IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727,
PP 29-35
www.iosrjournals.org

SWT Multi-Level Fingerprint Feature Combination for Gender Classification: SVM Approach.

Revate S.S. [1], Lothe S.S. [2], Deshmukh M.P. [3] , Deshmukh P.D. [4]
Assistant Professor, Shri Chhatrapati Shivjai College,Omerga Dist. Osmanabad, MS (INDIA) [1]
Assistant Professor, V.N.Naik College, Aurangabad, MS (INDIA) [2]
Assistant Professor, Balbhim Art's, Science & Commerce College, Beed, MS (INDIA) 3
Principal, MGM's Dr.G.Y.Pathrikar College of Computer Sci. & IT, Aurangabad MS (INDIA) [4]

Abstract: *in this paper; we have highlighting on Biometric Fingerprints SWT Multi-Level Feature Fusion, SVM Classification approach to automate the Gender Recognition System. As a need in forensic investigation facet day by day new solutions are designed to solve the crime investigating and other issues. So, we have used 3000 samples of classified fingerprint database. Multi-level 2-D Stationary Wavelet Transform (SWT), Singular Valued Decomposition (SVD) technique have used as a feature extraction methods. The fusions of these multilevel extracted features are used in further process. At last, Support Vector Machine (SVM) is used to classify the datasets.*

Keywords: *Biometric, Fingerprint, Gender, Forensic, Multi-Level*

I. Introduction

Biometric recognition (or simply biometrics) refers to the use of distinctive anatomical (e.g., fingerprints, face, iris, Knuckle) and behavioral (e.g., speech) characteristics, called biometric identifiers [1].Biometric system is much less susceptible to the same type of trial-and-error guessing than passwords or tokens for authentication system. Robustness is a function of the particular biometrics' permanence and stability. The number of potential biometric is as great and diverse as the number of the body's measureable parts. The realm of esoteric biometric adds new meaning to the phrase, "Your body as password" [2]. The human body provides the source for a number of biometric technologies (Biometric Traits) as shown in figure 1.

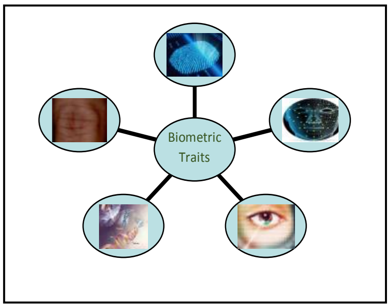


Figure 1: Biometric Traits

Global biometric systems market is estimated to value US$4.4 billion in 2015 and increase at a CAGR of 8.70% during the forecast period, to reach a peak of US$10.2 billion by 2025[3].In current era, fingerprint is used mostly in security application. It has a rich source of information. A fingerprint is one of the most used pieces of evidence in criminal forensics. A fingerprint is the feature pattern of one finger. It is believed with strong evidences that each fingerprint is unique. Each person has his own fingerprints with the permanent uniqueness. So fingerprints have being used for identification and forensic investigation for a long time [4], [5].

Gender classification from fingerprints is an important step in forensic anthropology in order to identify the gender of a criminal and minimize the list of suspects search. More sophisticated human-computer interaction systems can be built if they are able to identify a human's attribute such as gender. The system can be made more human-like and respond appropriately. A simple scenario would be a robot interacting with a human; it would require the knowledge of gender to address the human appropriately (e.g. as Mr. or Miss).

II. Literature Review

This literature review presents a critique of research paper related to this work. There are few researchers and academic scholars addressed the use of fingerprint for gender classification. Mark A. Acree (1999) shows that women tend to have a significantly higher ridge density than men. Mark also applied the Bayes' theorem and found that a ridge density of 11 ridges /25 mm^2 or less is more likely to be of male origin, and a ridge count of 12 ridges /25 mm^2 or more is most likely to be of female origin [6].

