J. Electrical Systems 20-4s (2024): 2453-2462

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Comparative Analysis of Handwritten Online Signature Verification and Forgery Detection Using Hybrid Wavelet Transform-1 and 2 with HMM Classifier

Journal of Electrical Systems

Abstract: - Online signature verification is a unique biometric feature. Provides static and dynamic features for 2D signature images. Hybrid wavelet transform -1 and 2 (HWT-1 and HWT-2) of size 256 is created using the Kronecker product of two orthogonal transforms such as DCT, DHT, Haar, Hadamard and Kekre with size 4 and 64. HWT has the ability to analyze signals such as wavelet transform at global and local levels. HWT-1 and HWT-2 are used for the 256 samples of the online Handwritten signature and the first 128 samples of the output are used as feature vectors for handwritten online signature verification and forgery detection. This feature vector is given to the Left-Right and Ergodic modelled HMM classifier for analysis. HMM is trained using 10 randomly chosen genuine signature samples and is used to test remaining 10 genuine signatures and 20 forged signatures of 40 users of SVC 2004 signature database. This process is iterated 20 times and then average values are calculated. Considering all the possible combination of HWT-1 and HWT-2 for DCT, DHT, Haar, Hadamard and Kekre transform for Left Right HMM model, DCT 4 Haar 64 HWT-1 offers best performance of FRR, FAR of 1.05%, 0.99% respectively for state 3. Considering all the possible combination of HWT-1 and HWT-2 for DCT, DHT, Haar, Hadamard and Kekre transform for Ergodic HMM model, DCT 4 DHT 64 offers best performance of FRR, FAR of 1.10%, 2.88% respectively for state 5. We conclude that comparing HWT-1 and HWT-2 combinations for Left Right and Ergodic HMM model, HWT-1 for Left Right model offer better performance.

Keywords: HWT, HMM, Signature Verification

Introduction:

Biometric features can be used to uniquely identify any person. There are two types of biometric features, Physical and Behavioural. Handwritten Signature falls into the category of Behavioural features such as Voice, Typing rhythm etc. For a long time, signatures have been used to authenticate an individual because they are very easy to get. Signatures are a type of biometric feature. There are two kinds of biometric features: Offline and online. An offline signature is a 2D image of a signature made on paper. An online signature has additional dynamic features like pressure applied by the user, the speed of writing, the way the pen is held etc. in addition to a 2D image. For

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computerizing the signature verification process, online signatures offer more advantages than offline signatures because of its dynamic features. [1][2][3][4]

Handwritten Signature Verification can be automated for document verification in different sectors such as Banking, Legal Documentation etc. There are two Signature Verification methods: Offline (static) and online (dynamic). Offline Signature offers a 2D image of the signature whereas online Signature has the added benefit that it also measures the user pressure applied, writing speed, pen inclination along with the 2D signature image. [5]

To generate training samples, the user will sign on the pressure sensitive writing pads. Each signature sample consists of X-coordinates: scaled cursor position along x-axis, Y-coordinates: scaling cursor position along y-axis, Time stamp: system time at time of signing Button status: status of button at time of signing (0 for pen up, 1 for pen down), Azimuth: clockwise rotation of the cursor around the z-axis, Altitude: angle upward toward positive z-axis, Pressure applied by hand varies during the signing process

Review

Handwritten online signature verification is an impoertant aspect of modern authentication systems, ensuring secure and reliable access to sensitive information. Within this domain, the integration of hybrid wavelet transform techniques has emerged as a promising approach, offering enhanced accuracy and robustness. [6][7] H. B. Kekre, Archana Athawale, and Dipali Sadavarti introduced a novel algorithm for creating a discrete wavelet transform through orthogonal transformation. Their approach involves utilizing an M × M orthogonal transformation matrix, denoted as P, where each element in every row of P is replicated M times to produce M mother wavelets. Consequently, the rows of the initial transformation matrix serve as the basis for these wavelets. Experimental results demonstrate that the Walsh wavelet outperforms the Walsh orthogonal transform in tasks such as image compression and reconstruction. [8]

