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A New Technique for Computationally Efficient Human Recognition

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Abstract: In this paper, a computationally efficient human recognition technique has been proposed using Unique Mapped Real Transform (UMRT) from ear biometric modality. This technique is time saving as well as robust against illumination changes and rotations. First, the input ear image is preprocessed to improve its overall visual appearance. The desired ear region is segmented out from the preprocessed image using constrained Delaunay triangulation segmentation technique. A computationally efficient and robust UMRT is then used to extract feature vectors which uniquely represent ear images of different persons. The performance of proposed feature vector extraction is studied by testing the feature vectors using the KNN classifier and Euclidean distance classifier. The proposed ear recognition technique is also compared with Uniform Local Binary Pattern (ULBP) based technique. Testing is carried out using IIT Delhi and internal GEAR ear database images and the results are encouraging.

Keywords: Computational simplicity, ear biometrics, integer transform, performance measures, UMRT feature extraction.

1 Introduction

Due to the recent smarter developments in human recognition, authentication of human identity is successfully accomplished using several life science metrics in our day-to-day life. Such human recognition using computational life science metrics called 'Biometrics' [1] in various environments of our daily affairs has become unavoidable so as to combat the inappropriate use of ATM debit/credit cards in supermarkets, traveling tickets booking, passenger authentication at airports/train stations, polling stations etc. Harmless, authenticated users have to claim their identities against malicious users in such really challenging environments. The purpose of negative recognition biometric systems is to detect malicious users and hence punish them who otherwise will intrude the system and destroy the authenticity of the entire system for which the biometric recognition is originally applied. The consequences of such intrusions by malicious users may even lead to the attack of terrorists. In negative recognition systems, harmless authenticated users are also subject to meticulous recognition procedures. Non-invasive acquisition of biometric modalities is performed to reduce the difficulties faced by public during invasive acquisition.

Biometric researchers have already started deploying non-invasive biometric recognition systems by acquiring biometric traits such as face, ear, iris etc,. in a non-invasive manner [1, 2]. Research has also been nowadays directed into the deployment of biometrics for remote authentication in multi-server environment [3]. The speed and the recognition accuracy with which such system can recognize persons also play a vital role in the development of a biometric recognition system. Ear can be regarded as a soft biometric which can be acquired in a non-invasive manner without disturbing the harmless users much. This particular physiological trait remains stable over years and is also robust against facial expressions.

Feature extraction plays a vital role in any automated biometric authentication system which is designed to identify and/or recognize humans. Though the process of person identification and that of person recognition seem to be similar, both of them are different. Ear images can be captured by methods as similar to that of face images and can very well be used for person identification and/or recognition [4]. An elaborate research has been

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performed earlier onto the biometric characteristics of ear modality and the following inferences are obtained.

1. The shape, appearance and texture of the human ear are unique for each individual so that the human ear can be practically used as a biometric modality. Almost all characteristics of human ear remain the same over time and very little changes occur during the lifetime of an individual.

2. Researchers have been emphasizing the use of ear recognition as a potentially important tool in the near future as the success rates of recognizing human based on their ear modalities increase.

Alphonse Bertillon, a French criminologist is being considered as the father of ‘Ear Biometrics’, who had recognized the importance of human identification from their ears. Alfred Iannarelli is regarded as a pioneer in ear biometrics who had contributed the first manual method of human recognition based on ear biometrics. He had examined over 10000 ears and was able to successfully prove the uniqueness of human ears. He developed an anthropometric technique consisting of 12 measurements which form the ‘Iannarelli System of Ear recognition’. He had also proved that even the ear images of identical twins have similar but not identical ear physiological features.

Several methods have been developed for extracting feature vectors from ear images and these feature vectors can be applied to a suitable classifier for subsequent identification / verification [6].

The research contribution by Nixon [5] uses force field transformation in order to find energy lines, wells and channels as ear features. In several research papers of Bowyer [7, 8], Principal Component Analysis (PCA) based approach is being proposed and eigen ears are obtained. Also, the outer ears can also be used for authentication according to the research contribution by Sanchez et al [9]. In several papers of Choras Michal [10–12], geometric feature extraction has been proposed. Ajay Kumar et al [13] has proposed a completely automated approach for the robust segmentation of curved region of interest using morphological operators and Fourier descriptors. There have been a lot of research papers in texture analysis of images using ‘Local Binary Pattern’ (LBP) operator [14–16] which finds a lot of applications in image processing such as face recognition, gender classification, texture classification etc,. Christian Rathgeb et al. [17] describes the experimental results of ear recognition using conventional techniques such as LBP, HOG techniques in the presence of image compression.