Miroslav Kralik et al. (2003), in his investigation shown that mean epidermal ridge breadth (MRB) as observed on ceramics can be used as an indicator of age (from birth to maturity) and sex of the artifact maker in adulthood. In adults, sexual dimorphism was clearly present even though artifacts were made from different types of ceramic clays. Ridge breadth is 9% greater in males than in females. He shows that the measurement of the epidermal ridge breadth of fingerprints on ceramics might be used as an indicator of the ceramists' age and sex. In every case, epidermal ridge breadth will remain one of the most important paleodermatoglyphic features [7]. Gholamreza Amayeh, et. al. (2008) has investigated the problem of gender classification from hand shape and used region and boundary features based on Zernike moments and Fourier descriptors. This experiment has done with database of 40 subjects containing 20 male and 20 female. It is found that 98% used score level fusion and LDA [8].

Esperanza Gutie´rrez-Redomero, et al. [2008], has proposed method that measures ridge density or the number of ridges in a given space. Database used in this study is obtained from all 10 fingerprints of 200 individuals. The results shows that women tend to have a significantly higher ridge density than men [9].

Manish Verma, et. al. (2008), proposed a method for gender classification from fingerprints. Features like ridge width, ridge thickness to valley thickness ratio (RTVTR), and ridge density were extracted. This method is experimented with the internal database of 400 fingerprints in which 200 were male fingerprints and 200 were female fingerprints Support Vector Machine (SVM) was used for the classification and 91% correct classification for male and female classes was achieved [10].

Jen Feng Wang, et. al. (2008), have worked on gender determination using fingertip features. For this research work 57 male and 58 female fingerprint totally 115 healthy adults fingerprint has been taken. They used ridge count, ridge density, and finger size features were used for classification. It has accurately achieved 86% result using both finger size and ridge count feature [11].

Vinod C. Nayak et. al. (2009), studied the gender differences in fingerprint ridge density in Chinese and Malaysian population. They used 200 subjects (100 males and 100 females) of Chinese origin and 100 subjects (50 males and 50 females) of Malaysian origin revealed that significant gender differences occur in the finger ridge density. In this research confirms that females have greater ridge density hence, finer ridge details than men in Chinese and Malaysian population. The mean ridge densities thus, can be used as a presumptive indicator of gender of an unknown print left at a crime scene. The study confirms the observations of earlier researchers and shows that racial differences exist in fingerprint ridge densities [12].

M. D. Nithin, et. al. (2011) has determined the gender based on finger ridge and has used Rolled fingerprints of 550 subjects. It shows that women have a significantly higher ridge count than men using Baye's theorem [13]. P. Gnanasivam, et. al. (2011) has proposed fast Fourier transform (FFT), discrete cosine transform (DCT) and power spectral density (PSD) to estimate gender by analyzing fingerprints. Author has used dataset of 400 persons of different age and gender. The identification rate was 92.88% for male and 94.85% for female samples [14].

Suchita Tarare et. al. (2015), this paper based on "Frequency Domain Approaches for Fingerprint Based Gender Classification.", states that fingerprint is used to identify gender of person. All training sample images are pre-processed and feature database is created by extracting features of all images using frequency domain technique (dwt, dct, bbdct). Using K-NN classifier testing fingerprint feature vector is compared with training sample feature database and classified as male or female fingerprint. The success percent for female using DWT is 65, using DCT is 64 and using BBDCT is 65.25. Likewise success percent for male using DWT, DCT and BBDCT is 52.25, 55.75 and 52 respectively [15].

S. S. Gornale et.al. (2015), in this research work, Haralick texture features are used to extract the gender information from fingerprints for classification of male and female. The experiment is conducted on fingerprints collected from different age groups of rural and urban people. A 45 samples of Male and 46 samples of female for rural and 65 Samples of Male and 60 samples of female for rural for the age group 15-20 years and for the age group 21-60 years respectively. It According to the experimental observations a 92% and 94% classification rate is achieved for linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) classifiers respectively [16].