Vinayak Bharadi, Vikas Singh, and Bhushan Nemade introduced a method for online signature recognition utilizing a hybrid wavelet transform. This technique incorporates the energy distribution of velocity magnitude, azimuth, altitude, and pressure as the feature vector, in conjunction with a K-nearest neighbors (KNN) classifier. The performance index derived from hybrid wavelet transform I surpasses that of hybrid wavelet transform II. Moreover, the feature vector based on azimuth and altitude demonstrates superior performance when compared to the one based on Signature Pressure Map. [9] H. B. Kekre, Tanuja Sarode, and Rachana Dhannawat proposed a method for image fusion employing hybrid wavelets derived from Discrete Cosine Transform (DCT), Hadamard, and Kekre transforms. Their approach demonstrated improved outcomes compared to conventional techniques. Notably, this method offers the flexibility to be applied to images of various sizes, thereby enhancing its utility. [10]

Sudeep D. Thepade, Jaya H. Dewan, and Anil T. Lohar investigated the utilization of a hybrid wavelet transform comprising Cosine, Sine, Slant, Kekre, Walsh, and Haar transforms for image compression. Various combinations of these transforms were explored in ratios of 1:16, 1:4, 1:1, 4:1, and 16:1 to generate the hybrid wavelet transform. The study found that for a compression ratio of 95%, the 4:1 ratio of Discrete Cosine Transform (DCT) to Haar transform yielded the most favorable results. Additionally, this combination performed well for compression ratios between 70% and 90% at a 1:1 ratio and for lower compression ratios at a 1:4 ratio [11] H.B. Kekre, Tanuja Sarode, and Prachi Natu explored a hybrid wavelet transform utilizing various combinations, such as 8-32, 16-16, and 32-8 of Discrete Cosine Transform (DCT) and Discrete Kekre Transform (DKT), to compress images across different color spaces. Among these, the KLUV color space exhibited the lowest Root Mean Square Error (RMSE) and Mean Average Error (MAE), while achieving the highest Structural Similarity Index (SSIM). In contrast, the RGB color space resulted in the minimum Average Fractional Change in Pixel Value (AFCPV). Notably, the 16-16 combination demonstrated superior performance across all metrics, including RMSE, MAE, SSIM, and AFCPV [12] Geeta B. Atkar and Sonal Gore employed a hybrid wavelet transform comprising Haar, Kekre, and Walsh transforms to facilitate the conversion of color images to grayscale and vice versa. Among the combinations investigated, the Kekre-Walsh combination yielded the most favorable outcomes in terms of Mean Square Error (MSE) [13]

H.B. Kekre, Tanuja Sarode, and Prachi Natu investigated the application of real Fourier transform, its wavelet transform, and a hybrid wavelet transform for image compression purposes. Their analysis revealed that the hybrid wavelet transform exhibited superior performance in terms of Mean Squared Error (MSE) and overall image quality. [14] H.B. Kekre, Tanuja Sarode, and Sachi Natu employed a hybrid wavelet transform consisting of Kekre and Discrete Cosine Transform (DCT) for watermarking images. Their research indicated that the DKT-DCT hybrid wavelet transform showed resilience against various attacks, including compression, cropping, noise addition, and resizing, outperforming both DCT and DKT individual transforms in terms of robustness [15]

Handwritten online signature verification is an important aspect of modern authentication systems, ensuring secure and reliable access to sensitive information. Within this domain, the integration of hybrid wavelet transform techniques has emerged as a promising approach, offering enhanced accuracy and robustness.