In this work, a new approach for ear recognition using computationally efficient Unique Mapped Real Transform (UMRT) applied over ear regions is being proposed. The ear regions from human side profile face images can be segmented by constrained Delaunay triangulation segmentation technique [18].

The paper is organized as follows: Section 2 describes the basics of Unique Mapped Real Transform (UMRT) and the placement algorithm of UMRT coefficients. Section 3 gives an overview of ear recognition. Section 4 describes the proposed ear recognition system where feature vectors are extracted from Delaunay segmented ear images using the UMRT methodology. Section 5 gives the test results, validates the recognition with performance measure curves such as Receiver Operating Characteristics (ROC) curves and also discusses the statistical aspects of ear recognition. Section 6 discusses the possible future enhancements to this proposed work.

2 Unique Mapped Real Transform (UMRT)

A new computationally efficient transform based texture analysis called Unique Mapped Real Transform by R.C.Roy et al [22] is found to be an evolving and a non-expansive integer transform. The 2D UMRT transform can be applied in various areas of image processing including biometrics.

The computation of forward and inverse Unique Mapped Real Transform involves only real additions. This UMRT and SMRT–Sequency mapped MRT, the enhanced version of UMRT have been successfully applied for medical diagnostic applications in R.C.Roy et al [19–21]. This has motivated the authors of this paper to apply the UMRT methodology to ear biometrics. In this paper, a biometric recognition system based on ear modality is being proposed using 2D UMRT.

The forward 2D UMRT transform of order N for calculating the N^2 UMRT coefficients on an $N \times N$ data [21] is follows,

$$X(U,V)^{(p)} = \sum_{\forall\ (u,v)|z=p} x(u,v) - \sum_{\forall\ (u,v)|z=p+M} x(u,v) \quad (1)$$

where $0 \le (U,V) \le N-1$, $0 \le p \le (M-1)$
and $M = N/2$, $z = (uU+vV)N$;
U,V are frequency indices and p is phase index.

The above equation (1) maps a 2D data of size NxN, into M redundant matrices of size $N \times N$. The placement algorithm for obtaining positional details of 8×8 2D UMRT coefficients is given in Table 1.

Out of the various MRT coefficients, the non-existent (zero valued) MRT coefficients and the redundancy in MRT coefficients can be removed to obtain N^2 unique coefficients in the form of $N \times N$ matrix. There are 64 basis images identified by (U,V,p) for $N = 8$ leading to 64 unique UMRT coefficients. Out of those 64 basis images, only few such are shown in Fig. 1.

The white cells in these basis images correspond to a value of ‘1’, black cells correspond to a value of ‘-1’ and grey cells correspond to a value of ‘0’. So, while computing UMRT coefficients, the pixel values in the respective positions of the image block are either added, subtracted or as such retained depending upon the color of the corresponding positions in the image block.

Table 1: Placement algorithm conveying positional details of 8×8 2D UMRT matrix.

	$V \rightarrow$							
$U \downarrow$	(0,0,0)	(0,1,0)	(0,2,0)	(0,1,1)	(0,4,0)	(0,1,2)	(0,2,2)	(0,1,3)
	(1,0,0)	(1,1,0)	(1,2,0)	(3,1,1)	(1,4,0)	(5,1,2)	(3,2,1)	(7,1,3)
	(2,0,0)	(2,1,0)	(2,2,0)	(6,1,1)	(2,4,0)	(2,1,2)	(6,2,2)	(6,1,3)
	(1,0,1)	(3,1,0)	(3,2,0)	(1,1,1)	(1,4,1)	(7,1,2)	(1,2,1)	(5,1,3)
	(4,0,0)	(4,1,0)	(4,2,0)	(4,1,1)	(4,4,0)	(4,1,2)	(4,2,2)	(4,1,3)
	(1,0,2)	(5,1,0)	(1,2,2)	(7,1,1)	(1,4,2)	(1,1,2)	(3,2,3)	(3,1,3)
	(2,0,2)	(6,1,0)	(6,2,0)	(2,1,1)	(2,4,2)	(6,1,2)	(2,2,2)	(2,1,3)
	(1,0,3)	(7,1,0)	(3,2,2)	(5,1,1)	(1,4,3)	(3,1,2)	(1,2,3)	(1,1,3)

The 2D UMRT texture features [22] are calculated as shown in Equation (2):

$$S(U,V) = \frac{\sum_{i=1}^{\mathrm{BL}} \Sigma_p |X(U,V)^{(p)}|}{N \times N} \tag{2}$$

where $N \times N$ is the size of the sub image block (i.e. $N = 8$);
$X(U,V)^{(p)}$ represents the UMRT coefficient specified by (U,V,p);
BL represents the number of sub image blocks;
The 2D UMRT texture features of dimensionality 22 are obtained as shown in Table 2.

