

FACE BASED MULTIMODAL BIOMETRICS AUTHENTICATION SYSTEM

MAMTA BANSAL



**DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY DELHI**

NOVEMBER 2015

FACE BASED MULTIMODAL BIOMETRICS AUTHENTICATION SYSTEM

by:

MAMTA BANSAL

Department of Electrical Engineering

Submitted
in fulfillment of the requirements of the degree of

DOCTOR OF PHILOSOPHY

to the



Indian Institute of Technology Delhi

November 2015

This Thesis is dedicated to my eternal love
“LADDU GOPAL”.

CERTIFICATE

This is to certify that the thesis titled "**Face Based Multimodal Biometric Authentication System**" being submitted by Ms. **Mamta Bansal** to the Department of Electrical Engineering, Indian Institute of Technology Delhi, for the award of the degree of **Doctor of Philosophy**, is a record of bonafide research work carried out by her under my guidance and supervision. In my opinion, the thesis has reached the standards fulfilling the requirements of the regulations relating to the degree.

The results contained in this thesis have not been submitted to any other university or institute for the award of any degree or diploma.

Date

New Delhi

Dr. M. Hanmandlu
Professor
Department of Electrical Engineering
Indian Institute of Technology Delhi
New Delhi-110016

ACKNOWLEDGEMENTS

Foremost, I pay my gratitude to my guide, Prof. M. Hanmandlu for providing me the constant encouragement and guidance at every stage of my research. Without his strong support and spirited motivation I could not have achieved my research goals. I could not imagine having a better supervisor than him for my Ph.D. study. I extend my thanks to my SRC members, Prof. K. K. Biswas, Prof. S. D. Joshi, and Prof. Sumantra Dutta Roy for their fruitful suggestions and critical comments during my research presentation.

I acknowledge the computational assistance rendered by Riby Bobby and Manika Bindal. My special thanks go to Neha Jain for her love and moral support. I am equally thankful to my friends cum lab mates Amioy kumar, Jyotsana Grover, Sridevi, Shikha, Sunny, Aparna, and Mr. Ashok bhateja. Special thanks to Jeevan and Abhinav who helped me in understanding some logics during simulations. Working with all of them has been a great pleasure and a lovable experience to me.

I would not dare to dream without the love and affection of my parents and in-laws. Words cannot suffice to express my gratitude to my Mother and Father who are the pillars of my strength and my husband who is a source of invigoration and enlightenment. Without their support and sacrifice I would not have reached this stage. I would also thank all other family members who invariably made my life so cozy and easy. My special love is to my elder brother Ajay for his protective cover and utmost care.

Finally, my greatest gratitude to the almighty for imparting me the passion and perseverance needed to complete this study.

Mamta Bansal

ABSTRACT

Several multimodal biometric systems have been developed in the literature because of the growing security requirements under the unconstrained environmental conditions. The face based multimodal biometric system comprising IR face, Iris, Ear as its constituents is proposed in this thesis and it is designed to work under both the constrained and unconstrained environments where the conventional methods may fail. With view to make the system more efficient several new features and classifiers are developed and implemented on the proposed multimodal biometric system.

The concept of the information set is evolved while representing the uncertainty in a collection of attribute/property values by the Hanman-Anirban entropy function. Four features, viz., Effective Exponential Information source value (EEI), Effective Multi Quadratic Information source value (EMQDI), Energy Feature (EF) and Sigmoid Function (SF) are proposed based on the information sets. Next Principal Component Analysis (PCA) is converted into Local Principal Independent Components (LPIC) using the information set based features which can handle the unconstrained conditions better than PCA. A new classifier called Inner Product Classifier (IPC) is developed using the normed-error vectors which are obtained by applying t-norms on the error vectors between the training feature vectors and test feature vector. The inner product of the aggregate of the original training feature vectors and the normed error vector is considered as the criterion for determining the identity of a user. This is applied for the classification of the constrained and unconstrained ear databases.

The information set consisting of the information values can be modified by using a filtering function and transformed using the Hanman transform which is a higher form of information set.

