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Handwritten online signature verification and Forgery Detection for Online Handwritten Signature using Hybrid Wavelet Transform-1 with HMM classifier

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Abstract: - Online signature verification employs a distinctive biometric trait by utilizing both static and dynamic features extracted from 2D signature images. A hybrid wavelet transform, denoted as HWT-1 with a size of 256, is formed through the Kronecker product of two orthogonal transforms, such as DCT, DHT, Haar, Hadamard, and Kekre, each with sizes 4 and 64. This HWT facilitates signal analysis at both global and local levels, akin to traditional wavelet transforms. Specifically, HWT-1 processes the 256 samples of online handwritten signatures, yielding 128 samples that constitute the feature vectors for signature verification and forgery detection. These feature vectors are then inputted into the Left-Right and Ergodic Hidden Markov Model (HMM) classifiers for further analysis. The HMMs are trained using 10 randomly selected genuine signature samples and subsequently tested with the remaining 10 genuine signatures and 20 forged signatures from the SVC 2004 signature database, repeating this process 20 times to compute average values. Among all possible combinations of HWT-1 utilizing DCT, DHT, Haar, Hadamard, and Kekre transforms for the Left-Right HMM model, the combination of DCT 4 and Haar 64 demonstrates the best performance with a False Rejection Rate (FRR) and False Acceptance Rate (FAR) of 1.05% and 0.99%, respectively, at state 3. Similarly, considering all feasible combinations of HWT-1 for the Ergodic HMM model, the combination of DCT 4 and Kekre 64 yields the optimal performance with an FRR and FAR of 1.24% and 1.33%, respectively, at state 3.

Keywords: HWT, HMM, Signature Verification.

1. Introduction

Online handwritten signature verification stands at the forefront of authentication systems, serving as a pivotal mechanism for ensuring secure access to digital resources and transactions. With the transition towards electronic transactions and the pervasive nature of digital documentation, the need for reliable and efficient methods of verifying handwritten signatures in online environments has become increasingly pronounced.[1] Unlike traditional paper-based signatures, online handwritten signatures are captured digitally using various input devices such as stylus pens, touchscreens, or graphics tablets. This digital capture process enables the collection of rich temporal and spatial information, including stroke trajectories, pen pressure, velocity, and timing, which can be

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leveraged for authentication purposes. [2] [3] The verification of online handwritten signatures poses unique challenges compared to offline counterparts. In addition to variability in writing styles, individuals' online signatures exhibit dynamic characteristics influenced by factors such as writing speed, pressure, and device properties. Furthermore, the inherent noise in digital signals and the potential for deliberate or unintentional alterations introduce additional complexities to the verification process. [4] Addressing these challenges requires the development of sophisticated algorithms and methodologies capable of accurately capturing, representing, and analysing the intricacies of online handwritten signatures. Researchers in this field draw upon a diverse range of disciplines, including signal processing, pattern recognition, machine learning, and biometrics, to design effective verification systems. [5]

The ultimate goal of online handwritten signature verification is twofold: to authenticate the identity of the signer and to detect attempts at forgery or unauthorized access. Achieving these objectives necessitates the extraction of discriminative features from signature signals, the utilization of robust classification algorithms, and the implementation of stringent evaluation protocols. As digital transactions continue to proliferate across various domains, including finance, legal, and administrative sectors, the importance of reliable online handwritten signature verification systems cannot be overstated. These systems play a crucial role in safeguarding sensitive information, preventing fraud, and upholding the integrity of digital transactions in an increasingly interconnected world. 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 computerizing the signature verification process, online signatures offer more advantages than offline signatures because of its dynamic features. [1]

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. [6] 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.

Related Work

Recent advancements in signature verification have focused on extracting discriminative features from signature signals. Feature extraction techniques such as Fourier Transform and Wavelet Transform have been widely explored to capture both spatial and temporal information. Moreover, deep learning-based approaches, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown promise in automatically learning hierarchical representations from raw signature data.