Table 2: UMRT texture features of dimensionality 22.

S(U,V)	U	V	p
S(0,0)	0	0	0
S(0,1)	0	1	0,1,2,3
S(1,0)	1	0	0,1,2,3
S(0,2)	0	2	0,2
S(2,0)	2	0	0,2
S(0,4)	0	4	0
S(4,0)	4	0	0,1,2,3
S(1,1)	1	1	0,1,2,3
S(3,1)	3	1	0,1,2,3
S(5,1)	5	1	0,1,2,3
S(7,1)	7	1	0,1,2,3
S(1,2)	1	2	0,1,2,3
S(2,1)	2	1	0,1,2,3
S(3,2)	3	2	0,1,2,3
S(6,1)	6	1	0,1,2,3
S(1,4)	1	4	0,1,2,3
S(4,1)	4	1	0,1,2,3
S(2,2)	2	2	0,2
S(6,2)	6	2	0,2
S(2,4)	2	4	0,2
S(4,2)	4	2	0,2
S(4,4)	4	4	0

Any biometric system which we come across in daily life, should capture probe images at a faster rate, process them and extract features with less feature extraction time and reveal the identification / authentication of the probe images The most important advantage of deploying UMRT for ear recognition is that the computation of UMRT coefficients involves only mere additions and/or subtractions of the pixel values in the corresponding image blocks. This simplicity in computation in turn leads to less time for feature extraction which plays an important role in a biometric recognition system. Also, the size of the resultant UMRT texture feature vector is only 22 when compared to conventional methods.

3 Overview of Ear Recognition

Biometric recognition systems have been developed and are already under deployment in various day-to-day applications of today's technological world. The quality of the biometric data captured by the respective biometric sensor is first analyzed in order to determine whether it is suitable for further processing in the subsequent stages of the biometric system. If required, the quality of the acquired data is enhanced in the pre-processing module. A set of feature vectors are extracted from the processed biometric data in the feature extraction module.

Robust ear biometric recognition systems are in great demand for enabling protection against crime and terrorism. However the problem of identifying a person by acquiring an input ear image and matching with the known ear images in a database is still a very tough problem. This is due to the variability of human ear images under diverse operating conditions such as illumination, rotation, camera viewpoints. The performance of ear recognition systems is greatly affected by these conditions especially when the biometric recognition systems have to match test image against train images of large scale databases. However, the main advantage of ear biometric systems over other biometric recognition systems is that the changes in facial expression and age do not considerably affect the appearance of an ear.

Experimental results involving partial ear shapes suggest that the performance of ear biometric system is not substantially affected by partial occlusions due to hair but the performance and hence recognition rate is certainly affected by large occlusions due to hair. This suggests that even in situations where the complete ear shapes cannot be acquired, partial ear shapes can be very well used for recognition. This emphasizes the practicability of using ear shape as a biometric.

