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

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***Abstract:* -** Online signature verification stands out as a distinctive biometric feature, offering both static and dynamic attributes within 2D signature images. A Hybrid Wavelet Transform-2 (HWT-2) with a size of 256 is constructed by employing the Kronecker product of two orthogonal transforms: DCT, DHT, Haar, Hadamard, and Kekre, each with sizes of 4 and 64. The HWT enables the analysis of signals at both global and local levels, akin to wavelet transforms. HWT-2 is applied to 256 samples of online handwritten signatures, and the first 128 samples of the output are utilized as feature vectors for the verification and forgery detection of online handwritten signatures. These feature vectors are inputted into Left-Right and Ergodic Hidden Markov Model (HMM) classifiers for analysis. The HMMs are trained using 10 randomly selected genuine signature samples, and subsequently tested on the remaining 10 genuine signatures and 20 forged signatures from 40 users of the SVC 2004 signature database. This process is repeated 20 times, and the average values are computed. Among all possible combinations of HWT-2 using DCT, DHT, Haar, Hadamard, and Kekre transforms for the Left-Right HMM model, the combination of DCT 4 and DHT 64 demonstrates the best performance, with False Rejection Rate (FRR) and False Acceptance Rate (FAR) values of 3.96% and 1.48%, respectively, for state 5. Similarly, for the Ergodic HMM model, the combination of DCT 4 and DHT 64 exhibits the best performance, with FRR and FAR values of 1.10% and 2.88%, respectively, for state 5. These results indicate that combinations of HWT-2 outperform individual orthogonal transforms, and further, that HWT-2 combinations within the Ergodic HMM model offer superior performance compared to the Left-Right HMM model.

Keywords: HWT, HMM, Signature Verification

Introduction:

Biometric features serve as unique identifiers for individuals and can be categorized into two types: Physical and Behavioral. Handwritten signatures belong to the Behavioral category, along with features like voice patterns and typing rhythm. Signatures have long been utilized for individual authentication due to their accessibility. They represent a form of biometric feature. Biometric features can further be classified into Offline and Online types. Offline signatures are static 2D images created on paper, while online signatures encompass additional dynamic elements such as pressure applied, writing speed, and pen grip, in addition to the 2D image. When it comes to

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automating signature verification processes, online signatures offer distinct advantages over offline ones due to their inclusion of 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]

For creating training samples, individuals will sign on pressure-sensitive writing pads. Each signature sample encompasses various parameters: X-coordinates represent the scaled cursor position along the x-axis, while Y-coordinates denote the scaled cursor position along the y-axis. Additionally, a timestamp records the system time at the moment of signing, while the button status indicates whether the pen was up (0) or down (1) during signing. Azimuth signifies the clockwise rotation of the cursor around the z-axis, while Altitude reflects the angle upward toward the positive z-axis. Notably, the pressure applied by the hand fluctuates throughout 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 an algorithm for generating a discrete wavelet transform employing orthogonal transformation. In this algorithm, for an M × M orthogonal transform matrix P, each element of every row is replicated M times to produce M mother wavelets. Consequently, the original transform matrix rows serve as wavelets. Experimental results demonstrated 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 method incorporates the energy distribution of velocity magnitude, azimuth, altitude, and pressure as the feature vector, alongside a K-nearest neighbors (KNN) classifier. The performance index achieved by hybrid wavelet transform I surpasses that of hybrid wavelet transform II. Additionally, the feature vector based on azimuth and altitude demonstrates superior performance compared to the one based on the Signature Pressure Map. [9]

H. B. Kekre, Tanuja Sarode, and Rachana Dhannawat applied hybrid wavelets derived from Discrete Cosine Transform (DCT), Hadamard, and Kekre transforms for image fusion, yielding superior outcomes compared to conventional methods. An advantage of this technique is its versatility, as it can be employed for images of varying sizes. [10]