SVC 2004

The SVC2004 database is a widely used benchmark dataset in the field of handwritten signature verification. The SVC2004 database consists of genuine and forged signature samples captured from 40 individuals, resulting in 20 genuine signatures and 20 forged signatures per individual. Each signature in the SVC2004 database was acquired using a digitizing tablet, ensuring high-resolution images suitable for detailed analysis. The dataset encompasses a diverse range of signature types, including static and dynamic signatures, providing a comprehensive representation of real-world signing behaviors. Additionally, the SVC2004 dataset incorporates variations in signature quality, size, and complexity, reflecting the inherent challenges encountered in signature verification tasks. To facilitate rigorous evaluation and comparison of signature verification algorithms, the SVC2004 database is accompanied by detailed ground truth annotations, specifying the authenticity of each signature sample. This enables researchers to quantify the performance of their systems in terms of metrics such as accuracy, precision, recall, and F1-score, fostering a standardized framework for assessing algorithmic efficacy. Furthermore, the SVC2004 database has been extensively utilized in academic research and benchmarking studies, serving as a benchmark for evaluating the robustness and generalization capabilities of various signature verification approaches. Its widespread adoption has contributed to the advancement of signature verification technology and facilitated collaboration and knowledge sharing within the research community. [16][17]

I. METHODOLOGY

The proposed system has been shown below. We use Hybrid Wavelet Transform-1 and 2 (HWT-1 and HWT-2) of the pressure components of online handwritten signature.

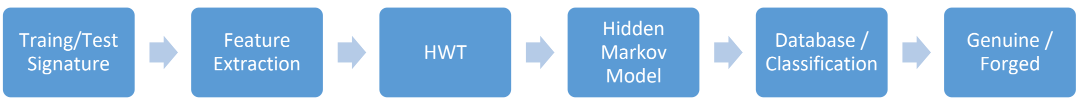


Figure 1. Proposed System

The HWT-1 matrix can be generated by the Kronecker product of two orthogonal transform matrices. Consider two orthogonal matrices X and Y respectively, with sizes a, b respectively such that N=ab.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1a} \\ x_{21} & x_{22} & \cdots & x_{2a} \\ \cdots & \cdots & \cdots & \cdots \\ x_{a1} & x_{a2} & \cdots & x_{aa} \end{bmatrix} \quad Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1b} \\ y_{21} & y_{22} & \cdots & y_{2b} \\ \cdots & \cdots & \cdots & \cdots \\ y_{b1} & y_{b2} & \cdots & y_{bb} \end{bmatrix}$$

In the process, the initial 'a' rows of the hybrid wavelet transform matrix are created by multiplying each element of the first row of the orthogonal transform matrix X with each column of the orthogonal transform matrix Y. Subsequently, for the next 'b' rows of the hybrid wavelet transform matrix, the second row of the orthogonal transform matrix X undergoes a shift rotation after being extended with zeros. Similarly, the subsequent rows of the hybrid wavelet transform matrix are generated iteratively, with each set comprising 'n' rows generated for each of the 'a-1' rows of the orthogonal transform matrix X, starting from the second row up to the last row. The values used in this process are 'a = 4', 'b = 64', and 'N = ab = 256'

For HWT-2 matrix, first N/2 rows of the matrix are formed by way of product of each element of first a/2 rows of the matrix X with each of the columns of the matrix Y. For subsequent ‘b’ wide variety of rows of matrix, the ‘a/2+1’th row of the orthogonal remodel matrix X is shift turned around after being appended with zeros. Next N/2 rows are generated as set of b rows each time for each of the ‘a/2’ rows of orthogonal transform matrix X beginning from ‘a/2+1’th row up to closing row. we've used Discrete Cosine transform (DCT), Discrete Hartley rework (DHT), Discrete Walsh rework (DWT) and Discrete Kekre remodel (DKT) to shape the Wavelet and HWT-2. the primary 128 samples of every signature is used to find HWT-2. The first 128 samples of the 256 samples output are used as characteristic vector. [8]

There are numerous topologies of Hidden Markov Model (HMM) such as Left to right, Ergodic and Ring etc. The Left to right and Ergodic models have been shown in fig 2 & 3. [18]

