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Analysis using HMM model for Online Signature Verification using Hybrid Wavelet Transform - II.

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Abstract: In this paper, feature vector is extracted from the online signature based on Hybrid Wavelet Transform II and then they are given to Hidden Markov Model based classifier. The samples and various combinations of Feature vector are tested and the system is analyzed based on their performance. On the first 128 samples of the pressure parameter Hybrid Wavelet Transform II was applied and 1-16 samples of the output were used as feature vector for signature verification. The performance of the system was compared by using Hidden Markov Model(HMM) classifier. The Left to Right topology of HMM was used as classifier. Considering Left to Right model for 1 – 16 samples KEKRE 128 offers best performance of FRR ranging from 5% to 11% . Considering Left to Right model for1 – 16 samples DCT 128 offers best performance of EER 4%.

Keywords: HMM Hybrid Wavelet Transform Online Signature Verification.

I. INTRODUCTION

The classification of biometrics can be done into two broad categories, Behavioral (signature verification, keystroke dynamics, handwriting, speech etc.) and Physiological (face, iris, fingerprint, he retina etc.). Human Signature is proven to be the most natural, widely accepted biometric attribute of a human being which can be used to authenticate human identity and is even less intrusive and has no negative or undesirable health connotations. Signatures are composed of special characters and therefore most of the time they can be unreadable. Also, intrapersonal variations and interpersonal differences make it necessary to analyze them as complete images and not as letters and words put together [1]. As signature is the primary mechanism both for authentication and authorization in legal transactions, the need for research in efficient auto-mated solutions for signature recognition and verification has increased in recent years. Recognition is finding the identification of the signature owner whereas Verification is the decision about whether the signature is genuine or forged. There are two types of signature verification that are online and offline. In offline, users write their signature on paper, digitize through an optical scanner or a camera, and the biometric system recognizes the signature analyzing its shape, length, height etc. but in online signature verification it also measures pressure applied by users, Speed of writing, inclination of pen along with the signature image obtained in the offline signature.

II. PROPOSED SYSTEM

A. Block diagram of proposed system:

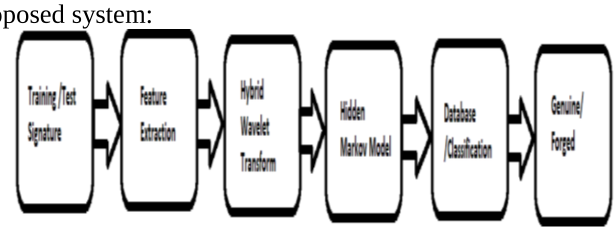

Fig. 1 Block diagram of proposed system

Training / Test Signature

The user will be asked to provide some sample signatures on pressure sensitive writing pads.

Feature Extraction

We are using the signature database of 1600 signatures, provided by The First International Signature Verification Competition (SVC 2004). It contains signatures of 40 users. Every user has 40 signatures, out of which, 20 are genuine and 20 are skilled forgeries.

Hybrid Wavelet Transform
1. Hybrid Wavelet Type I
Hybrid Wavelet matrix is used for multi resolution analysis of the Signature Pressure Information (Signature Map).
2. Hybrid Wavelet Type II
It is same as Hybrid Wavelet Type I, only change is that, while generating the Low Frequency Component we are repeating the multiplication N Times, Hence the LL component has the size of MXN.

Hidden Markov Model
During the verification, the feature of the test signature are compared with those stored in the database to decide whether the signature is genuine or forged. Performance measurement (genuine/Forged) Performance of the system will be measured on the basis of False Rejection Ratio (FRR) and False Acceptance Ratio (FAR).

