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SIGNATURE VERIFICATION USING LOW TRAINING SAMPLE REGIMES

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ABSTRACT

Signature verification systems often rely on a substantial number of user-enrolled samples to achieve high accuracy. However, real-world applications such as mobile banking and forensic verification often encounter constraints that limit the availability of training data. This study investigates the performance of a signature verification system trained with only 3 to 8 genuine signatures per user. Using the SVC 2004 dataset and hybrid wavelet transform (HWT)-based features, we analyze system behavior across different enrollment sizes and evaluate Equal Error Rate (EER), False Acceptance Rate (FAR), and False Rejection Rate (FRR). Results demonstrate that with optimized preprocessing and Hidden Markov Model (HMM) configurations, acceptable accuracy can be achieved even in low-sample regimes, with an EER of 5.1% using only 5 samples. These findings suggest that signature biometrics can be effectively deployed in limited-data scenarios.

1. INTRODUCTION

Biometric authentication systems strive to deliver high security while maintaining user convenience. Online signature verification, as a behavioral biometric, is particularly suitable for environments such as e-signatures, mobile banking, and forensics [1]. However, these scenarios often face challenges due to limited sample availability, either due to user reluctance or time constraints during enrollment [2][3].

While many biometric systems are evaluated using 10–20 training samples per user [4], this paper explores the feasibility of maintaining effective verification accuracy using only 3–8 training samples. By leveraging pressure-based hybrid feature extraction and carefully configured HMMs, we aim to balance between data efficiency and system robustness.

2. RELATED WORK

Research in limited-data biometric systems has primarily focused on face and fingerprint modalities [5][6]. In signature verification, Rattani and Derakhshani [7] and Ferrer et al. [8] explored performance under low enrollment and user-specific thresholds.

Most studies agree that accuracy decreases with fewer training samples, but recent advances in feature extraction—such as hybrid wavelets and pressure signal modeling—show promise for low-sample performance [9][10]. This study builds upon these techniques by quantifying their effect on verification metrics across 3–8 sample regimes.

3. DATASET AND PREPROCESSING

1) Dataset - SVC 2004 Dataset [11] - 40 users, 20 genuine and 20 forged signatures per user - Each signature includes x-y coordinates, pressure, azimuth, and timing events
2) Feature Selection - Pressure signal selected as the primary dynamic feature due to its proven discriminative strength [12] - Resampled to 128 points per signature using linear interpolation
3) Hybrid Wavelet Transform (HWT) - HWT-1 constructed using DHT-DCT pair [13] - 48 features extracted per signature (first 16 + middle 32 coefficients) - Normalized using z-score scaling
4) Symbol Generation - K-means clustering used to generate observation symbols (300 clusters) [14]

4. HIDDEN MARKOV MODEL SETUP

1) Configuration - Ergodic HMM with 4 hidden states - Uniform transition and emission probability initialization - Training iterations capped at 50 using Baum-Welch algorithm [15]
2) Training Sample Variants - Signature samples used per user: 3, 4, 5, 6, 7, 8 - Test set: remaining 17–12 genuine + 20 forged per variant
3) Evaluation Metrics - False Acceptance Rate (FAR) - False Rejection Rate (FRR) - Equal Error Rate (EER) - Average recognition time per sample

5. EXPERIMENTAL RESULTS

5.1. EER and Accuracy Trends:

Training Samples	FAR (%)	FRR (%)	EER (%)
3	9.1	10.4	9.8
4	7.3	8.1	7.7
5	4.9	5.3	5.1
6	4.6	4.9	4.7
7	4.3	4.5	4.4
8	4.2	4.3	4.25

Observations - Significant improvement from 3 to 5 samples - Performance plateau begins after 6 samples - Diminishing returns beyond 7–8 samples in EER reduction

System Efficiency - Training time for 5 samples: ~12 seconds per user - Model size remains below 1.2 MB due to efficient HWT features

6. DISCUSSION

Our experiments demonstrate that low-sample signature verification is feasible with proper signal processing and model optimization. Pressure-based hybrid wavelet features ensure high signal fidelity, compensating for reduced training diversity.

The marginal EER difference between 5 and 8 samples suggests that systems targeting rapid enrollment—such as on-the-fly authentication—can operate effectively with as few as 5 genuine signatures per user [16].

7. CONCLUSION

This study confirms the viability of accurate signature verification with minimal training samples. Using HWT-based pressure features and a compact HMM configuration, we achieve EER as low as 5.1% with only five samples.

These findings support practical applications in constrained environments such as mobile devices and digital onboarding platforms, where user data is limited but security cannot be compromised.

Future work may explore adaptive enrollment strategies and integrate deep learning models to further enhance performance in extreme low-data regimes.

CONFLICT OF INTERESTS

None.

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