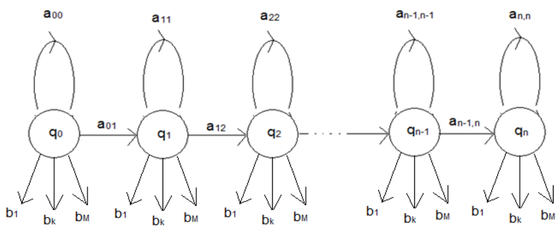


Figure 2 Left to Right HMM model

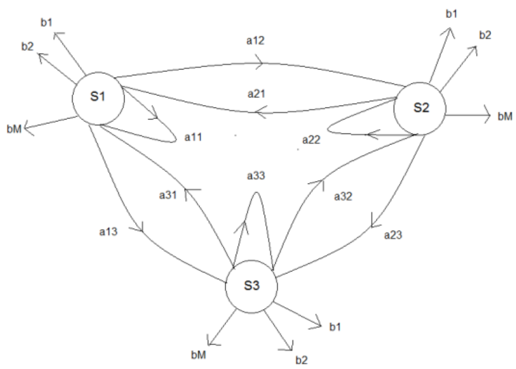


Figure 3 Ergodic HMM model

HMM is represented by the transition probability matrix (A), Observation matrix (B) and initial probability distribution matrix (π). [19]

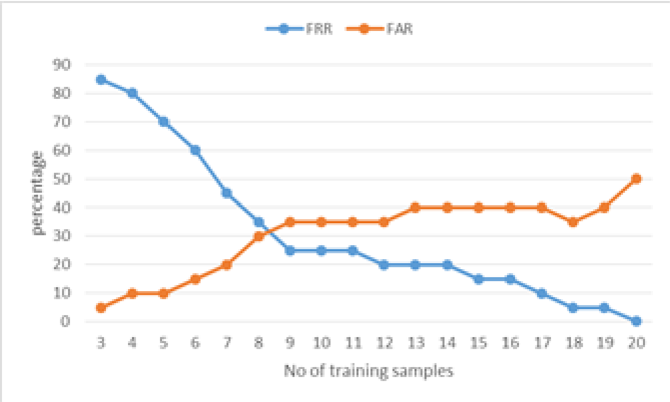
Consider a system which is in a distinct state (S1, S2… SN) at any point of time. In this experiment the number of states (N) of the model are 2,3,4,5. As the number of states increase, the time needed for training increases. The number of observations (M) corresponding to each state are 275. The output of HWT is a matrix of dimension [1 × 256]. The matrix elements from 1 to 128 corresponding to lower frequencies are chosen as a feature vector. Feature vectors are scaled into M number of observations.

Initial Probability Distribution (π): πi = P (q1= Si); $1 \leq i \leq N$. We assume the initial probability of the first state is 1 and the others are 0 which implies that in the beginning HMM is always in state 1. State transition probability (aij): aij = P (St = j / St-1= i). For the left-to-right HMM, aij=0 when i > j. we are using the HMM of first order so that aij=0 when j > i+1. For Ergodic HMM, aij ≠ 0 for i, j. Initially, the state transition matrix is generated using the random numbers such that = 1; $1 \leq i \leq N$ where i = present state and j = next state. Observation probability (bj): bj (k) = P (Vk at t / qt = Sj); $1 \leq j \leq N$; $1 \leq k \leq M$; the probability of generating a symbol Vk in state j. [20][21][22]

Statistics and machine learning toolbox of the MATLAB is used for implementation of HMM. Initially a randomly generated transition probability Matrix (A) is generated using MATLAB, Observation probability matrix (B) with equal probability for every symbol and initial state is assumed to be state 1. HMM is trained using 10 randomly chosen genuine signature samples and is used to test remaining 10 genuine signatures and 20 forged signatures of 40 users. This process is iterated 20 times and then average values are calculated.

I. RESULTS

The proposed system is evaluated on the basis of False Rejection Ratio (FRR) and False Acceptance Ratio (FAR). FRR refers to false rejection of genuine signature and FAR refers to false acceptance of forged signature.[16]



FRR is computed as ratio of the number of signatures detected as forged to the total number of genuine signatures tested. FAR is computed as ratio of the number of signatures detected as genuine to the total forged signatures tested. Testing has been carried out for 40 users and then the average FRR and FAR are calculated. [23][24][25]

Performance analysis for various combinations of HWT-2 for Left-Right model are shown in the table below.

