of different threshold values is shown in the Fig. 4. It is found from the figure that EER for JAFFE database is 30% for a threshold value of 18.5. The variation of FAR, FRR and TSR for varying threshold values have been tabulated in the table 3.

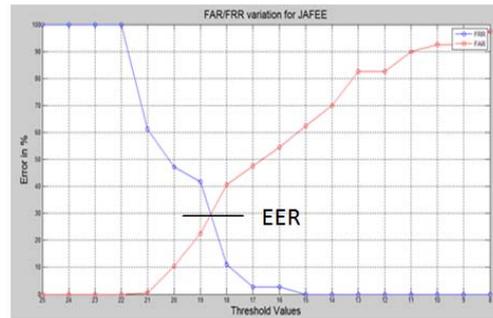


Fig. 4 FAR and FRR as a function of threshold value for the database JAFFE

Table 3 The Variation Of Frr, Far And Tsr With Threshold Values Of Nir Database

| ►► TSR | FRR   | FAR   | Threshold |
|--------|-------|-------|-----------|
| 0      | 100   | 0     | 25        |
| 0      | 100   | 0     | 24        |
| 0      | 100   | 0     | 23        |
| 0      | 100   | 0     | 22        |
| 0      | 100   | 0     | 21        |
| 8.34   | 91.66 | 3.12  | 20        |
| 20.84  | 79.16 | 12.50 | 19        |
| 45.84  | 54.16 | 31.25 | 18        |
| 50.00  | 50.00 | 37.50 | 17        |
| 62.50  | 37.50 | 56.25 | 16        |
| 70.834 | 29.16 | 62.50 | 15        |
| 79.17  | 20.83 | 65.62 | 14        |
| 83.34  | 16.66 | 65.62 | 13        |
| 95.84  | 4.166 | 75.00 | 12        |
| 95.84  | 4.166 | 81.25 | 11        |
| 95.84  | 4.166 | 96.87 | 10        |
| 95.84  | 4.166 | 96.87 | 9         |
| 95.84  | 4.166 | 100   | 8         |

The variation of FRR and FAR as a function of varying threshold values is depicted in the Fig. 5. The ERR is 45% at a threshold value of 16.5.

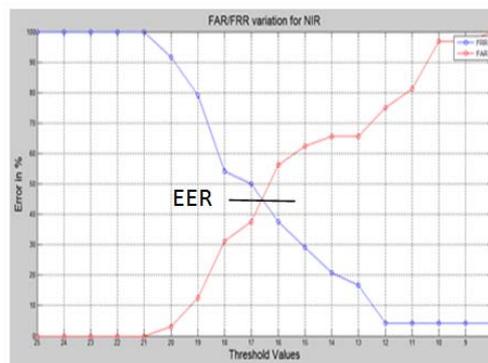


Fig. 5 FAR and FRR as a function of threshold value for the database NIR

## 6. Conclusion

In this work, Face recognition using FDCT via wrapping and SVM classifier has been proposed effectively for different databases. Here the face region of an image is obtained using Viola and Jones algorithm and resized to uniform dimensions of 100 x100. Final features were extracted using curvelet via wrapping technique. SVM classifier is used for matching. The parameters such as FRR, FAR and TSR were measured for different databases by varying the threshold values. Further, EER has been measured and compared. It is found that EER for L space k database is 11%, JAFFE database is 30% and 45% for NIR database. It is observed that EER is little more in NIR database due to blurring and intensity variation compared to other two databases.

## References

- [1] Marcos Faundez-Zanuy, "Biometric Security Technology," *Encyclopedia of Artificial Intelligence*, Vol. 1, pp. 262–264, 2009.
- [2] Y. S. Huang and S. Y. Chen, "A Geometrical-Model-Based Face Recognition," *IEEE International Conference on Image Processing*, pp. 3106-3110, 2015.
- [3] T. Ojala, M. Pietikainen and T. Maenpaa, "Multi-Resolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 24, pp. 971-987, 2002.
- [4] T. Ahonen, A. Hadid, and M. Pietikainen, "Face Description with Local Binary Patterns: Application to Face Recognition," *IEEE Transaction on Pattern Analysis and Machine Intelligence*, Vol. 28, No. 12, pp. 2037-2041, 2006.
- [5] Ngoc-Son Vu, Alice Caplier, "Face Recognition with Patterns of Oriented Edge Magnitudes," *European Conference on Computer Vision*, pp. 313–326, 2010.
- [6] Firoz Mahmud, Mst. Taskia Khatun, Syed Tauhid Zuhori, Shyla Afroge, Mumu Aktar and Biprodip pal, "Face Recognition using Principle Component Analysis and Linear Discriminant Analysis", *International Conference on Electrical Engineering and Information Communication Technology*, pp.1- 4, 2015.
- [7] Yi-Kang Shen, and Ching-Te Chiu, "Local Binary Pattern Orientation Based Face Recognition," *IEEE International Conference on Acoustics, Speech and Signal Processing*, pp. 1091-1095, 2015.
- [8] Jagadeesh H S, Suresh Babu K and Raja K B, "DBC based Face Recognition using DWT," *International Journal of Signal & Image Processing*, Vol. 3, No. 2, pp. 115-129, 2012.
- [9] Rangaswamy Y, Raja K B and Venugopal K R, "Face Recognition based on Oriented Complex Wavelets and FFT", *International Journal of Computer Applications*, Vol. 119, No. 24, pp. 27-34, 2015.
- [10] Ravi J, Saleem S Tevaramani and K B Raja, "Face Recognition using DT-CWT and LBP Features," *International Conference on Computing, Communication and Applications*, pp. 1-6, 2012.
- [11] Mohammad Da'san, Amin Alqudah and Olivier Debeir, "Face Detection using Viola and Jones Method and Neural Networks," *International Conference on Information and Communication Technology Research*, pp. 40-43, 2015.
- [12] Gordon Stein, Yuan Li and Yin Wang, "One Sample per Person Facial Recognition with Local Binary Patterns and Image Sub-Grids," *Annual Conference on Information Science and Systems*, pp. 1-5, 2016.
- [13] Ganapathi V Sagar, Savita Y Barker, K B Raja, K Suresh Babu and Venugopal K R, "Convolution based Face Recognition using DWT and Feature Vector Compression," pp. 444-449, 2015.
- [14] Ivanna K. Timotius, The Christiani Linasari, Iwan Setyawan, and Andreas A. Febrianto, "Face Recognition Using Support Vector Machines and Generalized Discriminant Analysis," *The 6th International Conference on Telecommunication Systems, Services, and Applications*, pp. 8-10, 2011.
- [15] Min Yao and Changming Zhu, "SVM and Adaboost-based Classifiers with Fast PCA for Face Recognition," *IEEE International Conference on Consumer Electronics*, pp. 1-5, 2016.
- [16] Paul Viola and Michael J. Jones, "Robust Real-Time Face Detection," *International Journal of Computer Vision*, Vol. 57, No. 2, pp.137-154,2004.
- [17] Emmanuel Candes, Laurent Demanet, David Donoho and Lexing Ying, "Fast Discrete Curvelet Transforms," *Multiscale Modeling & Simulation*, Vol. 5, pp. 861–899, 2006.
- [18] Daniel M. M. da Costa, Sarajane M. Peres and Clodoaldo A. M. Lima, "Face Recognition using Support Vector Machine and Multiscale Directional Image Representation Methods: A comparative study," *International Joint Conference on Neural Networks*, pp. 1-8, 2015.