Hybrid wavelet transforms (HWTs) have demonstrated superior performance in image compression compared to the orthogonal transforms from which they are derived. [7][8] Additionally, HWTs find applications in watermarking [9] and the conversion of color images to grayscale. [10] Various classifiers, including KNN, SVM, and NN, [11][12] have been utilized for signature verification. For instance, in one study, a KNN classifier was employed with HWTs of strain maps derived from online signatures as the feature vector, resulting in an Equal Error Rate (EER) of 30%. [13][14] In another study, an SVM classifier was used with a kernel feature extracted from the time series of online signatures, based on the detection of Longest Common Subsequences (LCSSs), yielding an EER of 6.84%. When combined with HMM, the SVM approach achieved a minimal EER of 1.96% and a False Rejection Rate (FRR) of 60.43%.[15]

Dynamic signature analysis, which involves capturing temporal dynamics such as pen pressure, velocity, and stroke order, has emerged as a crucial aspect of online signature verification. Dynamic features offer enhanced discriminative power and resilience against forgery attempts. Techniques such as velocity-based segmentation, pressure distribution analysis, and curvature-based features have been extensively investigated for their efficacy in characterizing signature dynamics. [1]

In [16], neural network classifier used with, the approximation and details of DWT of the pen position and pen movement angle as feature vector, the usage of all coefficients of DWT, 100% with trained signature, 90% with untrained signatures and FRR of 24%. Using selected 25 coefficients of DWT, success rate was 100% with trained signature, 95% with untrained signatures and FAR of 8%.

Methodology

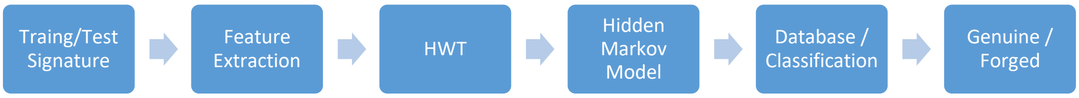


Figure 1. Proposed System

The proposed system is shown in figure-1. We use Hybrid Wavelet Transform-1 (HWT-1) of the pressure component of online handwritten signature. HWT-1 is formed by combining the two orthogonal transforms using Kronecker product. It has the ability to analyse the signal at global as well as local level like wavelet transform. [7] Consider matrices X and Y as shown below.

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

Hybrid wavelet transform matrix can be generated by the Kronecker product of two orthogonal transform matrices. Consider two orthogonal transform matrices X and Y of size a and b respectively then HWT will be of size N=a*b=ab. In the process, the hybrid wavelet transform matrix is constructed as follows: Initially, the first 'a' rows of the matrix are formed by taking the product of each element in the first row of the orthogonal transform matrix X with every 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. Likewise, the subsequent rows of the hybrid wavelet transform matrix are generated in sets of 'n' rows, with each set corresponding to each of the 'a-1' rows of the orthogonal transform matrix X, starting from the second row and continuing to the last row. [7][18] We have used a = 4 and b = 64 and N = ab = 256.

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. [17][1]

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. [21]

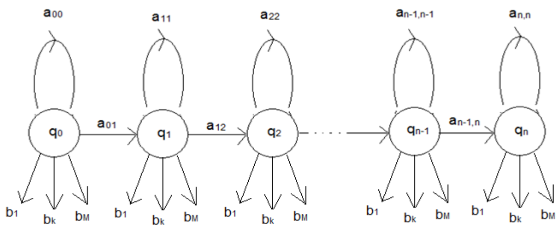


Figure 2 Left to Right HMM model

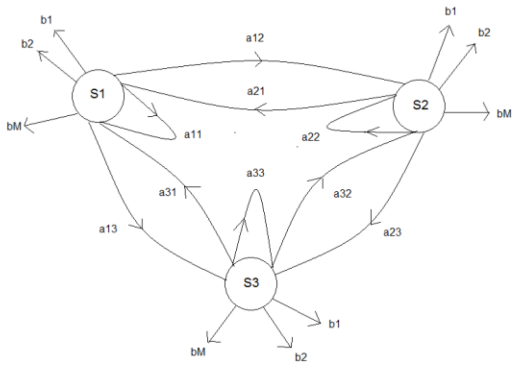


Figure 3 Ergodic HMM model

HMM is represented by the transition probability matrix (A), Observation matrix (B) and initial probability distribution matrix (π). We have used the Left-Right model and Ergodic models of HMM.