Table 1. FRR-FAR for Left Right Model for HWT-1 and HWT-2

	HWT-1		HWT-2		HWT-1		HWT-2	
NAME	State 2		State 2		State 3		State 3	
	FRR	FAR	FRR	FAR	FRR	FAR	FRR	FAR
Haar 4 DCT 64	13.76	6.46	6.94	14.55	10.42	4.89	8.23	3.73
Haar 4 DHT 64	2.31	9.44	12.51	8.00	1.16	14.96	17.40	3.84
Haar 4 Hadamard 64	1.79	12.22	14.12	5.26	5.31	9.44	2.70	3.36
Haar 4 Kekre 64	14.86	11.79	20.00	12.97	11.24	12.77	16.70	17.19
DHT 4 DCT 64	12.81	10.74	20.39	1.06	1.85	12.35	15.78	20.29
DHT 4 Haar 64	6.51	1.98	7.28	7.29	12.80	14.70	20.96	5.90
DHT 4 Hadamard 64	7.10	2.62	14.72	17.25	13.06	3.23	4.09	15.76
DHT 4 Kekre 64	13.48	4.20	4.03	5.45	10.21	3.53	6.79	12.62
DCT 4 DHT 64	10.99	8.10	3.26	17.24	7.90	5.17	17.19	2.85
DCT 4 Haar 64	10.74	5.69	18.78	20.63	1.05	0.99	16.77	17.85
DCT 4 Hadamard 64	6.53	0.41	18.39	4.55	3.06	8.08	18.28	6.81
DCT 4 Kekre 64	2.95	7.26	18.81	6.12	2.19	3.43	19.79	11.35
Hadamard 4 DCT 64	5.42	6.39	12.04	9.73	13.31	11.60	6.31	13.41
Hadamard 4 DHT 64	11.32	7.70	6.04	15.15	11.96	0.10	1.54	12.60
Hadamard 4 Haar 64	12.94	4.50	15.50	9.38	8.08	3.27	13.87	16.78
Hadamard 4 Kekre 64	15.98	6.36	17.65	3.20	12.00	3.01	15.02	17.41

Kekre 4 DCT 64	13.55	7.31	17.60	15.00	5.42	9.65	1.09	16.57
Kekre 4 DHT 64	6.20	8.70	9.86	12.07	5.27	15.41	10.54	19.60
Kekre 4 Haar 64	0.40	12.92	13.74	6.02	3.16	2.96	15.08	11.92
Kekre 4 Hadamard 64	12.59	14.42	20.48	3.98	11.00	9.83	15.83	2.99

	HWT-1		HWT-2		HWT-1		HWT-2	
NAME	State 4		State 4		State 5		State 5	
	FRR	FAR	FRR	FAR	FRR	FAR	FRR	FAR
Haar 4 DCT 64	12.55	6.53	19.20	19.45	13.66	8.82	20.95	3.84
Haar 4 DHT 64	2.03	10.70	16.88	13.11	14.78	15.04	6.70	20.41
Haar 4 Hadamard 64	12.54	10.65	20.05	1.41	15.62	6.22	14.23	4.55
Haar 4 Kekre 64	10.41	1.88	1.06	16.30	5.13	14.71	15.34	1.25
DHT 4 DCT 64	2.74	9.89	12.43	9.82	15.80	13.59	5.15	16.56
DHT 4 Haar 64	14.32	10.77	15.49	16.77	15.69	10.84	10.84	18.38
DHT 4 Hadamard 64	1.01	3.47	3.24	6.39	6.51	5.88	10.02	3.95
DHT 4 Kekre 64	3.37	1.18	18.43	19.89	1.67	9.97	11.76	5.02
DCT 4 DHT 64	6.84	0.49	15.97	11.66	8.18	9.68	3.96	1.48
DCT 4 Haar 64	14.86	4.59	1.00	9.54	6.01	5.31	18.42	12.97
DCT 4 Hadamard 64	0.59	2.39	15.15	7.60	3.17	8.96	7.04	5.38
DCT 4 Kekre 64	5.69	12.38	8.69	5.61	9.53	10.71	5.13	17.37
Hadamard 4 DCT 64	6.11	2.36	16.27	9.75	2.69	6.61	7.91	8.05
Hadamard 4 DHT 64	12.21	15.18	3.27	14.96	7.71	8.55	16.58	9.95
Hadamard 4 Haar 64	11.43	1.08	6.33	14.95	0.51	3.96	11.18	13.20
Hadamard 4 Kekre 64	3.85	10.43	1.47	20.98	4.61	11.59	8.91	5.33
Kekre 4 DCT 64	4.62	6.18	4.13	3.75	4.85	8.18	6.46	10.14
Kekre 4 DHT 64	11.62	1.16	16.35	7.37	3.34	3.98	20.74	9.61
Kekre 4 Haar 64	7.16	3.55	10.90	10.46	10.09	14.64	7.70	1.73
Kekre 4 Hadamard 64	6.49	2.15	12.32	13.24	14.25	2.26	4.92	6.17