III. Research Methods

a) Stationary Wavelet Transform (SWT)

The Stationary Wavelet Transform was proposed Wavelet transform is superior approach time-frequency analysis tools because its time scale width of the window can be stretched to match the original signal, especially in image processing analysis to make the decomposition time invariant [17], [18]. In order to preserve the invariance by translation, the down sampling operation must be suppressed and the decomposition obtained in redundant form, which is to be referred as Stationary Wavelet Transform. The redundancy of this transform facilitates the identification of salient features in a signal, especially for recognizing the noises. This approach gives good result for images but not for signal analysis .SWT has similar tree structure implementation without any sub-sampling. This balance of Perfect Reconstruction (PR) is preserved through level dependent zero padding interpolation of respective low pass and high pass filters in the filter bank structure. In image decomposition, separate the variables x, y of image and have the following wavelets [19], [20].

Vertical Wavelet (LH):	$\varphi^1 (x, y) =$	$\phi (x) \varphi (y)$	(1)
Horizontal Wavelet (HL):	$\varphi^2 (x, y) =$	$\varphi (x) \phi (y)$	(2)
Diagonal Wavelet (HH):	$\varphi^3 (x, y) =$	$\varphi (x) \varphi (y)$	(3)

Where, φ is the wavelet function and ϕ is the scaling function. The detailed signals contained in the three sub images as follows:

$$W_{j+1}^{1}(k_x, k_y) = \sum_{lx=-\infty}^{+\infty} \sum_{ly=-\infty}^{+\infty} g(lx)h(ly)c_{j,k+2+2^j}(lx, ly) \tag{4}$$

$$W_{j+1}^{2}(k_x, k_y) = \sum_{lx=-\infty}^{+\infty} \sum_{ly=-\infty}^{+\infty} h(lx)g(ly)c_{j,k+2+2^j}(lx, ly) \tag{5}$$

$$W_{j+1}^{3}(k_x, k_y) = \sum_{lx=-\infty}^{+\infty} \sum_{ly=-\infty}^{+\infty} g(lx)g(ly)c_{j,k+2+2^j}(lx, ly) \tag{6}$$

b) Singular Valued Decomposition (SVD):

The Singular Value Decomposition (SVD) is an algebraic technique for factoring any rectangular matrix into the product of three other matrices. The SVD is the factorization of any k X p matrix into three matrices, each of which has important properties. That is, any rectangular matrix A of k rows by p columns can be factored into U, S and V by using the equation (7).

$$A = U \bullet S \bullet V^T \tag{7}$$

Where $U = A \bullet A^T$ (8)

$$V = A^T \bullet A \tag{9}$$

And S is a k X p diagonal matrix with r non-zero singular values on the diagonal, where r is the rank of A. Each singular value is the square root of one of the Eigen values of both $A A^T$ and $A^T A$. The singular values are ordered so that the largest singular values are at the top left and the smallest singular values are at the bottom right, i.e., s1, 1 ≥ s2, 2 ≥ s3, 3 etc. Among the three rectangular matrices, S is a diagonal matrix which contains the square root Eigen values from U or V in descending order. These values are stored in a vector called Eigen vector (V) [21].

c) Support Vector Machines (SVM):

The SVM are used to classify the gender from the given fingerprints. It is based on the concept of decision planes that defines the decision boundaries. A set of objects having different class membership are separated by a decision plane. SVM is a nonlinear classifier often used for producing superior classification. An example for SVM classifier is as shown in the fig. 2. Classification task is based on separating lines to distinguish between objects of different class memberships, here its male and female classification.

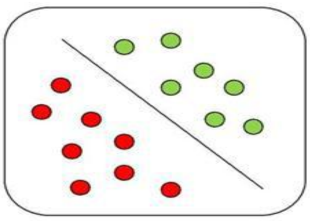


Figure 2: SVM Classifier

d) About Database

The databases of fingerprint images are online available Prof. T.S. Ibiyemi, Step-B, Project, Biometric Signal Processing Research & Development Laboratory, Electrical Engineering, University of Ilorin, Nigeria websites [22]. The online available database of all 10 fingers fingerprints is used (150 males and 150 females, Total 3000 fingerprint image) for research work. Fingerprint images were used i.e. LL(Left Little), LR(Left Ring), LM(Left Middle), LI(Left Index), LT(Left Thumb) , RT(Right Thumb), RI(Right Index), RM(Right Middle), RR(Right Ring) and RL(Right Little) fingerprints of each subject.