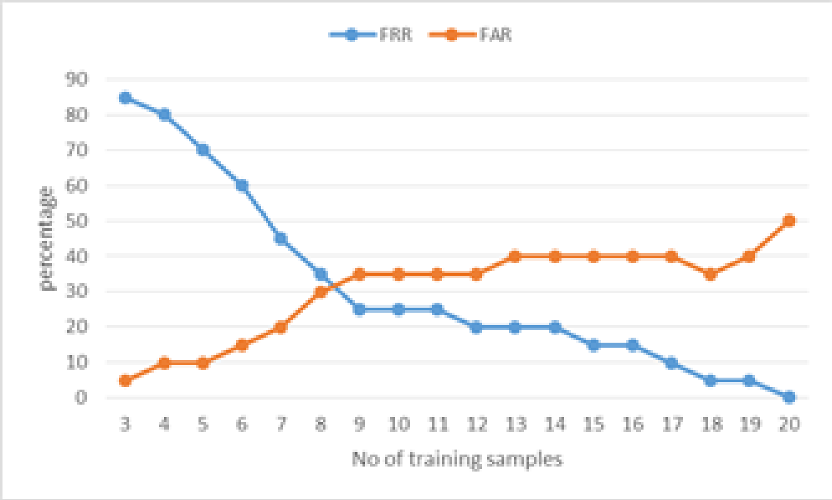
Consider a system characterized by distinct states (S1, S2… SN) at any given time. In this experiment, we vary the number of states (N) of the model, exploring values of 2, 3, 4, and 5. It's observed that as the number of states increases, the time required for training also increases. Each state is associated with a fixed number of observations (M), with M set to 275 in this study. The output of HWT -1 yields a matrix of dimension [1 × 256]. Subsequently, elements 1 to 128 of this matrix, corresponding to lower frequencies, are selected to form a feature vector. These feature vectors are then scaled to generate M observations. [18][19][20]

Initial Probability Distribution (π): $\pi i = P\ (q1= Si);\ 1 \leq i \leq N$. We assume the model to be in state 1 at start. So 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): $aij = P\ (St = j\ /\ St\text{-}1= i)$. 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): $bj\ (k) = P\ (Vk \text{ at } t\ /\ qt = Sj);\ 1 \leq j \leq N;\ 1 \leq k \leq M$; the probability of generating a symbol Vk in state j.

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.

2. Experimental Results

The evaluation of the proposed system is based on two key metrics: the False Rejection Ratio (FRR) and the False Acceptance Ratio (FAR). FRR signifies the rate of falsely rejecting genuine signatures, while FAR indicates the rate of falsely accepting forged signatures. [16]



The False Rejection Ratio (FRR) is determined by calculating the ratio of the number of genuine signatures incorrectly identified as forged to the total number of genuine signatures tested. Conversely, the False Acceptance Ratio (FAR) is computed as the ratio of the number of forged signatures incorrectly identified as genuine to the total number of forged signatures tested. These evaluations are conducted across 40 users, after which the average FRR and FAR are computed.

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.

Performance analysis for various combinations of HWT-1 for Left-Right model are shown in the table below.

Table 1. FRR-FAR for Left- Right Model

NAME	State 2		State 3		State 4		State 5	
	FRR	FAR	FRR	FAR	FRR	FAR	FRR	FAR
Haar 4 DCT 64	13.76	6.46	10.42	4.89	12.55	6.53	13.66	8.82
Haar 4 DHT 64	2.31	9.44	1.16	14.96	2.03	10.70	14.78	15.04
Haar 4 Hadamard 64	1.79	12.22	5.31	9.44	12.54	10.65	15.62	6.22
Haar 4 Kekre 64	14.86	11.79	11.24	12.77	10.41	1.88	5.13	14.71
Haar 256	8.33	13.89	7.60	15.09	12.87	6.44	3.38	12.46
DHT 4 DCT 64	12.81	10.74	1.85	12.35	2.74	9.89	15.80	13.59
DHT 4 Haar 64	6.51	1.98	12.80	14.70	14.32	10.77	15.69	10.84
DHT 4 Hadamard 64	7.10	2.62	13.06	3.23	1.01	3.47	6.51	5.88
DHT 4 Kekre 64	13.48	4.20	10.21	3.53	3.37	1.18	1.67	9.97
DHT 256	5.01	13.63	0.74	3.18	7.26	8.53	6.55	12.44
DCT 4 DHT 64	10.99	8.10	7.90	5.17	6.84	0.49	8.18	9.68
DCT 4 Haar 64	10.74	5.69	2.05	0.99	14.86	4.59	6.01	5.31
DCT 4 Hadamard 64	6.53	0.41	3.06	8.08	0.59	2.39	3.17	8.96
DCT 4 Kekre 64	2.95	7.26	2.19	3.43	5.69	12.38	9.53	10.71
DCT 256	0.81	7.81	3.67	3.44	7.47	4.37	8.30	4.44
Hadamard 4 DCT 64	5.42	6.39	13.31	11.60	6.11	2.36	2.69	6.61
Hadamard 4 DHT 64	11.32	7.70	11.96	0.10	12.21	15.18	7.71	8.55
Hadamard 4 Haar 64	12.94	4.50	8.08	3.27	11.43	1.08	0.51	3.96
Hadamard 4 Kekre 64	15.98	6.36	12.00	3.01	3.85	10.43	4.61	11.59
Hadamard 256	10.78	15.26	4.31	11.61	13.47	6.23	12.33	4.99
Kekre 4 DCT 64	13.55	7.31	5.42	9.65	4.62	6.18	4.85	8.18