In addition to the above four features, Hanman filter and Hanman transform features are also used for the representation of iris textures and tested on CASIA-Iris-V3-Lamp termed as *DB1I*, that contains eye images of 411 people.

Next, interactive features are developed from the above features in order to take care of the interaction between the features from adjacent windows. The effectiveness of these features are demonstrated on the IR face images with the help of two new classifiers called the Hanman classifier and the Weighted Hanman classifier that are developed by applying the Hanman-Anirban entropy function on the normed error vectors as used in IPC. The user identity corresponds to the least entropy value of the associated normed error vectors. The interactive features are evaluated using the proposed classifiers on *IITD IR face* (termed as *DB1F*) database with 1030 IR images from 103 users and on 9 other unconstrained IR databases containing occlusion, low resolution and noisy effects.

In order to handle the unconstrained conditions, a new entropy function having the provision to change the information source values unlike the Hanman-Anirban entropy function is formulated. The features from the previous chapters are modified in the light of the new entropy function. This entropy displays a peculiar characteristic that splits into two zones for a particular choice of its parameters not witnessed in other entropy functions. This new entropy function is utilized in changing the Hanman classifier to the Modified Hanman Classifier (MHC) that is shown to have better performance than that of SVM and KNN on IR face images. The new entropy based MHC is tested on the same databases of IR Face under the constrained and unconstrained conditions as used for evaluating the interactive features.

The new entropy features are applied to all three modalities of the proposed multimodal biometric system with each modality containing 100 users. To correct the erroneous scores,

Refines Score (RS) method is developed by utilizing the neighbourhood scores of the claimed samples. We have fused all three modalities under the unconstrained environment using the score level fusion alone and then improved the fusion by RS method. Here we have employed four fusion rules: sum, product, exponential sum, and tan-hyperbolic function out of which the product rule gives the best performance. The performance of the proposed multimodal biometric system is analyzed using the ROC plots.

CONTENTS

ACKNOWLEDGEMENTS	i
ABSTRACT	ii
CONTENTS	v
LIST OF FIGURES	xi
LIST OF TABLES.....	xx
ABBREVIATION.....	xxiv
Chapter 1 INTRODUCTION.....	1
1.1 Biometric based Authentication	1
1.1.1 The need of multimodal biometric system in surveillance applications.....	1
1.2 Motivation for the Proposed Face based Multimodal Biometric System	2
1.2.1 The Components of Face based Multimodal Biometric System	3
1.3 The Issues Addressed in the Thesis.....	5
1.3.1 The Issues for the Ear Biometric System.....	5
1.3.2 The Issues for IR Face biometric system.....	6
1.3.3 The Issues for the Iris Biometric system.....	6
1.4 The Directions for Addressing the above Issues.....	7
1.4.1 Representation of Uncertainty.....	7
1.4.2 Formulation of Information Sets.....	7
1.4.3 Development of Interactive Features.....	8
1.4.4 Formulation of New Entropy function.....	8
1.4.5 Design of New Classifiers.....	8

1.4.6	Refinement of Erroneous Scores.....	9
1.4.7	Adoption of the Score Level Fusion Methodology.....	9
1.5	Contributions of the thesis	10
1.6	The Organization of the thesis.....	10
Chapter 2	ROBUST EAR BASED AUTHENTICATION USING INFORMATION SET BASED FEATURES	13
2.1	Introduction.....	13
2.1.1	Motivation and Related Work.....	13
2.1.2	Literature Survey on Ear based Authentication.....	14
2.2	Information Sets.....	17
2.3	New Features.....	22
2.3.1	Effective Information source value.....	22
2.3.2	Effective Exponential Information Source value (EEI).....	23
2.3.3	Effective Multi quadratic Information Source value (EMQDI).....	23
2.3.4	Energy features (EF).....	23
2.3.5	Sigmoid Features (SF).....	24
2.4	The Proposed LPIC Model.....	25
2.4.1	The advantages LPIC over PCA.....	26
2.5	Formulation of Inner Product Classifier (IPC).....	27
2.5.1	Algorithm for IPC.....	28
2.6	Databases.....	30
2.6.1	Publically available constrained Ear database.....	30
2.6.2	Synthesized Ear databases in the unconstrained condition.....	31