B. Working principle:
We will use statistics and machine learning toolbox of the MATLAB 13. Initially we assumed a randomly generated transition probability Matrix (A) generated using MATLAB, Observation probability matrix (B) with equal probability for every symbols and HMM to be in state 1. HMM is trained using HMMtrain for 3 to 20 genuine training signature samples, number of states from 2 to 5 and symbols from 200 to 750. After HMM is trained, it is used to test 20 genuine and 20 forged signatures of 40 users Testing is carried out for 40 users and then the average FRR and FAR are calculated In FRR-FAR plot, the point where two graphs cross each other is referred as Equal Error Rate (EER). At this point the value of FRR and FAR is minimum. We will choose the EER such that it is the nearest number of training samples such that FRR and FAR are minimum. Two more parameters, Additional Acceptance rate and Additional Rejection Rate, for measurement are introduced. Value of AAR and ARR ranges from -100 to 100. For better performance, value of AAR and ARR should be positive and as high as possible. Positive AAR value implies that the number of test genuine signatures correctly identified are more than the number of genuine training signatures. Positive ARR value implies that the number of test forged signatures correctly identified are more than the number of training genuine signatures. Comparison of various combinations of DCT, DHT, HAAR, HADAMARD and KEKRE for 1 – 16 and 33 – 64 samples of hybrid wavelet transform I and II is been carried out.

III.HARDWARE COMPONENT REQUIRED

Wacom pressure pad :
The user will be asked to provide some sample signatures on pressure sensitive writing pads. One of such writing pads, Wacom Intuos Pro is shown in the figure.

Fig. 2 Wacom Intuos ProEvery signature consist of X-coordinate - scaled cursor position along the x-axis, Y-coordinate - scaled cursor position along the y-axis, Time stamp - system time at which the event was posted, Button status - current button status (0 for pen-up and 1 for pen down), Azimuth - clockwise rotation of cursor about the z-axis, Altitude - angle upward toward the positive z-axis, Pressure - adjusted state of the normal pressure. For the current research the signature samples from 40 different users are taken, 40samples are taken for each user out of which 20 are genuine and 20 are forged. Pressure applied by the tip of the pen on the pressure sensitive pad varies during the process of signing. This pressure is chosen for the feature vector.

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IV. RESULTS

TABLE 1: COMPARISONS OF VARIOUS DCT COMBINATIONS (1-16 SAMPLES) FOR LEFT TO RIGHT MODEL.

DCT DHT	STATES	2	3	4	5
	SYMBOLS	500	325	300	400
	EER	8	7	8	10
	FRR	39	33	36	31
	FAR	46	50	41	34
	AAR	21	32	24	19
	ARR	14	15	19	16
DCT HAAR	STATES	2	3	4	5
	SYMBOLS	475	375	300	475
	EER	7	6	8	11
	FRR	44	33	36	29
	FAR	38	47	41	29
	AAR	21	37	24	16
	ARR	27	23	19	16
DCT HADAMARD	STATES	2	3	4	5
	SYMBOLS	450	350	325	400
	EER	6	6	6	10
	FRR	37	34	30	30
	FAR	42	42	51	42
	AAR	33	36	40	20
	ARR	28	28	19	8
DCT KEKRE	STATES	2	3	4	5
	SYMBOLS	450	450	450	500
	EER	11	13	15	18
	FRR	22	19	17	9
	FAR	30	20	18	9
	AAR	23	16	8	1
	ARR	15	15	7	1
DCT 128	STATES	2	3	4	5
	SYMBOLS	275	400	475	475
	EER	4	8	10	11
	FRR	35	30	31	27
	FAR	63	46	37	32
	AAR	45	30	19	18
	ARR	17	14	13	13

TABLE 2: COMPARISONS OF VARIOUS DHT COMBINATIONS (1-16 SAMPLES) FOR LEFT TO RIGHT MODEL.