Sudeep D. Thepade, Jaya H. Dewan, and Anil T. Lohar explored a hybrid wavelet transform incorporating Cosine, Sine, Slant, Kekre, Walsh, and Haar transforms for image compression. These transforms were combined in various ratios of 1:16, 1:4, 1:1, 4:1, and 16:1 to generate the hybrid wavelet transform. Among these combinations, the 4:1 ratio of Discrete Cosine Transform (DCT) to Haar transform provided optimal results for a compression ratio of 95%. Furthermore, this combination demonstrated effectiveness for compression ratios between 70% and 90% at a 1:1 ratio, as well as for lower compression ratios at a 1:4 ratio. [11]

H.B. Kekre, Tanuja Sarode, and Prachi Natu employed a hybrid wavelet transform with 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. They found that 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). Conversely, the RGB color space demonstrated the minimum Average Fractional Change in Pixel Value (AFCPV). Notably, the 16-16 combination showcased superior performance across all metrics, including RMSE, MAE, SSIM, and AFCPV.[12]

Atkar Geeta B. and Gore Sonal applied a hybrid wavelet transform composed of Haar, Kekre, and Walsh transforms to facilitate the conversion of color images to grayscale and subsequently back to color. Among the combinations examined, 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 explored real Fourier transform, its wavelet transform, and a hybrid wavelet transform for image compression purposes. Their findings revealed that the hybrid wavelet transform outperformed both real Fourier transform and its wavelet counterpart 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 combining Kekre and Discrete Cosine Transform (DCT) for image watermarking. Their investigation revealed that the DKT-DCT hybrid wavelet transform demonstrated robustness against various attacks, including compression, cropping, noise addition, and resizing, outperforming both DCT and DKT individual transforms. [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-2 (HWT) of the pressure component of online handwritten signature.

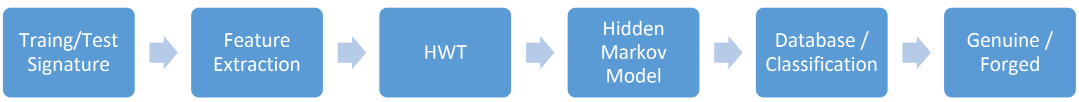


Figure 1. Proposed System

The HWT-2 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.

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

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 have 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]