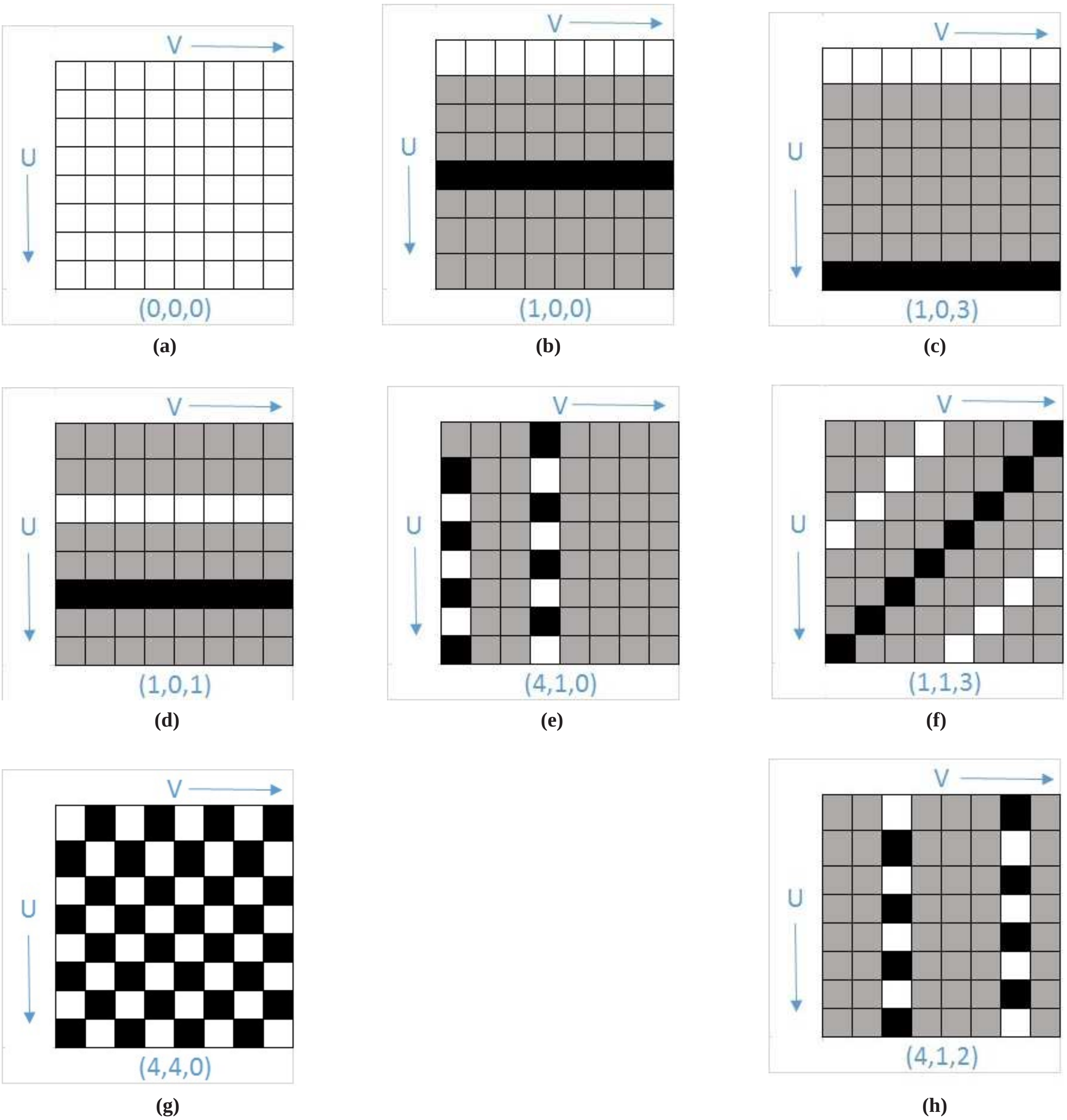

Fig. 1: Examples for basis images of 8×8 2D UMRT.

Algorithms for ear recognition can be categorized into three types namely appearance based techniques, force field transformation based techniques and geometric techniques. Appearance based techniques namely Principal Component Analysis (PCA) or Independent Component Analysis (ICA) etc., use either global or local appearance of the ear image for recognition. Force field based techniques involve transformation of an ear image into a force field and subsequent feature extraction using force field energy functions as discussed in [5]. Geometric techniques involve representation of ear images by either using neighborhood graphs obtained from Voronoi diagrams [15] or by exploiting shapes of contours of ear [10–12].

4 Proposed Feature Extraction

This paper is focused on a computationally efficient ear recognition model built using Unique Mapped Real Transform and this model is found to be robust, rotationally invariant and also invariant against illumination changes.

The proposed UMRT based person authentication is applied on ear images collected from IIT Delhi ear database [13]. The ear image is segmented from each ear image using constrained Delaunay triangulation segmentation [18]. The UMRT methodology is applied on segmented ear region and feature vector of dimensionality 22 (i.e. length 22) is extracted.

The process of ear recognition and authentication consists of two phases namely enrollment phase and identification and/or verification phase. The enrollment phase consists of extracting feature vectors from the gallery ear images, using the proposed Unique Mapped Real Transform (UMRT) technique called templates. The identification / verification phase consists of extracting feature vectors from the probe ear images by a similar UMRT technique. The feature vectors of the probe ear images are compared against the stored template ear images for generating match scores.