IV. Experimental Work

The database of all 10 fingers is collected includes 150 males and 150 females. The number of fingerprint images used for processing is 3000. Besides, background and the complete fingerprint image are not necessary due to that first remove the background of image. After that, calculates Centroid (the centre of mass of a geometric object of uniform density) of image and cropped the interested area. The cropped image further resized and pre-processed. The 2D stationary wavelet decompositions (2D SWT) are applied on pre-processed image at different three levels. The energy values for each sub band (Approximation, Horizontal, Vertical and Diagonal) are calculated using equation no. 10 for fingerprint images.

$$E_K = \frac{1}{RC}\sum_1^r \sum_1^c \left| X_K(i,j) \right| \qquad (10)$$

These sub band four energy values are stored in vector E1X4 for Level1 to Level3 form the MF1X12.Furthermore, the SVD factorization method is applied on same pre-processed image. The output of factorization is stored in vector S1X128 .The Multi-Level fusion of SWT is formed the vector as below equation 11,

MF1X12=E1X4 (L1) U E1X4 (L2) U E1X4 (L3) (11)

(MF is Multilevel Fusion, E1X4 (L1) at energy level1, E1X4 (L2) at energy level2, E1X4 (L3) at energy level3)

The Multi-Level Vector and SVD factorized values of Vectors again concatenated as below equation 12,

MF1x140 = E1X12 U S1X128 (12)

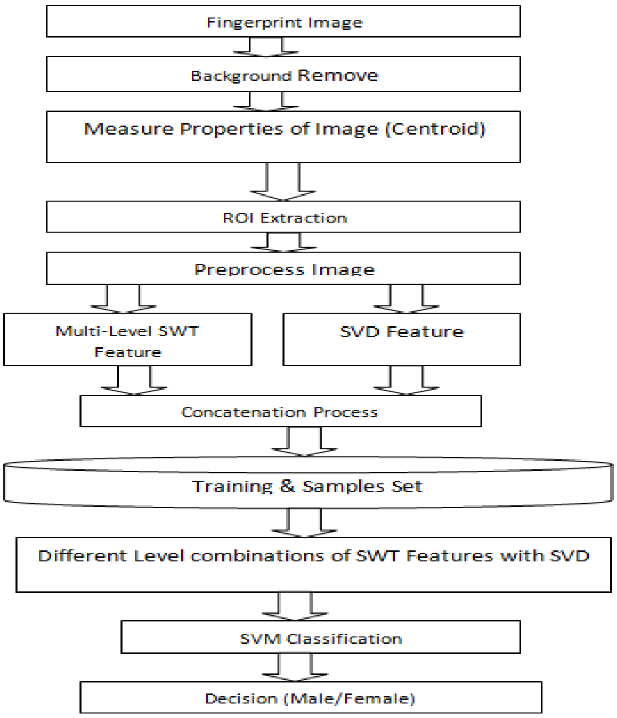


Figure 3: Experimental steps

It is found that generated vector of each fingerprint using equation 3 for 300 subjects including 150 males and 150 female's fingerprint. And generated vector used as a Dataset. One subject has 10 finger's fingerprint images.