We have kept the number of training samples same, as 10 and number of symbols to be 275, for all trials.

For Left – Right model of HMM, comparing the performance of HWT-1 and HWT-2 for best FRR- FAR, we have following results.

Considering various Haar Transform combinations of HWT-1 and HWT-2, HWT-1 offers better performance than HWT-2 as shown in table. Haar 4 Hadamard 64 HWT-2 offers best performance of FRR, FAR of 2.70%, 3.36% respectively for state 3. Considering various DHT Transform combinations of HWT-1 and HWT-2, HWT-1 offers better performance than HWT-2 as shown in table. DHT 4 Hadamard 64 HWT-1 offers best performance of FRR, FAR of 1.01%, 3.47% respectively for state 3. Considering various DCT Transform combinations of HWT-1 and HWT-2, HWT-1 offers better performance than HWT-2 as shown in table. DCT 4 Haar 64 HWT-1 offers best performance of FRR, FAR of 1.05%, 0.99% respectively for state 3. Considering various Hadamard Transform combinations of HWT-1 and HWT-2, HWT-1 offers better performance than HWT-2 as shown in table. Hadamard 4 Haar 64 HWT-1 offers best performance of FRR, FAR of 0.51%, 3.96% respectively for state 5. Considering various Kekre Transform combinations of HWT-1 and HWT-2, HWT-1 offers better performance than HWT-2 as shown in table. Kekre 4 Haar 64 HWT-1 offers best performance of FRR, FAR of 3.16%, 2.96% respectively for state 3 respectively.

For given state and Left – Right model of HMM, comparing the performance of HWT-1 and HWT-2 for best FRR-FAR are as follows.

For state 2, DCT 4 Hadamard 64 HWT-1 offers best performance of FRR, FAR of 6.53%, 0.41% respectively. For state 3, DCT 4 Haar 64 HWT-1 offers best performance of FRR, FAR of 1.05%, 0.99% respectively. For state 4, DCT 4 Hadamard 64 HWT-1 offers best performance of FRR, FAR of 0.59%, 2.39% respectively. For state 5, Hadamard 4 Haar 64 HWT-1 offers best performance of FRR, FAR of 0.51%, 3.96% respectively.

Considering all the possible combination of HWT-1 and HWT-2 for DCT, DHT, Haar, Hadamard and Kekre transform for Left Right HMM model, DCT 4 Haar 64 offers best performance of FRR, FAR of 1.05%, 0.99% respectively for state 3.