2.7	Evaluation.....	32
2.7.1	Average Time evaluation.....	33
2.7.2	Performance evaluation under constrained conditions.....	33
2.7.3	Robustness evaluation under unconstrained condition.....	36
2.8	Conclusions.....	43
Chapter 3	A HIGHER FORM OF INFORMATION SET WITH AN APPLICATION TO IRIS BASED ATHEUNTICATION.....	44
3.1	Introduction.....	44
3.1.1	Motivation	45
3.1.2	A brief review of Iris as a Biometric	45
3.2	Higher Form of Information Sets	49
3.2.1	Hanman Transforms	49
3.2.2	The Adaptive Hanman-Anirban Entropy function	50
3.2.3	Application of the Adaptive Hanman-Anirban Entropy in the formulation of Transforms	52
3.2.4	Hanman Transform Features	54
3.2.5	Hanman filter	54
3.2.6	Hanman Filter Features	56
3.3	Derivation of Information set based Features	57
3.3.1	Effective Gaussian Information Source value (EGI)	57
3.3.2	Total Effective Gaussian Information, $\bar{\mu}I$ (TEGI)	57
3.4	An Application to Iris Based Authentication	57
3.4.1	Segmentation of Iris and Generation of Strips	58

3.5	Results and Discussion	59
3.5.1	The Features used for Comparison.....	60
3.5.2	Identification Performance Evaluation.....	60
3.5.3	Majority Voting.....	61
3.5.4	A Comparison with the Existing Methods	64
3.5.5	Verification evaluation	64
3.6	Conclusions	65
Chapter 4	INFRARED FACE BASED AUTHENTICATION USING INTERACTIVE FEATURES.....	67
4.1	Introduction.....	67
4.1.1	Motivation for IR face recognition.....	71
4.1.2	A brief outline of the work of this chapter.....	72
4.2	Extraction of IR Face images.....	73
4.2.1	ROI extraction.....	73
4.3	A brief Introduction to Information sets.....	74
4.3.1	The Old Features.....	74
4.3.2	Effective Inverse Multi-quadratic Information Source value (EIMQDI).....	75
4.4	The formulation of the Interactive features.....	75
4.5	Formulation of two Classifiers using Information Processing.....	78
4.6	Evaluation of Performance.....	84
4.6.1	Performance evaluation under the constrained conditions.....	84
4.6.2	Robustness evaluation under the unconstrained conditions.....	88
4.7	Discussion of Results.....	102

4.8	Conclusions.....	103
Chapter 5 FORMULATION OF NEW ENTROPY FUNCTION AND CLASSIFIER		
	FOR IR FACE BASED AUTHENTICATION.....	106
5.1	Introduction.....	106
5.1.1	A brief survey of entropy functions.....	106
5.1.2	Motivation for the new entropy for IR face biometric.....	107
5.2	Entropy formulation.....	108
5.2.1	Properties of the new entropy function.....	110
5.2.2	Variants of entropy function.....	116
5.2.3	Graphical interpretation of entropy function.....	119
5.3	New features.....	122
5.3.1	Effective Gaussian Information Source value (EGI).....	123
5.3.2	Effective Exponential Information Source value (EEI).....	123
5.4	Formulation of Modified Hanman classifier based on the New Entropy Function.	124
5.5	Evaluation Databases.....	125
5.5.1	Database used under the constrained conditions.....	125
5.5.2	Synthesized IR database under the unconstrained conditions.....	125
5.6	Performance evaluation.....	126
5.6.1	Performance evaluation under the constrained conditions.....	126
5.6.2	Robustness evaluation of the system under the unconstrained conditions.....	128
5.7	Conclusions.....	135