Kekre 4 DHT 64	6.20	8.70	5.27	15.41	11.62	1.16	3.34	3.98
Kekre 4 Haar 64	0.40	12.92	3.16	2.96	7.16	3.55	10.09	14.64
Kekre 4 Hadamard 64	12.59	14.42	11.00	9.83	6.49	2.15	14.25	2.26
Kekre 256	15.55	9.94	9.38	0.12	11.90	11.16	13.88	6.91

Performance analysis for various combinations of HWT-1 for Ergodic model are shown in the table below.

Table 1. FRR-FAR for Ergodic Model

NAME	State 2		State 3		State 4		State 5	
	FRR	FAR	FRR	FAR	FRR	FAR	FRR	FAR
Haar 4 DCT 64	0.13	18.04	5.52	8.12	7.77	0.89	16.82	18.18
Haar 4 DHT 64	20.57	9.93	15.76	6.65	5.18	13.41	4.53	7.92
Haar 4 Hadamard 64	11.82	1.69	20.42	14.77	5.78	1.73	17.61	6.60
Haar 4 Kekre 64	20.43	3.74	12.71	3.56	2.16	9.56	7.31	9.73
Haar 256	10.24	2.60	1.43	19.09	7.42	10.93	19.07	6.36
DHT 4 DCT 64	9.01	18.54	3.47	10.48	14.87	12.75	16.45	1.52
DHT 4 Haar 64	13.11	7.72	17.70	7.03	8.84	11.51	19.30	19.12
DHT 4 Hadamard 64	0.50	9.12	2.70	17.18	15.54	12.53	3.08	5.55
DHT 4 Kekre 64	5.34	3.37	12.49	13.85	15.98	19.56	7.99	17.34
DHT 256	3.94	14.34	6.12	19.12	11.87	3.02	4.69	3.61
DCT 4 DHT 64	12.22	4.99	2.30	1.57	0.80	17.84	19.18	18.67
DCT 4 Haar 64	15.76	15.02	17.03	2.17	3.40	17.93	17.71	3.43
DCT 4 Hadamard 64	1.95	12.30	20.91	9.03	15.48	13.14	9.50	15.80
DCT 4 Kekre 64	20.38	14.89	1.24	1.33	3.32	12.37	7.73	7.88
DCT 256	1.69	19.49	15.25	5.20	5.00	14.41	14.14	6.60
Hadamard 4 DCT 64	8.67	2.92	4.30	17.85	19.42	10.36	13.26	19.87
Hadamard 4 DHT 64	8.49	8.87	19.35	18.65	19.46	16.44	20.25	12.37
Hadamard 4 Haar 64	18.49	2.39	8.75	2.84	1.54	20.38	15.98	15.52
Hadamard 4 Kekre 64	2.32	3.83	9.28	18.90	5.82	1.90	18.78	17.06
Hadamard 256	3.92	18.65	7.65	12.42	13.84	5.67	8.25	14.34
Kekre 4 DCT 64	19.28	17.47	7.14	5.06	16.23	4.04	6.77	17.75
Kekre 4 DHT 64	5.11	13.74	12.48	2.14	12.29	12.57	4.61	8.22
Kekre 4 Haar 64	17.18	6.62	5.96	12.65	0.35	18.13	19.61	17.11
Kekre 4 Hadamard 64	1.45	6.45	10.37	15.52	2.97	2.90	15.01	14.35
Kekre 256	0.29	3.82	9.78	2.86	4.42	11.28	1.09	3.95

3. Discussion

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.