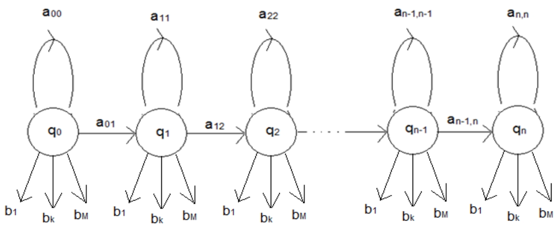


Figure 2 Left to Right HMM model

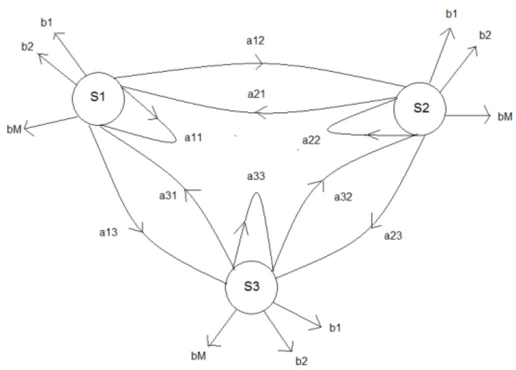


Figure 3 Ergodic HMM model

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

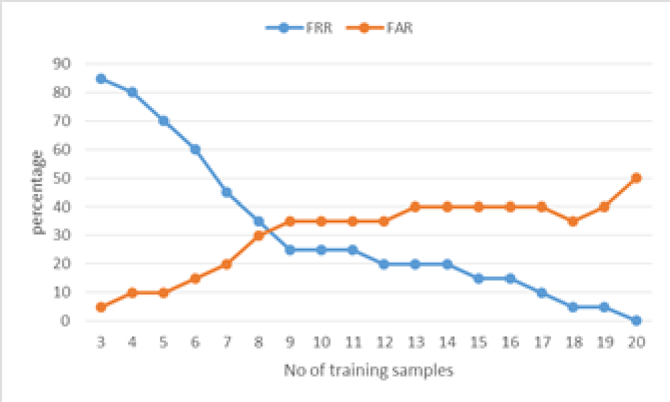
Consider a system which is in a distinct state (S1, S2… SN) at any point of time. In this experiment the number of states (N) of the model are 2,3,4,5. As the number of states increase, the time needed for training increases. The number of observations (M) corresponding to each state are 275. The output 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. [23][24][25]

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.



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.

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

NAME	State 2		State 3		State 4		State 5	
	FRR	FAR	FRR	FAR	FRR	FAR	FRR	FAR
Haar 4 DCT 64	6.94	14.55	8.23	3.73	19.20	19.45	20.95	3.84
Haar 4 DHT 64	12.51	8.00	17.40	3.84	16.88	13.11	6.70	20.41
Haar 4 Hadamard 64	14.12	5.26	2.70	3.36	20.05	1.41	14.23	4.55
Haar 4 Kekre 64	20.00	12.97	16.70	17.19	1.06	16.30	15.34	1.25
Haar 256	4.24	8.25	8.58	11.79	15.84	12.06	8.32	14.76
DHT 4 DCT 64	20.39	1.06	15.78	20.29	12.43	9.82	5.15	16.56
DHT 4 Haar 64	7.28	7.29	20.96	5.90	15.49	16.77	10.84	18.38
DHT 4 Hadamard 64	14.72	17.25	4.09	15.76	3.24	6.39	10.02	3.95
DHT 4 Kekre 64	4.03	5.45	6.79	12.62	18.43	19.89	11.76	5.02
DHT 256	16.50	2.90	15.50	20.37	15.36	3.20	17.88	9.27
DCT 4 DHT 64	3.26	17.24	17.19	2.85	15.97	11.66	3.96	1.48
DCT 4 Haar 64	18.78	20.63	16.77	17.85	1.00	9.54	18.42	12.97
DCT 4 Hadamard 64	18.39	4.55	18.28	6.81	15.15	7.60	7.04	5.38
DCT 4 Kekre 64	18.81	6.12	19.79	11.35	8.69	5.61	5.13	17.37
DCT 256	6.16	8.19	9.73	6.52	6.25	6.09	19.65	1.28
Hadamard 4 DCT 64	12.04	9.73	6.31	13.41	16.27	9.75	7.91	8.05
Hadamard 4 DHT 64	6.04	15.15	1.54	12.60	3.27	14.96	16.58	9.95
Hadamard 4 Haar 64	15.50	9.38	13.87	16.78	6.33	14.95	11.18	13.20
Hadamard 4 Kekre 64	17.65	3.20	15.02	17.41	1.47	20.98	8.91	5.33
Hadamard 256	19.36	12.39	8.98	7.06	3.81	7.17	16.33	13.59
Kekre 4 DCT 64	17.60	15.00	1.09	16.57	4.13	3.75	6.46	10.14
Kekre 4 DHT 64	9.86	12.07	10.54	19.60	16.35	7.37	20.74	9.61
Kekre 4 Haar 64	13.74	6.02	15.08	11.92	10.90	10.46	7.70	1.73

Kekre 4 Hadamard 64	20.48	3.98	15.83	2.99	12.32	13.24	4.92	6.17
Kekre 256	19.93	3.33	11.59	4.62	8.56	4.17	3.88	8.37

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, for best FRR- FAR we have following results.