Chapter 6	DEVELOPMENT OF FACE BASED MULTIMODAL AUTHENTICATION SYSTEM BASED ON NEW ENTROPY FEATURES USING THE REFINED DECISION METHOD.....	137
6.1	Introduction.....	137
6.2	Classification	140
6.2.1	The Method of Refined Decisions by using Cohort Scores	142
6.3	Fusion of IR Face, Ear and Iris Databases	146
6.3.1	The Traditional score level fusion techniques	147
6.3.2	RD based score level fusion	147
6.4	Experimental performance	148
6.4.1	Performance evaluation on the constrained database	148
6.4.2	The Results of the Unconstrained databases	155
6.5	Conclusions	177
Chapter 7	CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORK.....	179
7.1	Conclusions	179
7.2	Contributions of the thesis	188
7.3	Drawbacks	189
7.4	Suggestions for Future Work	190
	REFERENCES.....	192
	APPENDIX A	207
	LIST OF PUBLICATIONS	209
	BRIEF BIO-DATA OF AUTHOR	210

LIST OF FIGURES

Fig. 1.1	Occluded faces due to different reasons.....	6
Fig. 2.1	Extraction of a feature vector from an Ear image.....	22
Fig. 2.2	Example of DB3E image that contained pose variation.....	31
Fig. 2.3	The ROC of the average authentication on DB2E using LPIC feature with (a) IPC (b) EC	35
Fig. 2.4	The ROC of the average authentication on DB3E using LPIC features with (a) IPC (b) EC	35
Fig. 2.5	ROC of the average authentication using LPIC feature on brightness database (SB80DB3E) using (a) IPC (b) EC	39
Fig. 2.6	ROC of the average authentication using LPIC features on the contrast database (SC20DB3E) using (a) IPC (b) EC	39
Fig. 2.7	ROC of the average authentication using LPIC feature on 15% side occluded (S15SODB3E) with (a) IPC (b) EC.....	40
Fig. 2.8	ROC of the average authentication using LPIC features on 18% top occluded (S18TODB3E) using IPC (b) EC.....	40
Fig. 2.9	ROC of the average authentication using LPIC feature on the Poisson noisy database (SG10NDB3E)Using (a) IPC (b)EC.....	41
Fig. 2.10	ROC of the average authentication using LPIC features on Gaussian noisy database (SG10NDB3E) using (a) IPC (b) EC	41
Fig. 2.11	The ROC of the average authentication using LPIC feature on Salt and Pepper noisy database (SSP10NDB3E) using (a) IPC (b) EC	41

Fig. 2.12	The ROC of the average authentication using LPIC features on the resolution database (SR20DB3E) with (a) IPC (b) EC	42
Fig. 3.1	Sample image of (a) iris and the (b) rectangular strip that is generated from it	58
Fig. 3.2	Generation of iris strip devoid of occlusions and eyelids.....	59
Fig. 3.3	Example iris images in CASIA-Iris-Lamp	59
Fig. 3.4	ROC of Average authentication by k fold validation using different features with (a) IPC (b) EC	65
Fig. 4.1	The block diagram of ROI extraction	74
Fig. 4.2	Steps in face normalization	74
Fig. 4.3	Sample images of IR database	84
Fig. 4.4	The ROC of the average authentication of the proposed features with WHC	88
Fig. 4.5	The ROC of the average authentication of the proposed features with EC.....	88
Fig. 4.6	Sample Images of the Occluded database at different locations.....	89
Fig. 4.7	The ROC of the average authentication of the proposed features on S40MODB1F database using (a) HC (b) IPC (c) EC.....	92
Fig. 4.8	The ROC of the average authentication of the proposed features on S40TODB1F database using (a) HC (b) IPC (c) EC.....	93
Fig. 4.9	The ROC of the average authentication of the proposed features on S40BODB1F database using (a) HC (b) IPC (c) EC.....	94
Fig. 4.10	The ROC of the average authentication of the proposed features on S45LODB1F database using (a) HC (b) IPC (c) EC.....	95