Examining different combinations of Haar Transform within HWT-1, it was found that Haar 4 DHT 64 achieved the most favorable performance with an FRR of 2.31% and a FAR of 9.44% for state 2. Similarly, among various DHT Transform combinations, DHT 256 exhibited the best performance, yielding an FRR of 0.74% and a FAR of 3.18% for state 3. In the case of DCT Transform combinations, DCT 4 Haar 64 demonstrated superior performance, achieving an FRR of 1.05% and a FAR of 0.99% for state 3. Furthermore, among Hadamard Transform combinations, Hadamard 4 Haar 64 showed the most promising performance, with an FRR of 0.51%

and a FAR of 3.96% for state 5. Lastly, considering various Kekre Transform combinations, Kekre 4 HAAR 64 offered the best performance with an FRR of 3.16% and a FAR of 2.96% for state 3.

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

In the evaluation across different states, it was found that for state 2, DCT 4 Hadamard 64 demonstrated the optimal performance, achieving an FRR of 6.53% and a FAR of 0.41%. Meanwhile, for state 3, DCT 4 Haar 64 showed the best performance with an FRR of 1.05% and a FAR of 0.99%. In the case of state 4, DCT 4 Hadamard 64 exhibited superior performance, yielding an FRR of 0.59% and a FAR of 2.39%. Lastly, for state 5, Hadamard 4 Haar 64 displayed the most promising performance, with an FRR of 0.51% and a FAR of 3.96%

Considering all the possible combination of HWT-1 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.

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

Exploring different combinations of Haar Transform within HWT-1, it was found that Haar 4 DCT 64 achieved the top performance, with an FRR of 7.77% and a FAR of 0.89% for state 4. Among various DHT Transform combinations, DHT 4 Kekre 64 exhibited the best performance, yielding an FRR of 5.34% and a FAR of 3.37% for state 2. In terms of DCT Transform combinations, DCT 4 Kekre 64 demonstrated superior performance, achieving an FRR of 1.24% and a FAR of 1.33% for state 3. When considering various Hadamard Transform combinations, Hadamard 4 Kekre 64 showed the most promising performance, with an FRR of 2.32% and a FAR of 3.83% for state 2. Lastly, among various Kekre Transform combinations, Kekre 256 offered the best performance, with an FRR of 0.29% and a FAR of 3.82% for state 2

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

In the assessment across different states, it was determined that for state 2, Kekre 256 exhibited the optimal performance, with an FRR of 0.29% and a FAR of 3.82%. Meanwhile, for state 3, DCT 4 Kekre 64 showed the best performance, achieving an FRR of 1.24% and a FAR of 1.33%. In the case of state 4, Kekre 4 Hadamard 64 demonstrated superior performance, yielding an FRR of 2.97% and a FAR of 2.90%. Lastly, for state 5, Kekre 256 displayed the most promising performance, with an FRR of 1.09% and a FAR of 3.95%.

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

Conclusion

In the proposed approach, HWT-1 combined with an HMM classifier was utilized for the verification of handwritten online signatures and the detection of forgery within the online handwritten signatures in the SVC 2004 database. After exploring various combinations of HWT-1 with transforms such as DCT, DHT, Haar, Hadamard, and Kekre for both Left Right HMM and Ergodic HMM models, it was found that DCT 4 Haar 64 exhibited the most favorable performance, achieving an FRR of 1.05% and a FAR of 0.99% for state 3 in the Left Right HMM model. Similarly, in the Ergodic HMM model, the combination of DCT 4 Kekre 64 demonstrated the best performance, yielding an FRR of 1.24% and a FAR of 1.33% for state 3. These results indicate that the combinations involving HWT-1 outperform their respective orthogonal transforms. Furthermore, it was observed that the combinations of HWT-1 within the Left Right HMM model generally outperformed those within the Ergodic HMM model. Consequently, it can be concluded that employing HWT-1 with HMM constitutes a viable method for extracting feature vectors in online signature-based biometric systems, specifically for the verification of handwritten online signatures and the detection of forgery

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