Considering various Haar Transform combinations of HWT-2, Haar 4 Hadamard 64 offers best performance of FRR, FAR of 2.70%, 3.36% respectively for state 3. Considering various DHT Transform combinations of HWT-2, DHT 4 Hadamard 64 offers best performance of FRR, FAR of 3.24%, 6.39% respectively for state 4. Considering various DCT Transform combinations of HWT-2, DCT 4 DHT 64 offers best performance of FRR, FAR of 3.96%, 1.48% respectively for state 5. Considering various Hadamard Transform combinations of HWT-2, Hadamard 256 offers best performance of FRR, FAR of 3.81%, 7.17% respectively for state 4. Considering various Kekre Transform combinations of HWT-2, Kekre 4 DCT 64 offers best performance of FRR, FAR of 4.13%, 3.75% respectively for state 4 respectively.

For given state and Left – Right model of HMM, best FRR- FAR are as follows.

For state 2, DHT 4 Kekre 64 offers best performance of FRR, FAR of 4.03%, 5.45% respectively. For state 3, Haar 4 Hadamard 64 offers best performance of FRR, FAR of 2.70%, 3.36% respectively. For state 4, Kekre 4 DCT 64 offers best performance of FRR, FAR of 4.13%, 3.75% respectively. For state 5, DCT 4 DHT 64 offers best performance of FRR, FAR of 3.96%, 1.48% respectively.

Considering all the possible combination of HWT-2 for DCT, DHT, Haar, Hadamard and Kekre transform for Left Right HMM model, DCT 4 DHT 64 offers best performance of FRR, FAR of 3.96%, 1.48% respectively for state 5.

NAME	State 2		State 3		State 4		State 5	
	FRR	FAR	FRR	FAR	FRR	FAR	FRR	FAR
Haar 4 DCT 64	6.32	5.10	10.94	8.01	4.90	18.59	4.65	6.19
Haar 4 DHT 64	5.33	10.01	14.30	1.45	11.77	6.36	4.08	1.27
Haar 4 Hadamard 64	8.68	2.50	14.64	9.70	5.64	18.55	14.44	1.33
Haar 4 Kekre 64	8.15	4.11	8.04	11.63	9.06	11.77	1.80	20.65
Haar 256	10.57	20.37	13.69	17.19	16.55	9.83	11.66	7.96
DHT 4 DCT 64	6.86	15.65	12.05	16.65	1.91	16.55	5.94	15.14
DHT 4 Haar 64	5.48	20.32	12.81	10.12	14.18	17.75	3.80	5.00
DHT 4 Hadamard 64	5.70	13.23	6.07	12.26	17.71	8.83	13.90	13.75
DHT 4 Kekre 64	2.08	3.02	17.94	17.48	13.83	6.10	4.42	8.71
DHT 256	15.53	13.34	7.05	19.85	13.93	18.95	12.82	14.71
DCT 4 DHT 64	8.94	14.59	4.15	12.77	10.84	1.97	1.10	2.88
DCT 4 Haar 64	20.48	17.80	10.42	8.46	9.13	17.25	10.64	16.11
DCT 4 Hadamard 64	11.38	20.62	8.80	10.23	19.63	7.55	20.11	5.43
DCT 4 Kekre 64	9.47	11.33	19.25	12.06	18.68	8.90	16.67	9.82
DCT 256	19.63	16.72	11.48	7.23	17.24	10.71	4.27	6.32
Hadamard 4 DCT 64	6.08	13.27	13.03	20.65	19.32	6.87	19.66	4.85
Hadamard 4 DHT 64	13.58	19.41	4.42	8.01	17.63	10.58	8.03	7.91
Hadamard 4 Haar 64	6.81	9.64	9.33	10.95	12.03	3.83	8.48	5.87
Hadamard 4 Kekre 64	17.55	7.74	13.71	21.00	10.29	18.94	12.63	3.30
Hadamard 256	16.80	18.93	19.45	20.84	14.44	8.15	1.71	9.95
Kekre 4 DCT 64	7.48	9.94	10.56	5.14	9.96	11.26	12.51	4.31

Kekre 4 DHT 64	20.59	7.44	4.39	8.19	10.15	9.70	14.91	13.96
Kekre 4 Haar 64	6.19	13.14	18.07	13.22	7.60	8.57	4.42	17.42
Kekre 4 Hadamard 64	14.34	17.87	6.42	10.34	12.91	17.18	4.60	17.87
Kekre 256	15.67	10.53	5.78	8.48	10.17	10.28	6.39	10.55

For Ergodic model of HMM, for best FRR- FAR we have following results.