The proposed UMRT based ear recognition model is as shown in Fig. 2. Each gallery ear image from the chosen database is applied as input to the proposed model during the enrolment phase. The input image from ear database is pre-processed to improve its visual appearance. Then the desired ear region is segmented out using Delaunay segmentation technique. The Region of Interest (ROI) ear region is now applied to the feature extraction module where feature vectors of length 22 are extracted from each gallery ear image using UMRT technique. The dimensionality of feature vectors play an important role in the computing requirements and hardware implementation of any biometric system.

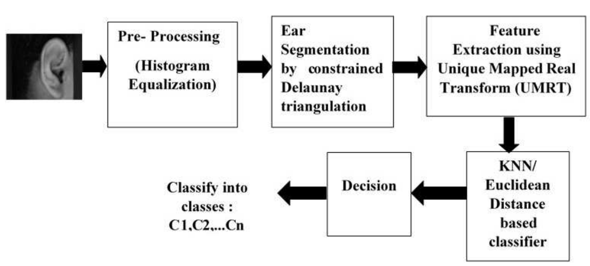

Fig. 2: Block diagram of the proposed system.

A similar procedure is applied for the probe ear image whose identity has to be claimed and the feature vector Fi is extracted using UMRT based feature extraction. A KNN classifier is built to classify the probe ear images based on the UMRT feature vectors. A distance based classifier is also constructed for classifying the feature vectors of probe ear images by calculating the distance between the probe ear image and each of gallery ear images. This is performed by the classifier and the subsequent decision modules. The identity of probe ear image is claimed based on minimum Euclidean distance.

5 Results and Discussion

The above explained ear recognition model is tested on right and left ear images of 75 persons from IIT Delhi ear database [13] as well as on 'GEAR' internal ear database consisting of 50 ear images (both right and left ear images) posed by 25 persons. The proposed ear recognition technique is developed using MATLAB R2013 in Intel Core i7 processor. The ear images from training set, evaluation set as well from test set are segmented using constrained Delaunay triangulation segmentation technique to separate the region of interest ear region from the background. The IIT Delhi and the internal GEAR ear databases are randomly divided into training, evaluation and testing sets. Each test is performed thrice times and an average result is calculated [25].

The performance of the proposed ear recognition model can be analyzed by plotting the various curves such as Receiver Operating Characteristics (ROC), Cumulative Match Characteristics (CMC) and Expected Performance Characteristics (EPC). These curves can be plotted using the PhD toolbox developed by Vitomir Struc [23, 24] in the Faculty of Electrotechnical Engineering at University of Ljubljana. The PhD (Pretty helpful Development functions for) face recognition toolbox is intended to help researchers not only working in the field of face recognition but also in any biometric modality.

The Receiver Operator Characteristic, Expected Performance Characteristic and Cumulative Match Characteristic curves for the analyzing the performance of the proposed UMRT based ear recognition technique are shown in Figs. 3–6. Various performance measures of the proposed UMRT method and ULBP method are compared in Table 3. It is found that the UMRT method outperforms the ULBP method in terms of dimensionality of feature vector, extraction time and rank one recognition rate.

The UMRT based ear recognition methodology is effective in achieving illumination invariant, rotation invariant ear recognition and is tested using IIT Delhi ear database and an internal ear database named GEAR.

Table 3: Comparison of performance measures of proposed UMRT method and ULBP method.

Performance Measures	Proposed UMRT method	ULBP Method
Time for feature vector extraction (in sec)	15.6	32.85
Dimensionality of feature vector	22	256
Rank one recognition rate (in %)	90.91	81.82
Verification rate at 1% FAR on test set (in %)	75	100
Verification rate at 0.1% FAR on test set (in %)	25	25
Equal error rate on evaluation set (%)	18.18	1.7
Minimal half total error rate on evaluation set (%)	12.12	1.7
Verification rate at 1% FAR on evaluation set (in %)	63.64	63.64
Verification rate at 0.1% FAR on evaluation set (in %)	9.09	9.09
Verification rate at 0.01% FAR on evaluation set (in %)	9.09	9.09