DHT DCT	STATES	2	3	4	5
	SYMBOLS	500	475	500	350
	ERR	8	8	9	9
	FRR	33	34	31	25
	FAR	43	39	37	34
	AAR	27	26	24	30
	ARR	17	21	18	21
DHT HAAR	STATES	2	3	4	5
	SYMBOLS	350	475	450	500

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	ERR	6	8	9	10
	FRR	34	32	29	29
	FAR	46	38	38	37
	AAR	36	28	26	21
	ARR	24	22	17	13
DHT HADAMARD	STATES	2	3	4	5
	SYMBOLS	500	450	275	500
	ERR	8	8	5	11
	FRR	31	32	29	31
	FAR	47	41	52	28
	AAR	29	28	46	14
	ARR	13	19	23	17
DHT KEKRE	STATES	2	3	4	5
	SYMBOLS	475	500	450	475
	ERR	12	13	15	16
	FRR	23	22	15	13
	FAR	27	20	14	19
	AAR	17	13	10	7
	ARR	13	15	11	1
DHT 128	STATES	2	3	4	5
	SYMBOLS	375	500	500	500
	ERR	7	9	10	12
	FRR	32	33	31	24
	FAR	40	35	29	30
	AAR	33	22	19	16
	ARR	25	20	21	10

TABLE 3: COMPARISONS OF VARIOUS HAAR COMBINATIONS (1-16 SAMPLES) FOR LEFT TO RIGHT MODEL.

HADAMARD DCT	STATES	2	3	4	5
	SYMBOLS	375	500	375	500
	EER	6	9	8	12
	FRR	30	32	33	27
	FAR	45	42	42	26
	AAR	40	23	27	13
	ARR	25	13	18	14
HADAMARD DHT	STATES	2	3	4	5
	SYMBOLS	500	300	500	500
	EER	8	6	8	10
	FRR	31	31	31	29
	FAR	35	49	36	29
	AAR	29	39	29	21
	ARR	25	21	24	21
HADAMARD HAAR	STATES	2	3	4	5
	SYMBOLS	425	500	500	475
	EER	8	9	10	10
	FRR	34	30	31	34
	FAR	37	39	30	36
	AAR	26	25	19	16
	ARR	23	16	20	14

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	STATES	2	3	4	5
	SYMBOLS	500	500	500	500
	EER	11	15	13	14
	FRR	34	16	25	25
	FAR	31	44	27	22
	AAR	11	9	10	5
HADAMARD KEKRE	ARR	14	-19	8	8
	STATES	2	3	4	5
	SYMBOLS	475	475	425	475
	EER	5	5	6	9
	FRR	38	39	34	32
	FAR	52	51	45	32
	AAR	37	36	36	23
HADAMARD 128	ARR	23	24	25	23

TABLE 4: COMPARISONS OF VARIOUS HADAMARD COMBINATIONS (1-16 SAMPLES) FOR LEFT TO RIGHT MODEL.

HAAR DCT	STATES	2	3	4	5
	SYMBOLS	450	475	350	500
	EER	7	8	7	11
	FRR	41	37	32	31
	FAR	42	36	52	24
	AAR	24	23	33	14
	ARR	23	24	13	21
HAAR DHT	STATES	2	3	4	5
	SYMBOLS	375	450	425	450
	EER	6	9	9	11
	FRR	37	37	33	26
	FAR	49	42	35	21
	AAR	33	18	22	19
	ARR	21	13	20	24
HAAR HADAMARD	STATES	2	3	4	5
	SYMBOLS	350	275	500	425
	EER	6	5	9	10
	FRR	31	32	32	30
	FAR	49	57	40	33
	AAR	39	43	23	20
	ARR	21	18	15	17
HAAR KEKRE	STATES	2	3	4	5
	SYMBOLS	450	400	475	500
	EER	12	12	16	17
	FRR	21	20	14	11
	FAR	35	33	22	12
	AAR	19	20	6	4
	ARR	5	7	-2	3

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HAAR 128	STATES	2	3	4	5
	SYMBOLS	325	475	500	475
	EER	6	10	11	13
	FRR	32	30	32	24
	FAR	57	37	33	28
	AAR	38	20	13	11
	ARR	13	13	12	7

TABLE 5: COMPARISONS OF VARIOUS KEKRE COMBINATIONS (1-16 SAMPLES) FOR LEFT TO RIGHT MODEL.