$FDataSet_{150X140} = Subject_{150} \; X \; MF_{1x140}$ (13)

$$MDataSet_{150X140} = Subject_{150} \ X \ MF_{1x140} \quad (14)$$

$$DataSet_{300X140} = FDataSet_{150X140} \ X \ MDataSet_{150X140} \quad (15)$$

(FDataSet for Female, MDataSet for Male and DataSet for Both)

SVM classifier is used the 100 Female sample test and 100 Male sample from **DataSet$_{300X140}$**. The training data also used from same but except sample test of both. The classifiers are used sample test and training set, in different combination of SWT Levels Features with SVD. And then used it as dataset, Classifier make the decision about gender of the subject i.e. Female or Male. Calculate the Classification accuracy as equation 16:

$$Accuracy(\%) = \left(\frac{\#ofcorrectlyClassifiedExamples}{\#ofTrainingExamples} \right) X100 \quad (16)$$

V. Result And Analysis

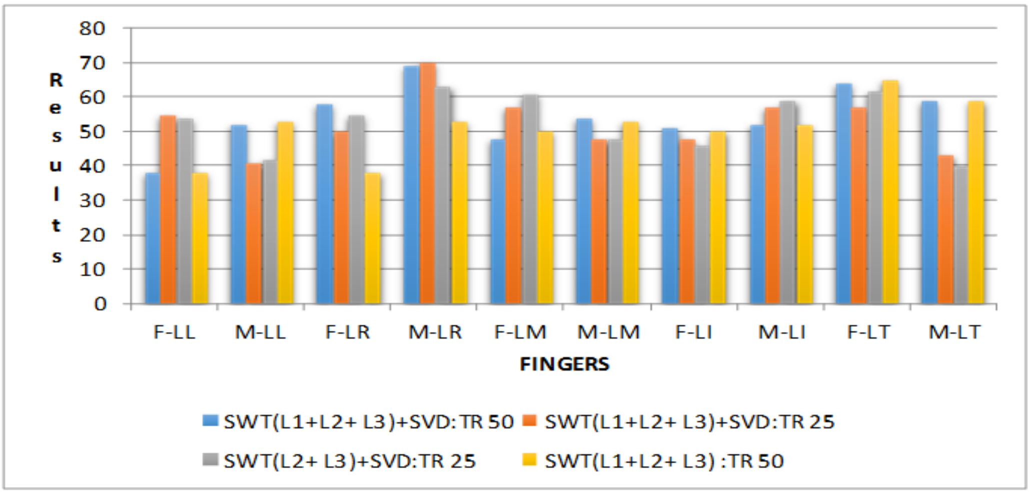
The Multi-Level Features of Stationary Wavelet Transform (SWT) and Singular Valued Decomposition (SVD) fusion for gender classification. The SWT Feature fusion Level2, Level3 and SVD; Training size is 25; result is up to 87% for males Right Ring finger. And also the SWT only multilevel fusion of Level1, Level2 & Level3; Training size is 50; result is up to 65% for female Left thumb Finger using SVM classifier. The table 1 and table 2 shows the classification results of each left and right fingers and also it is shown in graphical format in graph 1 and graph 2.

Table 1: Method I Result of Left Hand

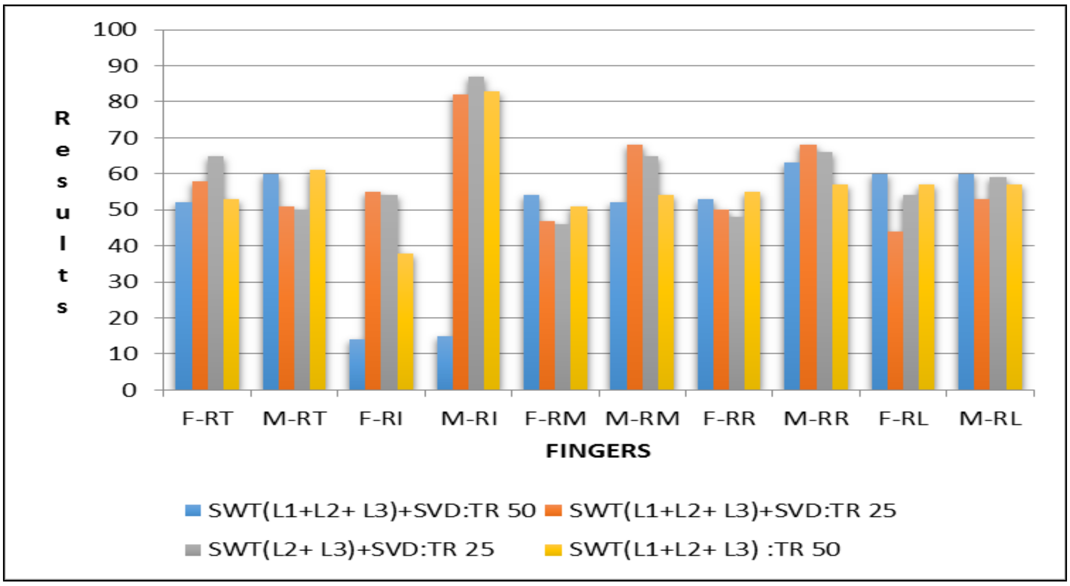
Training SET SIZE	Feature Fusion	F-LL	M-LL	F-LR	M-LR	F-LM	M-LM	F-LI	M-LI	F-LT	M-LT
50	SWT(L1+L2+ L3)+SVD:TR 50	38	52	58	69	48	54	51	52	64	59
25	SWT(L1+L2+ L3)+SVD:TR 25	55	41	50	70	57	48	48	57	57	43
25	SWT(L2+ L3)+SVD:TR 25	54	42	55	63	61	48	46	59	62	40
50	SWT(L1+L2+ L3) :TR 50	38	53	38	53	50	53	50	52	65	59