Fig. 4.11	The ROC of the average authentication of the proposed features on S45RODB1F database using (a) HC (b) IPC (c) EC.....	96
Fig. 4.12	The ROC of the average authentication of the proposed features on S5RDB1F database using (a) HC (b) WHC (c) EC.....	98
Fig. 4.13	Sample images of noisy database.....	99
Fig. 4.14	The ROC of the average authentication of proposed features on SSP30NDB1F database by using (a) WHC (b) HC (c) EC.....	100
Fig. 4.15	The ROC of the average authentication of proposed features on SG30NDB1F database by using (a) WHC (b) HC (c) EC.....	101
Fig. 4.16	The ROC of the average authentication of proposed features on SPG20SP20NDB1F database by using (a) WHC (b) HC (c) EC.....	102
Fig. 5.1	Plot of information gain $G(p_i)$ as the probability increases (a) when α consider some +ve value let say $\alpha=0.6, 1, 2, 3$ and $\beta=2$. (b) $\alpha = -0.6, -1, -2, -3$ and $\beta=2$	110
Fig. 5.2	Tsallis Entropy for the +ve and -ve values of α	119
Fig. 5.3	Effect of 'b' on the new entropy for the +ve values of α with (a) $b=0$ and (b) $b=1$	119
Fig. 5.4	Effect of b on the entropy curve for the +ve values of α with (a) $b=0$, (b) $b=0.3$, (c) $b=1$ for $\gamma=2$	120
Fig. 5.5	Effect of b on the entropy curve for -ve values of α with (a) $b=0$, 5(b) $b=1$	120
Fig. 5.6	(a) The entropy curve for higher +ve values of α with $\gamma=2$, and (b) For the -ve values of α and γ	121

Fig. 5.7	The entropy curve for the -ve values of γ and the +ve values of α (a) $\gamma = -1$ and, (b) $\gamma = -2$ 122
Fig. 5.8	ROC of the average authentication performance of the proposed features with (a) MHC (b) EC 128
Fig. 5.9	ROC of the average performance of the proposed features on S40MODB1F by (a) MHC (b) EC 131
Fig. 5.10	ROC of the average performance of the proposed features on S40TODB1F with (a) MHC (b) EC 131
Fig. 5.11	ROC of the average performance of the proposed features on S40BODB1F with (a) MHC (b) EC.....131
Fig. 5.12	ROC of the average performance of the proposed features on S45LODB1F with (a) MHC (b) EC 132
Fig. 5.13	ROC of the average authentication performance of the proposed features on S45RODB1F Database with (a) MHC (b) EC 132
Fig. 5.14	ROC of the average performance of the proposed features on SG30NDB1F with (a) MHC (b) EC 133
Fig. 5.15	ROC of the average performance of the proposed features on SSP30NDB1F with (a) MHC (b) EC 134
Fig. 5.16	ROC of the average performance of the proposed features on S5RDB1F with (a) MHC (b) EC.....135
Fig. 6.1	Block diagram of Claimed Template, Query Sample, Cohort Templates, and dissimilarity scores between the query and claimed templates and between the query and cohort templates.....144

Fig. 6.2	Block Diagram of 6.2(a) improved FRR and 6.2(b) improved FAR by Refined Decision method 145
Fig. 6.3	Sample images of IITD IR Face (DB1F) database.....148
Fig. 6.4	Sample images of an Ear Database (DB4E) 148
Fig. 6.5	Sample images of iris database.....149
Fig. 6.6	Sample image of iris and the rectangular strip that is generated from it.....149
Fig. 6.7	Generation of iris strip devoid of occlusions and eyelids 149
Fig. 6.8	ROC of the average authentication performance of the proposed features on DB1F (a) EGI and (b) EEI with different combinations of α and γ having $\alpha=0.2,1,2$ & $\gamma=1,2,3$ 150
Fig. 6.9	ROC of the average authentication performance of the proposed features on DB4E (a) using EGI and (b) using EEI with different combinations of α and γ having $\alpha=0.2,1,2$ & $\gamma=1,2,3$ 151
Fig. 6.10	ROC of the average authentication performance of the proposed features on DB2I (a) using EGI feature and (b) using EEI feature with different setting of α and γ with $\alpha=0.2,1,2$ & $\gamma=1,2,3$ 151
Fig. 6.11	ROCs of the average authentication rate based on the features from the proposed entropy and the existing entropies using EC on different modalities (a) DB1F (b) DB4E (c) DB2I 152
Fig. 6.12	ROCs of the average authentication rates based on RD, cohort by Kumar (2008) and EC with the proposed features of three modalities (a) DB1F (b) DB4E (c) DB2I 153