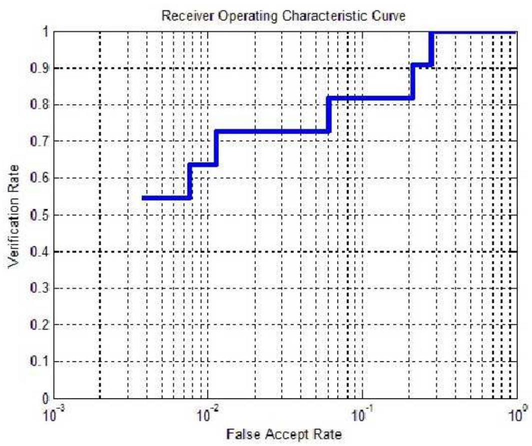

Fig. 3: Receiver Operating Characteristic Curve (VR vs. FAR) of UMRT method.

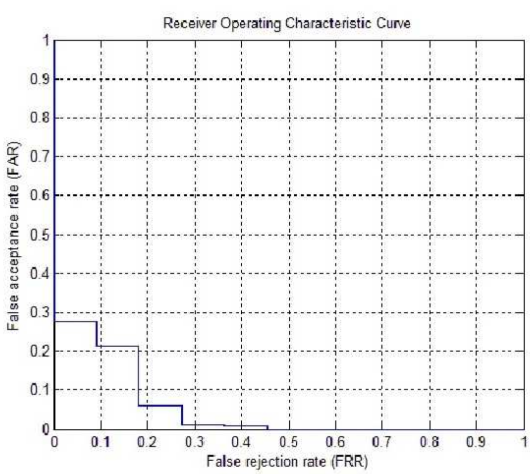

Fig. 4: Receiver Operating Characteristics (FAR vs. FRR) of UMRT method.

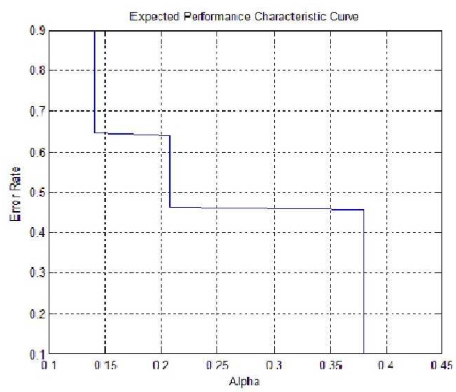

Fig. 5: Expected Performance Characteristics of UMRT method.

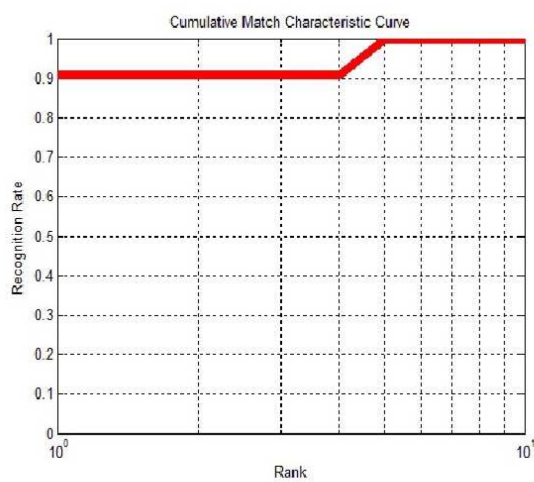

Fig. 6: Cumulative Match Characteristics of UMRT method.

6 Conclusion

In this paper, a computationally efficient and robust ear recognition technique is being proposed using Unique Mapped Real Transform (UMRT) and feature vectors of length 22 are extracted. The extracted feature vectors are found to be invariant against rotations and illumination changes. This work can be applied to real time person identification based on ear biometric modalities. The feature vectors are extracted from the segmented ear images using UMRT of order 8×8. Further improvement in recognition accuracy can be obtained by changing the order of UMRT. Suitable dimensionality reduction techniques can be further suggested which will reduce the dimensionality of feature vectors leading to reduction of memory requirements and less execution time. As this proposed work gives promising results, this can be applied for automatic ear recognition in video sequences and also in remote applications.

References

[1] Anil K. Jain, Handbook of Biometrics, Springer Science, 2008.

[2] Arun A. Ross, Karthik Nandakumar, Anil K. Jain, Handbook of Multibiometrics, International Series on Biometrics, Springer Science, 2006.

[3] Xuelei Li, Qiaoyan Wen, Wenmin Li, Hua Zhang, Zhengping Jin, A biometric-based Password Authentication with key Exchange Scheme using Mobile Device for Multi-Server Environment, Applied Mathematics and Information Sciences, **9(3)**, 1123–1137, (2015).