Table 2: Method I Result of Right Hand

Training SET SIZE	Feature Fusion	F-RT	M-RT	F-RI	M-RI	F-RM	M-RM	F-RR	M-RR	F-RL	M-RL
50	SWT(L1+L2+ L3)+SVD:TR 50	52	60	14	15	54	52	53	63	60	60
25	SWT(L1+L2+ L3)+SVD:TR 25	58	51	55	82	47	68	50	68	44	53
25	SWT(L2+ L3)+SVD:TR 25	65	50	54	87	46	65	48	66	54	59
50	SWT(L1+L2+ L3) :TR 50	53	61	38	83	51	54	55	57	57	57



Graph 1: Graphical representation results (Left Hand)



Graph 2: Graphical representation results (Right Hand)

VI. Conclusion

This fusion of SWT multi-levelled with SVD set and applied the SVM classifiers and database size is larger than earlier methods, then the result is 87% for males and 65% for female. Gender classification from fingerprints is an important step in forensic anthropology in order to identify the gender of a criminal and minimize the list of suspects during the search and much more. In future as a researcher, we will further work to improve the same by using large hybrid combination of dataset and different classifier techniques. The scope in the future to find global frequency based feature threshold value to achieve the gender classification through fingerprints biometric globally.

Acknowledgements

Authors would like to acknowledge and thanks to University Grants Commission (UGC), India for granting UGC SAP (II) DRS Phase-I & Phase-II F. No. 3-42/2009 & 4-15/2015/DRS-II Biometrics: Multimodal System Development Laboratory facility and One Time Research Grant F. No. 4-10/2010 (BSR) & 19-132/2014 (BSR) supporting to this work and Department of Computer Science and Information Technology ,Dr. Babasaheb Ambedkar Marathwada University, Aurangabad, Maharashtra, India.

References

[1]. Davide Maltoni ,Salil Prabhakar, Dario Maio, Anil K. Jain Salil Prabhakar, "Handbook of Fingerprint Recognition", Second Edition, Springer,2009.

[2]. John D. Woodward, Jr. Nicholas M. Orlans, Peter T.Higgins, 'Biometrics', McGrew-Hill @2003

[3]. [Online] Available: http://www.prnewswire.com/news-releases/biometric-systems-market-2015---2020-research-reports-518453221.html dt.11/10/2015.

[4]. D.A. Ashbaugh, Quantitative–Qualitative Friction Ridge Analysis: An Introduction to Basic and Advanced Ridgeology, CRC Press, 1999.

[5]. CDEFFS: The ANIS/NIST Committee to Define an Extended Fingerprint Feature Set, 2007. , [Online] Available : http://fingerprint.nist.gov/standard/cdeffs/index.html

[6]. Mark A. Acree, "Is there a gender difference in fingerprint ridge density?", Forensic Science International 102, Elsevier, 1999.