Fig. 6.13	ROC of the average authentication of fusion of DB1F, DB4E and DB2I (a) Traditional Score level fusion with EGI (b) RD based Score level fusion with EGI (c) Traditional Score level fusion with EEI (d) RD based Score level fusion with EE.....	154
Fig. 6.14	Sample images of Synthesized Top occlusion databases (a) S40TODB1F, (b) S40TODB4E, (c) S40TODB2I	155
Fig. 6.15	ROCs of the average authentication based on the features from the proposed entropy and the existing entropies using EC on top occlusion databases (a) S40TODB1F (b) S40TODB4E (c) S40TODB2I	156
Fig. 6.16	Performance evaluation of RD classifier using EGI and EEI in comparison to Cohort and EC on top occlusion databases (a) S40TODB1F, (b) S40TODB4E, (c) S40TODB2I	157
Fig. 6.17	ROC of the average authentication of fusion on S40TODB1F, S40TODB4E, S40TODB2I (a) Traditional Score level fusion using EGI feature (b) RD based Score level fusion with EGI (c) Traditional Score level fusion with EEI (d) RD based Score level fusion using EEI.....	158
Fig. 6.18	Sample images of synthesized bottom occlusion database (a) S40BODB1F, (b) S40BODB4E, (c) S40BODB2I	159
Fig. 6.19	ROCs of the average authentication rates based on the features from the proposed entropy and the existing entropies using EC on bottom occlusion databases (a) S40BODB1F (b) S40BODB4E (c) S40BODB2I	160

Fig. 6.20	Performance evaluation of RD, Cohort and EC on bottom occlusion databases with both EGI and EEI (a) S40BODB1F, (b) S40BODB4E, (c) S40BODB2I 161
Fig. 6.21	ROC of the average authentication on S40BODB1F, S40BODB4E, S40BODB2I (a) Traditional Score level fusion with EGI (b) RD based Score level fusion with EGI (c) Traditional Score level fusion with EEI (d) RD based Score level fusion with EEI.....162
Fig. 6.22	Sample images of Synthesized database incorporating different environment (a) S20MODB1F (b) S50SODB4E (c) SB90DB2I 163
Fig. 6.23	ROCs of the average authentication rates based on the features from the proposed entropy and the existing entropies using EC on different databases (a) S20MODB1F, (b) S50SODB4E, (c) SB90DB2I 164
Fig. 6.24	Performance evaluation of RD classifier using EGI and EEI in comparison to Cohort and EC on different databases (a) S20MODB1F, (b) S50SODB4E, (c) SB90DB2I.....165
Fig. 6.25	ROC of the average authentication on S20MODB1F, S50SODB4E, SB90DB2I (a) Traditional Score level fusion with EGI (b) RD based Score level fusion with EGI (c) Traditional Score level fusion with EEI (d) RD based Score level fusion with EEI.....166
Fig. 6.26	Sample images of Gaussian noise affected database 167
Fig. 6.27	ROCs of the average authentication rates based on the features from the proposed entropy and the existing entropies using EC on the Gaussian noisy databases (a) SG30NDB1F (b) SG30NDB4E (c) SG20NDB2I 168

Fig. 6.28	Performance evaluation of RD, Cohort and EC on the Gaussian noisy databases with EGI and EEI (a) SG30NDB1F(b) SG30NDB4E (c) SG20NDB2I.....	168
Fig. 6.29	ROC of the average authentication on SG30NDB1F, SG30NDB4E and SG20NDB2I (a) Traditional Score level fusion with EGI (b) RD based Score level fusion with EGI (c) Traditional Score level fusion with EEI (d) RD based Score level fusion with EEI.....	170
Fig. 6.30	Sample images of salt and pepper noise affected databse (a) SSP40NDB1F (b) SSP40NDB4E (c) SSP20NDB2I	170
Fig. 6.31	ROCs of the average authentication rates based on the features from the proposed entropy and the existing entropies using EC on the Salt and pepper noisy databases (a) SSP40NDB1F (b) SSP40NDB4E (c) SSP20NDB2I.....	171
Fig. 6.32	Performance evaluation of RD, Cohort and EC on Salt and Pepper noisy databases with EGI and EEI (a) SSP40NDB1F, (b) SSP40NDB4E, (c) SSP20NDB2I.....	172
Fig. 6.33	ROC of the average authentication of fusion on SSP40NDB1F, SSP40NDB4E and SSP20NDB2I (a) Traditional Score level fusion with EGI (b) RD based Score level fusion with EGI (c) Traditional Score level fusion with EEI (d) RD based Score level fusion with EEI.....	173
Fig. 6.34	Sample images of low resolution database (a) S10RDB1F (b) S10RDB4E (c) S20RDB2I	173
Fig. 6.35	ROCs of the average authentication rates from the proposed entropy and the existing entropies using EC on the low resolution databases (a)S10RDB1F (b)S10RDB4E (c) S20RDB2I	175