Table 1. FRR-FAR for Ergodic Model for HWT-1 and HWT-2

NAME	HWT-1		HWT-2		HWT-1		HWT-2	
	State 2		State 2		State 3		State 3	
	FRR	FAR	FRR	FAR	FRR	FAR	FRR	FAR
Haar 4 DCT 64	0.13	18.04	6.32	5.10	5.52	8.12	10.94	8.01
Haar 4 DHT 64	20.57	9.93	5.33	10.01	15.76	6.65	14.30	1.45
Haar 4 Hadamard 64	11.82	1.69	8.68	2.50	20.42	14.77	14.64	9.70
Haar 4 Kekre 64	20.43	3.74	8.15	4.11	12.71	3.56	8.04	11.63
DHT 4 DCT 64	9.01	18.54	6.86	15.65	3.47	10.48	12.05	16.65
DHT 4 Haar 64	13.11	7.72	5.48	20.32	17.70	7.03	12.81	10.12
DHT 4 Hadamard 64	0.50	9.12	5.70	13.23	2.70	17.18	6.07	12.26
DHT 4 Kekre 64	5.34	3.37	2.08	3.02	12.49	13.85	17.94	17.48
DCT 4 DHT 64	12.22	4.99	8.94	14.59	2.30	1.57	4.15	12.77
DCT 4 Haar 64	15.76	15.02	20.48	17.80	17.03	2.17	10.42	8.46
DCT 4 Hadamard 64	1.95	12.30	11.38	20.62	20.91	9.03	8.80	10.23
DCT 4 Kekre 64	20.38	14.89	9.47	11.33	1.24	1.33	19.25	12.06
Hadamard 4 DCT 64	8.67	2.92	6.08	13.27	4.30	17.85	13.03	20.65
Hadamard 4 DHT 64	8.49	8.87	13.58	19.41	19.35	18.65	4.42	8.01
Hadamard 4 Haar 64	18.49	2.39	6.81	9.64	8.75	2.84	9.33	10.95
Hadamard 4 Kekre 64	2.32	3.83	17.55	7.74	9.28	18.90	13.71	21.00
Kekre 4 DCT 64	19.28	17.47	7.48	9.94	7.14	5.06	10.56	5.14
Kekre 4 DHT 64	5.11	13.74	20.59	7.44	12.48	2.14	4.39	8.19
Kekre 4 Haar 64	17.18	6.62	6.19	13.14	5.96	12.65	18.07	13.22
Kekre 4 Hadamard 64	1.45	6.45	14.34	17.87	10.37	15.52	6.42	10.34

NAME	HWT-1		HWT-2		HWT-1		HWT-2	
	State 4		State 4		State 5		State 5	
	FRR	FAR	FRR	FAR	FRR	FAR	FRR	FAR
Haar 4 DCT 64	7.77	0.89	4.90	18.59	16.82	18.18	4.65	6.19
Haar 4 DHT 64	5.18	13.41	11.77	6.36	4.53	7.92	4.08	1.27
Haar 4 Hadamard 64	5.78	1.73	5.64	18.55	17.61	6.60	14.44	1.33
Haar 4 Kekre 64	2.16	9.56	9.06	11.77	7.31	9.73	1.80	20.65
DHT 4 DCT 64	14.87	12.75	1.91	16.55	16.45	1.52	5.94	15.14
DHT 4 Haar 64	8.84	11.51	14.18	17.75	19.30	19.12	3.80	5.00

DHT 4 Hadamard 64	15.54	12.53	17.71	8.83	3.08	5.55	13.90	13.75
DHT 4 Kekre 64	15.98	19.56	13.83	6.10	7.99	17.34	4.42	8.71
DCT 4 DHT 64	0.80	17.84	10.84	1.97	19.18	18.67	1.10	2.88
DCT 4 Haar 64	3.40	17.93	9.13	17.25	17.71	3.43	10.64	16.11
DCT 4 Hadamard 64	15.48	13.14	19.63	7.55	9.50	15.80	20.11	5.43
DCT 4 Kekre 64	3.32	12.37	18.68	8.90	7.73	7.88	16.67	9.82
Hadamard 4 DCT 64	19.42	10.36	19.32	6.87	13.26	19.87	19.66	4.85
Hadamard 4 DHT 64	19.46	16.44	17.63	10.58	20.25	12.37	8.03	7.91
Hadamard 4 Haar 64	1.54	20.38	12.03	3.83	15.98	15.52	8.48	5.87
Hadamard 4 Kekre 64	5.82	1.90	10.29	18.94	18.78	17.06	12.63	3.30
Kekre 4 DCT 64	16.23	4.04	9.96	11.26	6.77	17.75	12.51	4.31
Kekre 4 DHT 64	12.29	12.57	10.15	9.70	4.61	8.22	14.91	13.96
Kekre 4 Haar 64	0.35	18.13	7.60	8.57	19.61	17.11	4.42	17.42
Kekre 4 Hadamard 64	2.97	2.90	12.91	17.18	15.01	14.35	4.60	17.87