[7]. Miroslav Králík, Vladimír Novotný , "Epidermal Ridge Breadth: An Indicator Of Age And Sex In Paleodermatoglyphics" , Variability and Evolution, Vol. 11: 5–30,. Tabs. 5, Figs. 9. Adam Mickiewicz University, Faculty of Biology, Institute of Anthropology, Poznań, 2003.

[8]. Gholamreza Amayeh, George Bebis and Mircea Nicolescu, "Gender Classification from Hand Shape", IEEE transaction, 978-1-4244-2340-8, 2008.

[9]. Esperanza Gutie´rrez-Redomero, Concepcio´n Alonso, Esther Romero and Virginia Galera, "Variability of fingerprint ridge density in a sample of Spanish Caucasians and its application to sex determination", Forensic Science International ,Elsevier ,2008.

[10]. Manish Verma and Suneeta Agarwal, "Fingerprint Based Male-Female Classification'', in Proceedings of the International workshop on Computational Intelligence in Security for Information systems ,Genoa, Italy,PP:251-257, 2008.

[11]. Jen Feng Wang,"Gender Determination using Fingertip Features". Internet Journal of Medical,;3(2):22-8, Update Jul-Dec 2008.

[12]. Vinod C. Nayak, Prateek Rastogi , Tanuj Kanchan , K. Yoganarasimha , G. Pradeep Kumar Ritesh G. Menezes ,“Sex differences from fingerprint ridge density in Chinese and Malaysian population”, Forensic Science International Elsevier Ireland Ltd.,2009.
[13]. M.D. Nithin, B. Manjunatha, D.S. Preethi , B.M. Balaraj , “ Gender differentiation by finger ridge count among South Indian population”, Journal of Forensic and Legal Medicine , Elsevier, 2011.
[14]. P. Gnanasivam, S. Muttan, “Gender Identification Using Fingerprint through Frequency Domain Analysis”, European Journal of Scientific Research, Vol.59 No.2, pp.191- 199, 2011.
[15]. Suchita Tarare, Akhil Anjikar, Mukesh Raghuwanshi , “Frequency Domain Approaches for Fingerprint Based Gender Classification” , International Journal of Innovative Research in Computer and Communication Engineering, Vol. 3, Issue 4, , ISSN(Online): 2320-9801,ISSN (Print): 2320-9798, April 2015.
[16]. S. S. Gornale, Mallikarjun Hangarge, Rajmohan Pardeshi, Kruthi R, “Haralick Feature Descriptors for Gender Classification Using Fingerprints: A Machine Learning Approach”, International Journal of Advanced Research in Computer Science and Software Engineering, ISSN: 2277 128X Volume 5, Issue 9, September 2015.
[17]. S. Mallat, "A Theory of Multiresolution Signal Decomposition: The Wavelet Representation," IEEE Trans.
[18]. Pattern Analysis and Machine Intelligence, vol. 11, pp. 674-693, 1989.
[19]. J. C. Pesquet, H. Krim, and H. Carfantan, "Time-invariant orthonormal wavelet representations," IEEE Trans. Signal Processing, vol. 44, pp. 1964–1970, Aug. 1996.
[20]. Warin Chumsamrong and et al, "Using Stationary Wavelet Transform in the classification of SAR Images", 19th Asian Conf. on Remote Sensing, 16-20 Nov, 1998.
[21]. X. H. Wang, Robert S. H. Istepanian, and Yong Hua Song, "Microarray Image Enhancement by Denoising Using Stationary Wavelet Transform" IEEE Tran. On Nanobioscience, Vol. 2, No. 4, 2003
[22]. [Online] Available : https://www.cs.cf.ac.uk/Dave/Multimedia/node228.html , access on 07/02/2016.
[23]. [Online] Available : http://www.unilorin.edu.ng/step-b/biometrics/ ,Access on 06/05/2014