Fig. 6.36	Performance evaluation of RD, Cohort and EC on the low resolution databases with EGI and EEI (a) S10RDB1F (b) S10RDB4E (c) S20RDB2I	175
Fig. 6.37	ROC of the average authentication by the fusion of S10RDB1F, S10RDB4E, S20RDB2I (a) Traditional Score level fusion with EGI (b) RD based Score level fusion with EGI (c) Traditional Score level fusion with EEI (d) RD based Score level fusion with EEI.....	176

LIST OF TABLES

Table 2.1	Average time taken to calculate recognition rate	33
Table 2.2	Average Recognition rate in percentage on databases with IPC	34
Table 2.3	Average Recognition rate in percentage on databases with SVM and KNN.....	35
Table 2.4	Average Recognition rate in percentage on Brightness Database SBDB3E using IPC	36
Table 2.5	Average Recognition rate in percentage on Contrast Database SCDB3E and Occlusion Database SODB3E using IPC	37
Table 2.6	Average Recognition rate in percentage on Noise Database SNDB3E using IPC	37
Table 2.7	Average Recognition rate in percentage on Resolution Database SRDB3E using IPC	37
Table 3.1	Features and their mean recognition rates with different classifier RD after k fold validation.....	60
Table 3.2	Majority voting results for different features with IPC	62
Table 3.3	Comparison of the Existing Features using SVML.....	64
Table 4.1	The average recognition rate using different s-norms by SVM and KNN	85
Table 4.2	The Average recognition rates with different s-norms by WHC and HC.....	86
Table 4.3	The Average recognition rate with Frank s-norm using IPC.....	86
Table 4.4	A comparison of the Average Recognition rate by using the existing methods	87

Table 4.5	The Average recognition rate in % on the Occluded database using HC and WHC.....	90
Table 4.6	The Average recognition of the proposed features on SVML, KNN and IPC in % on the occluded database.....	91
Table 4.7	The Average recognition rate in % on low resolution and noisy databases.....	99
Table 4.8	The average recognition rate of PCA in % on low resolution and noisy database.....	99
Table 5.1	Average recognition rate in % on DBIF database with EGI	127
Table 5.2	Average recognition rate in % on DB1F database with EEI	127
Table 5.3	Average recognition rate in % on DB1F using the existing entropies classified by SVML and KNN.....	127
Table 5.4	Average recognition rate in % on DB1F using the existing face recognition methods.....	128
Table 5.5	Average recognition rate in % on different occluded databases with EGI	129
Table 5.6	Average recognition rate in % on different occluded databases with EEI	129
Table 5.7	Average recognition rate in % on the occluded database using different entropy	129
Table 5.8	Average Recognition rate in % on the unconstrained database with PCA by MHC	130
Table 5.9	Average recognition rate in % on different noisy databases using EGI.....	132