Considering various Haar Transform combinations of HWT-2, 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-2, 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 HWT-2, DCT 4 DHT 64 offers best performance of FRR, FAR of 1.10%, 2.88% respectively for state 5. Considering various Hadamard Transform combinations of HWT-2, Hadamard 4 DHT 64 offers best performance of FRR, FAR of 4.42%, 8.01% respectively for state 3. Considering various Kekre Transform combinations of HWT-2, Kekre 4 DHT 64 offers best performance of FRR, FAR of 4.39%, 8.19% respectively for state 3 respectively.

For given state and Ergodic model of HMM, 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, Hadamard 4 DHT 64 offers best performance of FRR, FAR of 4.42%, 8.01% respectively. For state 4, DCT 4 DHT 64 offers best performance of FRR, FAR of 10.84%, 1.97% 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 DHT 64 offers best performance of FRR, FAR of 1.10%, 2.88% respectively for state 5.

Table 1. FRR-FAR for Ergodic Model

Conclusion

We have used 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-2 for DCT, DHT, Haar, Hadamard and Kekre transform for Left Right HMM model, DCT 4 DHT 64 offers best performance of FRR, FAR of 3.96%, 1.48% respectively for state 5. Considering all the possible combination of 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 HWT-2 combinations offer better performance than respective orthogonal transforms. We also conclude that HWT-2 combinations of Ergodic HMM model offer better performance than Left Right HMM model. Therefore, we conclude that HWT-2 with HMM has been a feasible method for feature vector extraction of online signature vector based biometric systems for Handwritten online signature verification and forgery detection.

References:

[1] A. K. Jain, A. Ross and S. Prabhakar, "An Introduction to Biometric Recognition," IEEE Transactions on Circuits and Systems for Video Technology, vol. 14, no. 1, p 4-20, Jan 2004.

[2] K. Huang and H. Yan, "Signature verification using fractal transformation," Proc. 15th Int. Conf. Pattern Recog. (ICPR-15), Barcelona, Spain, Sept 2000.

[3] S. Nanavati, M. Thieme, and R. Nanavati, Biometrics: Identity Verification in a Networked World. New York: Wiley, 2002, p 123–131.

[4] K. Veeramacheneni, L. A. Osadciw and P. K. Varshney, "An adaptive multimodal biometric management algorithm," IEEE Trans. Systems, Man and Cybernetics. Part C, vol. 35, no. 3, p. 344–356, Aug 2005.

[5] 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.

[6] H. B. Kekre, T. K. Sarode and S. D. Thepade, "Inception of HWT using Two Orthogonal Transforms and It's use for Image Compression," (IJCSIS) International Journal of Computer Science and Information Security, vol. 9, no. 6, p 80-87, Jun 2011.

[7] H. Kekre, T. Sarode and P. Natu, "Colour Image Compression using DKT-DCT Hybrid Wavelet Transform in Various Colour Spaces," International Journal of Signal Processing, Image Processing and Pattern Recognition, vol. 7, no. 5, pp. 105-124, 2014.

[8] H. B. Kekre, A. Athawale and D. Sadavarti, "Algorithm To Generate Kekre's Wavelet Transform from Kekre's Transform," IJSET, June 2010.

[9] V. A. Bharadi, V. I. Singh and B. Nemade, "Hybrid Wavelets based Feature Vector Generation from Multidimensional Data set for On-line Handwritten Signature Recognition," in IEEE International Conference - Confluence 2014, Amity University UP India, Sept 2014.

