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PRESSURE DYNAMICS AS A KEY FEATURE IN ONLINE SIGNATURE BIOMETRICS

Dr. Vinayak A. Bharadi [1], Dr. Manoj Chavan [3]

[1] Information Technology Department, Finolex Academy of Management and Technology, Ratnagiri (MH), India
[2] Electronics & Telecommunication Engineering Department, Thakur College of Engineering & Technology, Mumbai, India

Corresponding Author
Dr. Vinayak A. Bharadi,
vinayak.bharadi@famt.ac.in

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ABSTRACT

Online signature verification has gained prominence as a behavioral biometric modality due to its non-intrusive acquisition and inherent individual variability. Among several dynamic parameters captured during the signing process—pressure, azimuth, altitude, and timing—this study identifies pressure as the most discriminative feature. Through systematic experimentation using the SVC 2004 dataset and Hybrid Wavelet Transform (HWT) based feature extraction, we compare classification performance using individual and combined features. The results demonstrate that pressure alone achieves higher accuracy and lower Equal Error Rate (EER) than azimuth or timing features. Statistical analysis confirms pressure's superior consistency, discriminatory power, and robustness against forgery.

1. INTRODUCTION

Biometric authentication based on behavioral traits is increasingly being used in digital security applications, with online signature verification emerging as a popular choice due to its intuitive, user-friendly nature and legal acceptability [1][2]. Online signatures capture not just the shape of the written text but also dynamic parameters such as pressure, pen azimuth and altitude, and inter-point timing, offering a rich set of features for identity verification [3].

Among these, pressure dynamics—i.e., the force exerted by the pen during signing—has been suggested as a potential standalone indicator due to its subtle inter-user and intra-user variability [4]. However, comprehensive comparative studies against other dynamic features are limited in scope. This paper aims to fill that gap by evaluating pressure in isolation and in combination with other parameters, using identical preprocessing and modeling techniques.

2. RELATED WORK

Earlier studies in biometric literature have investigated various dynamic features for signature verification. Jain et al. [5] proposed using a combination of trajectory and dynamic data, while Plamondon and Srihari [6] focused on temporal segmentation and stroke modeling. Fierrez et al. [7] found that time-based features such as stroke duration and velocity offered moderate accuracy.

Kholmatov and Yanikoglu [8] demonstrated improved verification performance when combining pressure with positional data. More recent studies by Rattani and Derakhshani [9], Hassanat and Jassim [10], and Galbally et al. [11] have investigated pressure and pen dynamics for enhanced verification performance. However, the specific comparative potential of pressure versus other features remains underexplored. This research isolates pressure and quantitatively benchmarks it against azimuth, altitude, and timing using identical wavelet-based preprocessing and HMM-based classification.

3. DATASET AND FEATURE EXTRACTION

1) **Dataset Overview:** SVC 2004 Dataset [12] - 40 users, 20 genuine and 20 forged samples per user - Each signature recorded as a time sequence of x-y coordinates, pressure, azimuth, altitude, and timestamp
2) **Feature Types Defined -Pressure:** Normalized pen force values over time - Azimuth: Angle of pen rotation in the horizontal plane - Altitude: Elevation angle of the pen - Timing: Time intervals between sample points
3) **Preprocessing and Extraction:** Resampled each sequence to 128 time steps - Applied Hybrid Wavelet Transform (HWT-1) using DHT-KEKRE and DCT-HADAMARD bases [13][14] - Extracted 48 key coefficients per feature vector (first 16, middle 32): Quantized features into 300 observation symbols using K-means clustering [15]

4. EXPERIMENTAL FRAMEWORK

1) Modeling Approach - Hidden Markov Models (HMM) trained for each user with 4 hidden states - Separate models created for pressure, azimuth, altitude, and timing-based feature vectors - Training: 15 genuine signatures per user - Testing: 5 genuine + 20 forgeries per user
2) Evaluation Metrics - False Acceptance Rate (FAR) - False Rejection Rate (FRR) - Equal Error Rate (EER) - Variance in feature stability (inter- and intra-user)

5. RESULTS AND ANALYSIS

5.1. ACCURACY COMPARISON

Feature	EER (%)	FAR (%)	FRR (%)
Pressure	4.2	4.5	3.9
Azimuth	7.1	6.8	7.4
Altitude	6.4	6.0	6.8
Timing	5.8	5.9	5.7

Stability and Variance Analysis: Pressure values exhibited lowest intra-user variance (avg. $\sigma^2 = 0.12$) - Azimuth showed high fluctuation due to natural wrist rotations - Timing and altitude more sensitive to writing speed and posture

Fusion vs. Standalone Use: Fusion (pressure + timing) improved accuracy slightly (EER = 3.8%) - However, pressure alone was close in performance with less complexity

6. DISCUSSION

Our findings establish that pressure is a highly stable and discriminative feature for online signature verification. Unlike azimuth or altitude, which vary significantly with pen grip and writing posture, pressure is relatively consistent for an individual and difficult to replicate by an impostor [16].

Moreover, pressure's resistance to performance degradation across different sessions and devices has been noted in prior works [17][18]. The wavelet-based transformation further enhances its discriminatory power by isolating key frequencies related to pen strokes.

7. CONCLUSION

This research confirms that pressure dynamics offer superior accuracy, robustness, and usability in online signature verification compared to other dynamic features. While feature fusion can offer marginal gains, pressure alone is often sufficient and more computationally efficient.

Given the pressure sensor availability in modern stylus devices, we recommend prioritizing pressure-based models for commercial biometric systems, especially in mobile environments.

CONFLICT OF INTERESTS

None.

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