KEKRE DCT	STATES	2	3	4	5
	SYMBOLS	425	300	425	500
	EER	9	7	12	13
	FRR	31	32	26	27
	FAR	37	43	36	27
	AAR	24	33	14	8
	ARR	18	22	4	8
KEKRE DHT	STATES	2	3	4	5
	SYMBOLS	450	500	350	375
	EER	8	11	8	12
	FRR	32	29	30	19
	FAR	42	28	36	32
	AAR	28	16	30	21
	ARR	18	17	24	8
KEKRE HAAR	STATES	2	3	4	5
	SYMBOLS	500	450	425	500
	EER	10	11	12	14
	FRR	33	28	24	21
	FAR	38	30	32	21
	AAR	17	17	16	9
	ARR	12	15	8	9
KEKRE HADAMARD	STATES	2	3	4	5
	SYMBOLS	375	450	425	500
	EER	6	9	10	13
	FRR	34	29	28	23
	FAR	49	41	46	21
	AAR	36	26	22	12
	ARR	21	14	4	14
KEKRE 128	STATES	2	3	4	5
	SYMBOLS	450	500	475	475
	EER	16	17	19	19
	FRR	11	10	5	5
	FAR	16	11	2	2
	AAR	9	5	0	0
	ARR	4	4	3	3

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The performance of various DCT combinations is shown in the Table. Best FRR – FAR: FRR – FAR should be as minimum as possible. DCT KEKRE offers best performance with FRR 9% & FAR of 9 %. Best ERR: ERR should be as minimum as possible in terms of training samples. In this case Orthogonal DCT offers better performance than the other combinations of DCT HWT-2 with 4 training samples. Best state wise FRR – FAR: For the given state from 2 to 5 FRR and FAR should be as minimum as possible . DCT KEKRE offers best performance for 2 to 5 states compared to orthogonal DCT transform Best Number of Symbol: Testing was carried out for number of symbols from 275 to 500. It proves that the best performance is offered by 450 – 500 symbols.The performance of various DHT combinations is shown in the Table. Best FRR – FAR: FRR – FAR should be as minimum as possible. DHT KEKRE offers best performance with FRR 13% & FAR of 9 %.Best ERR: ERR should be as minimum as possible in terms of training samples. In this case DHT HADAMARD offers better performance than the other combinations of DCT HWT-2 with 5 training samples.Best state wise FRR – FAR: For the given state from 2 to 5 FRR and FAR should be as minimum as possible . DHT KEKRE offers best performance for 2 to 5 states compared to orthogonal DHT transform Best Number of Symbol: Testing was carried out for number of symbols from 275 to 500. It proves that the best performance is offered by 450 – 500 symbols. The performance of various HAAR combinations is shown in the Table. Best FRR – FAR: FRR – FAR should be as minimum as possible. HAAR KEKRE offers best performance with FRR 11% & FAR of 12 %. Best ERR: ERR should be as minimum as possible in terms of training samples. In this case HAAR HADAMARD offers better performance than the other combinations of DCT HWT-2 with 5 training samples. Best state wise FRR – FAR: For the given state from 2 to 5 FRR and FAR should be as minimum as possible . HAAR KEKRE offers best performance for 2 to 5 states compared to orthogonal HAAR transform Best Number of Symbol: Testing was carried out for number of symbols from 275 to 500. It proves that the best performance is offered by 450 – 500 symbols.The performance of various HADAMARD combinations is shown in the Table. Best FRR – FAR: FRR – FAR should be as minimum as possible. HADAMARD KEKRE offers best performance with FRR 16% & FAR of 44 %. Best ERR: ERR should be as minimum as possible in terms of training samples. In this case Orthogonal HADAMARD offers better performance than the other combinations of DCT HWT-2 with 5 training samples. Best state wise FRR – FAR: For the given state from 2 to 5 FRR and FAR should be as minimum as possible. HADAMARD KEKRE offers best performance for 2 to 5 states compared to orthogonal HADAMARD transform Best Number of Symbol: Testing was carried out for number of symbols from 275 to 500. It proves that the best performance is offered by 500 symbol. The performance of various KEKRE combinations is shown in the Table. Best FRR – FAR: FRR – FAR should be as minimum as possible. Orthogonal KEKRE offers best performance with FRR 5% & FAR of 2 %. Best ERR: ERR should be as minimum as possible in terms of training samples. In this case KEKRE HADAMARD offers better performance than the other combinations of DCT HWT-2 with 6 training samples.Best state wise FRR – FAR: For the given state from 2 to 5 FRR and FAR should be as minimum as possible . Orthogonal KEKRE offers best performance for 2 to 5 states compared with hybrid combinations of KEKRE. Best Number of Symbol: Testing was carried out for number of symbols from 275 to 500. It proves that the best performance is offered by 475 symbol.