Table 5.10	Average recognition rate in % on different noisy databases using EEI.....	133
Table 5.11	Average recognition rate in % on noisy database using the different entropies	133
Table 5.12	Average recognition rate in %on the very low resolution databases using EGI	134
Table 5.13	Average recognition rate in % on very low resolution databases using EEI	134
Table 5.14	Average recognition rate in% on the low resolution databases using different entropy function	135
Table 6.1	Performance evaluation of RD, Cohort and EC corresponding to Fig. 6.12	153
Table 6.2	Performance evaluation of RD based score level fusion compared to the traditional score level fusion.....	155
Table 6.3	Performance evaluation of RD as compared with EC on Top occlusion database corresponding to Fig. 6.16.....	157
Table 6.4	Performance evaluation of RD based score level fusion compared to the traditional score level fusion on top occlusion database.....	159
Table 6.5	Performance evaluation of RD, Cohort and EC on bottom occlusion database	161
Table 6.6	Performance evaluation of RD based score level fusion as compared to the traditional score level fusion on bottom occlusion database.....	162
Table 6.7	Performance evaluation of RD as compared to Cohort and EC on Miscellaneous database	165

Table 6.8	Performance evaluation of RD based score level fusion and the Traditional Score level fusion on Miscellaneous database.....	166
Table 6.9	Performance evaluation of RD, Cohort and EC on Gaussian noisy database ...	169
Table 6.10	Performance evaluation of RD based score level fusion and the traditional score level fusion using scores from Gaussian noisy databases	170
Table 6.11	Performance evaluation of RD, Cohort and EC on salt and pepper noisy database	172
Table 6.12	Performance evaluation of RD based score level fusion and the traditional score level	173
Table 6.13	Performance evaluation of RD, Cohort and EC on the low resolution	175
Table 6.14	Performance evaluation of the RD based score level fusion and the traditional score level fusion on low resolution database	176
Table A.1	Recognition rate of entropy using probability and information source value	207
Table A.2	The recognition rates obtained using probabilistic entropy, possibilistic entropy, information values	208
Table A.3	The values of the fuzzifier and variance for comparison.....	208
Table A.4	Statistical Analysis of K-fold validation by using MQD feature.....	208

ABBREVIATION

Full name	Abbreviation	Symbol
<i>Features</i>		
Information Set		$\mathcal{H}$
Effective Information Source value		$\bar{I}(k)$
Effective Exponential Information Source value	EEI	$\bar{I}^e(k)$
Effective Gaussian Information Source value	EGI	$\bar{I}^g(k)$
Effective Multi quadratic Information Source value	EMQDI	$\bar{I}^{MQD}(k)$
Effective Inverse multi-quadratic Information source value	EIMQDI	$\bar{I}^{invMQD}(k)$
Total Effective Gaussian Information	TEGI	
Energy Feature	EF	$E(k)$
Sigmoid feature	SF	$S(k)$
Hanman Transform	HT	$H^T(I)$
Hanman Filter	HF	$H_{ij}(s)$
Local Principal Independent Component	LPIC	
Exponential membership function		μ_{ij}^e
Gaussian membership function		μ_{ij}^g
Multiquadratic membership function		μ_{ij}^{MQD}
Inverse Multiquadratic membership function		μ_{ij}^{invMQD}

Conventional Features

Principal Component analysis	PCA	
Independent Component analysis	ICA	
Local binary patterns	LBP	
Shannon entropy		H^{Sh}
Pal and Pal entropy		H^{PP}
Tsallis entropy		H^{TS}
Renyi entropy		H^{RN}
Hanman-Anirban entropy		H
Probability		p_{ij}
Fuzzifier		$f_{h(ref)}^2$

Databases

Perpinan Ear database	DB1E
IIT Delhi Ear Database Version1 with 125 users	DB2E
IIT Delhi Ear Database Version1 with 221 users	DB3E
IITD Ear database	DB4E
IITD IR Face database	DB1F
CASIA-Iris-V3-Lamp	DB1I
IIT Iris database	DB2I

Classifiers

Euclidean classifier	EC
Support Vector machine with linear kernel with degree 3	SVML
Support Vector machine with polynomial kernel with degree 3	SVMP
Inner Product Classifier	IPC

Hanman Classifier	HC
Weighted Hanman classifier	WHC
Modified Hanman classifier	MHC
Refined Scores	RS
Euclidean Distance	ED
<i>Performance Evaluation</i>	
Receiver Operating Characteristic	ROC
False Acceptance rate	FAR
False Rejection rate	FRR
Genuine Acceptance rate	GAR