We have kept the number of training samples same, as 10 and number of symbols to be 275, for all trials.

For Ergodic model of HMM, comparing the performance of HWT-1 and HWT-2 for best FRR- FAR, we have following results.

Considering various Haar Transform combinations of HWT-1 and HWT-2, HWT-2 offers better performance than HWT-1 except for state 4 as shown in table. Haar 4 DHT 64 offers best performance of FRR, FAR of 4.08%, 1.27% respectively for state 5. Considering various DHT Transform combinations of HWT-1 and HWT-2, HWT-2 offers better performance than HWT-1 as shown in table. DHT 4 Kekre 64 offers best performance of FRR, FAR of 2.08%, 3.02% respectively for state 2. Considering various DCT Transform combinations of of HWT-1 and HWT-2, HWT-1 offers better performance than HWT-2 except for state 5 as shown in table. DCT 4 Kekre 64 HWT-1 offers best performance of FRR, FAR of 1.24%, 1.33% respectively for state 3. Considering various Hadamard Transform combinations of HWT-1 and HWT-2, HWT-1 offers better performance than HWT-2 except for state 5 as shown in table. Hadamard 4 Kekre 64 HWT-1 offers best performance of FRR, FAR of 2.32%, 3.83% respectively for state 2. Considering various Kekre Transform combinations of HWT-1 and HWT-2, HWT-1 offers better performance than HWT-2 except for state 5 as shown in table. Kekre 4 Hadamard 64 HWT-1 offers best performance of FRR, FAR of 2.97%, 2.90% respectively for state 3 respectively.

For given state and Ergodic model of HMM, comparing the performance of HWT-1 and HWT-2 for best FRR-FAR are as follows.

For state 2, DHT 4 Kekre 64 offers best performance of FRR, FAR of 2.08%, 3.02% respectively. For state 3, DCT 4 Kekre 64 HWT-1 offers best performance of FRR, FAR of 1.24%, 1.33% respectively. For state 4, Kekre 4 Hadamard 64 HWT-1 offers best performance of FRR, FAR of 2.97%, 2.90% respectively. For state 5, DCT 4 DHT 64 offers best performance of FRR, FAR of 1.10%, 2.88% respectively.

Considering all the possible combination of HWT-2 for DCT, DHT, Haar, Hadamard and Kekre transform for Ergodic HMM model, DCT 4 Kekre 64 HWT-1 offers best performance of FRR, FAR of 1.24%, 1.33% respectively for state 3.

Conclusion

We have used HWT-1 and HWT-2 with HMM classifier for Handwritten online signature verification and forgery detection of online handwritten signature on SVC 2004 database in the proposed method. Considering all the possible combination of HWT-1 and HWT-2 for DCT, DHT, Haar, Hadamard and Kekre transform for Left Right HMM model, DCT 4 Haar 64 HWT-1 offers best performance of FRR, FAR of 1.05%, 0.99% respectively for state 3. Considering all the possible combination of HWT-1 and HWT-2 for DCT, DHT, Haar, Hadamard and

Kekre transform for Ergodic HMM model, DCT 4 DHT 64 offers best performance of FRR, FAR of 1.10%, 2.88% respectively for state 5. We conclude that comparing HWT-1 and HWT-2 combinations for Left Right and Ergodic HMM model, HWT-1 for Left Right model offer better performance. Therefore, we conclude that HWT-1 with Left Right HMM has been a feasible method for feature vector extraction and online Handwritten signature verification and forgery detection.

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