V. CONCLUSION

By comparing various combinations of DCT DHT HAAR HADAMARD KEKRE for 1-16 samples of HWT-2 we come to following conclusions: FRR-FAR : Orthogonal KEKRE transform offers best performance with 5% and 2% respectively.EER : Orthogonal DCT transform offers best performance of 4 training samples. State wise FRR – FAR: Orthogonal KEKRE offers best performance for 2 to 5 states .No of symbols :The best performance is offered at 475 symbol by KEKRE 128

REFERENCE

[1] Meenakshi S. Arya, Vandana S. Ianmdar, “A Preliminary Study on Various Off-line Hand Written Signature Verification Approaches” International Journal of Computer Applications (0975 – 8887) Volume 1 – No. 9 2010.

[2] Vu Nguyen; Blumenstein, M.; Muthukkumarasamy V.; Leedham G., “Off-line Signature Verification Using Enhanced Modified Direction Features in Conjunction with Neural Classifiers and Support Vector Machines”, in Proc. 9th IntConf on document analysis and recognition, vol 02, pp. 734-738, Sep 2007.

[3] T. Ohishi, Y. Komiya, H. Morita, and T. Matsumoto, “Pen-input online signature verification with position, pressure, inclination trajectories,” in Proc. 15th Int. Parallel Distrib. Process. Symp. (IPDPS-15), San Francisco, CA, Apr. 2001, p. 170.

[4] Dr. H. B. Kekre, Archana Athawale&DipaliSadavarti. “Algorithm to Generate Wavelet Transform from an Orthogonal Transform”

[5] L. R. .Rabiner B. H. Juang .” An Introduction to HiddenMarkov Models” .

[6] DonatoImpedovo and Giuseppe Pirlo. ” Impedovo and Giuseppe Pirlo”

[7] Zhong-Hua Quan, De-Shuang Huang, Kun-Hong Liu, Kwok-Wing Chau“A Hybrid HMM/ANN Based Approach for Online Signature Verification”.

[8] Sudeep D. Thepade*, Jaya H. Dewan, Anil T. Lohar“Extended Performance Comparison of Hybrid Wavelet Transform for Image Compression with Varying Proportions of Constituent Transforms “.

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[9] MarcusLiwicki, Muhammad Imran Malik, C. Elisa van den Heuvel†, Xiaohong Chen‡, Charles Berger†, ReinoudStoel†, Michael Blumenstein§, and Bryan Found “Signature Verification Competition for Online and Offline Skilled Forgeries”.
[10] Donato Impedovo and Giuseppe Pirlo, "Automatic Signature Verification: The State of the Art," IEEE Transaction on Systems, MAN. and Cybernatics Part C: Application and Reviews, vol. Vol 28, no. No 5, September 2008.
[11] Dr. Vinayak Ashok Bharadi, Mr. Vikas I Singh and Mr. Bhushan Nemade“Hybrid Wavelets based Feature Vector Generation from Multidimensional Data set for On-line Handwritten Signature Recognition”.
[12] Mr.Manoj Chavan,Dr. Ravish R. Singh,Dr. Vinayak Bharadi“Online Signature Verification using Hybrid Wavelet Transform with Hidden Markov Model”.
[13] Mr.Manoj Chavan,Dr. Ravish R. Singh,Dr. Vinayak Bharadi“Handwritten Signature Verification using Hidden Markov Model with Hybrid Wavelet Transform ”. Iaetsd journal for advanced research in applied sciences volume 4, issue 7, dec/2017.