[10] H. B. Kekre, T. Sarode and R. Dhannawat, " IMAGE FUSION USING KEKRE'S HYBRID WAVELET TRANSFORM," in IEEE International Conference on Communication, Information & Computing Technology (ICCICT, Mumbai India, Oct 2012 .

[11] S. D. Thepade, J. H. Dewan and A. T. Lohar, "Extended Performance Comparison of Hybrid Wavelet Transform for Image Compression with Varying Proportions of Constituent Transforms," in IEEE International Conference on Advanced Computing Technologies (ICACT 2013), Rajampet India, Sept 2013.

[12] H. Kekre, T. Sarode and P. Natu, "Colour Image Compression using DKT-DCT Hybrid Wavelet Transform in Various Colour Spaces," International Journal of Signal Processing, Image Processing and Pattern Recognition, vol. 7, no. 5, pp. 105-124, 2014.

[13] G. B. Atkar and S. Gore, "ENHANCED PERFORMANCE OF COLOR TO GRAY AND BACK BY USING HYBRID WAVELET TRANSFORMS," International Journal of Emerging Technology and Advanced Engineering, vol. 3, no. 4, April 2013.

[14] H. Kekre, T. Sarode and N. Prachi, "Image Compression Using Real Fourier Transform, Its Wavelet Transform and Hybrid Wavelet with DCT," International Journal of Advance Computer Science and Application, vol. 4, no. 5, 2013.

[15] H. Kekre, T. Sarode and S. Natu, "Robust Watermarking Technique using Hybrid Wavelet Transform Generated from Kekre Transform and Discrete Cosine Transform," International Journal of Scientific and Research Publications, vol. 4, no. 2, Feb 2014.

[16] D. Impedovo and G. Pirlo, "Automatic Signature Verification: The State of the Art," IEEE Transaction on Systems, MAN and Cybernatics Part C: Application and Reviews, vol. 28, no.5, Sept 2008.

[17] SVC2004 Home. http://www.cse.ust.hk/svc2004/. Accessed 02 Dec 2011.

[18] S. Garcia-Salicetti and B. Dorizzi, "On using the Viterbi path along with HMM likelihood information for online signature verification," IEEE Trans. Syst., Man, Cybern. B, vol. 37, no. 5, p 1237–1247, Oct 2007.

[19] L. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," Proceedings of IEEE, vol. 77, no. 2, p 257-286, Feb 1989.

[20] L. YANG, B. K. WIDJAJA and P. R., "APPLICATION OF HIDDEN MARKOV MODELS FOR SIGNATURE VERIFICATION," Pattern Recognition, vol. 28, no. 2, pp. 161-170, 1995.

[21] J. J. Igarza, I. Goirizelaia, K. Espinosa, I. Hernaez, R. Mendez and J. Sanchez, "Online Handwritten Signature Verification Using Hidden Markov Models," CIARP'03, pp. 391-399, 2003.

[22] M. M. Shafiei and H. R. Rabiee, " A New On-line Verification Algorithm Using Variable length Segmentation and Hidden Markov Models," in Seven th International Conference on Document Analysis and Recognition (ICDAR'03), Singapore, 2003.

[23] M. Chavan, R. Singh, V. Bharadi, "Online Signature Verification Using Hybrid Wavelet Transform," International Journal of Electrical and Computer Engineering (IJECE), vol. 10, no. 2, April 2020, p 1823~1832.

[24] M. Chavan, R. R. Singh and V. A. Bharadi, "Online Signature Verification using HWT with Hidden Markov Model" in Proc 4th International Conference on Computing, Communication, Control and Automation (ICCUBEA), Pune, India Aug 2017.

[25] M. Chavan, R. R. Singh and V. A. Bharadi, "Handwritten Signature Verification using Hidden Markov Model with HWT" in Proc 4th International Conference on Computing, Communication, Control and Automation (ICCUBEA), Pune, India Aug 2017.