[4] A. Iannarelli, Ear Identification, Paramont Publishing, 1989.

[5] D.J. Hurley, M.S. Nixon, J.N. Carter, Automatic Ear Recognition by Force Field Transformations, IEE Colloquium on Biometrics, (2000).

[6] M. Burge, and W. Burger, Ear Biometrics in Computer Vision, Proc. 15th International Conf. of Pattern Recognition. 822–826, (2000).

[7] B. Victor, K.W. Bowyer and S. Sarkar, An Evaluation of Face and Ear Biometrics, Proc. of Intl. Conf. on Pattern Recognition, 429–432, (2002).

[8] K. Chang, B. Victor, K.W. Bowyer and S. Sarkar, Comparison and Combination of Ear and Face Images in Appearance-Based Biometrics, IEEE Trans. on PAMI, **25(9)**, (2003).

[9] B. Moreno, A. Sanchez and J.F. Velez, On the Use of Outer Ear Images for personal Identification in Security Applications, IEEE International Cornahan Conference on Security Technology, 469–476, (1999).

[10] Choras Michal, Feature Extraction Based on Contour Processing in Ear Biometrics, IEEE Workshop on Multimedia Communications and Services, MCS'04, 15–19, Cracow, (2004).

[11] Choras Michal, Human Ear Identification Based on Image Analysis, in L. Rutkowski et al. (Eds): Artificial Intelligence and Soft Computing, ICAISC 2004, Springer-Verlag LNAI **3070**, 688–693, (2004).

[12] Choras Michal, Ear Biometrics Based on Geometrical Method of Feature Extraction, in F.J. Perales and B.A. Draper (Eds.): Articulated Motion and Deformable Objects, AMDO 2004, Springer-Verlag LNCS **3179**, 51–61, (2004).

[13] Ajay Kumar and Chenye Wu, Automated human identification using ear imaging, Pattern Recognition, **41(5)**, (2012).

[14] T. Ojala, M. Pietikainen and D. Harwood, A Comparative Study of Texture Measures with Classification based on Feature Distributions, Pattern Recognition, **19(3)**, 51–59, (1996).

[15] Matti Pietikainen, Abdenour Hadid, Guoying Zhao, Timo Ahonen, Computer Vision Using Local Binary Patterns, Computational Imaging and Vision, **40**, Springer-Verlag, (2011).

[16] N.B. Boodoo-Jahangeer and S. Baichoo, LBP-based ear recognition, Proceedings of IEEE 13th International Conference on Bioinformatics and Bioengineering (BIBE),1–4 (2013).

[17] Rathgeb, Christian, A. Pflug, J. Wagner and C. Busch, Effects of image compression on ear biometrics, IET Biometrics (2016).

[18] Z. Hu, H. Yan and X. Lin, Clothing segmentation using foreground and background estimation based on the constrained Delaunay triangulation, Pattern Recognition, **4(5)**, 1581–1592 (2008).

[19] R.C. Roy and R. Gopikakumari, A new transform for 2D signal representation (MRT) and some of its properties, in Proc IEEE International Conference on Signal Processing and Communications, 363–367 (2004).

[20] M.S. Anishkumar, R.C. Roy and R. Gopikakumari, A new Image Compression and Decompression Technique based on 8×8 MRT, GVIP Journal, **6(1)**, 51–53, (2006).

[21] Rajesh Cherian Roy, Development of a new transform MRT, Ph.D Dissertation, Cochin University of Science and Technology, 2009.

[22] B. Manju, V.L. Jaya, K. Meenakshy and R. Gopikakumari, 8×8 SMRT based texture descriptors, Lecture notes on Software Engineering, **3(4)** Nov. 2015.

[23] V. Struc and N Pavesic, The Complete Gabor-Fisher Classifier for Robust Face Recognition, EURASIP Advances in Signal Processing, **1**, 1–26, (2010).

[24] V. Struc and N.Pavesic, Gabor based Kernel Partial-Least-Squares Discrimination Features for Face Recognition, Informatica (Vilnius), **20(1)**, 115–138 (2009).

[25] K. Meena, A. Suruliandi and R. Reena Rose, Face Recognition Based on Local Derivative Ternary Pattern, IETE Journal of Research, **60(1)**, 20–32 (2014).

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