
An Adaptive Case-Based Reasoning Approach for Biometric Signature Authentication using Dynamic Time Warping

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ABSTRACT

The present study develops an adaptive framework based on Case-Based Reasoning (CBR) for handwritten signature authentication. The system employs Dynamic Time Warping (DTW) to handle temporal variations in signature sequences and maintains an evolving case repository to support continuous learning. The integration of structural and behavioral features improves authentication accuracy and enhances the detection of forged signatures. The results indicate improved performance over conventional methods in terms of reliability and consistency.

1. Introduction

Case-Based Reasoning (CBR) is an experience-driven computational approach in which previously solved instances are reused to tackle new problems. While it has been successfully applied in areas such as plagiarism analysis, its implementation in biometric authentication is more challenging due to the dynamic nature of human input patterns.

Handwritten signatures exhibit variability influenced by factors such as writing speed, pen pressure, and natural fluctuations over time. These variations complicate the verification process and reduce the reliability of static models. Addressing these inconsistencies requires an adaptive solution. The system integrates temporal alignment with a learning framework to deal with intra-class variations and enhance performance stability.

2. Related Work



A variety of techniques have been explored for signature verification, including Artificial Neural Networks, Hidden Markov Models, and Dynamic Time Warping. Although these approaches achieve reasonable accuracy, many of them operate on static models and lack mechanisms for continuous learning. As a result, their performance may decline when encountering new or evolving signature patterns.

3. Proposed Framework

The proposed system consists of three major stages:

1. Preprocessing
2. Feature Extraction
3. Similarity Matching using DTW

As depicted in Figure 1, the system uses a sequential pipeline for signature verification.

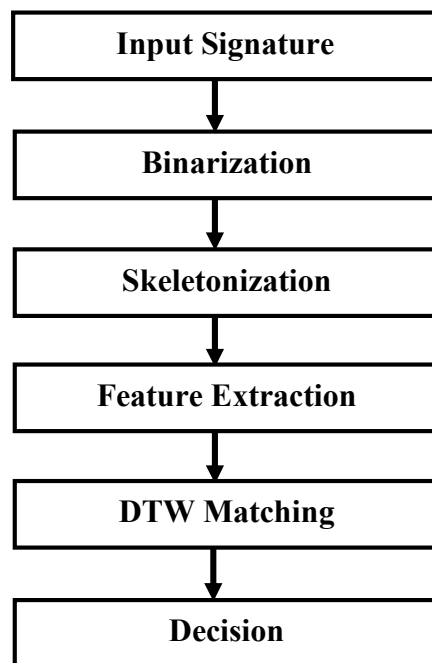


Figure 1. Proposed Architecture of the Signature Verification System

[Input Signature → Binarization → Skeletonization → Feature Extraction → DTW Matching → Decision]

4. Methodology



4.1 Preprocessing

- Otsu’s Binarization
- Skeletonization (single-pixel width representation)

4.2 Feature Extraction

The signature image is partitioned into a **12 × 8 grid**, producing **96 segments**. These local features, combined with 20 global features, result in a **164-dimensional feature vector**. The grid-based segmentation shown in Figure 2 enables detailed local feature analysis of the signature.

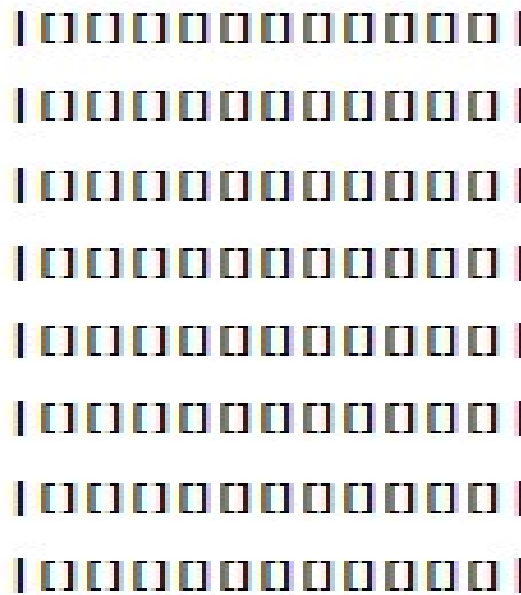


Figure 2. Grid-Based Segmentation of Signature Image (12 × 8 = 96 Cells)

5. Mathematical Model

5.1 Pixel Density

$$D(i, j) = B(i, j) / T(i, j)$$

Where:

B(i, j): Number of black pixels in the grid cell

T(i, j): Total number of pixels in the grid cell

5.2 Euclidean Distance



$$d = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}$$

5.3 Dynamic Time Warping

$$D(i, j) = \text{cost}(i, j) + \min (D(i-1, j), D(i, j-1), D(i-1, j-1))$$

These equations support comparison of signature patterns and improve the accuracy of similarity evaluation in the system.

6. Dynamic Time Warping

Dynamic Time Warping (DTW) is a sequence alignment technique that minimizes temporal distortions between two time-dependent signals by identifying an optimal warping path. It determines the best alignment by reducing cumulative distance across sequences.

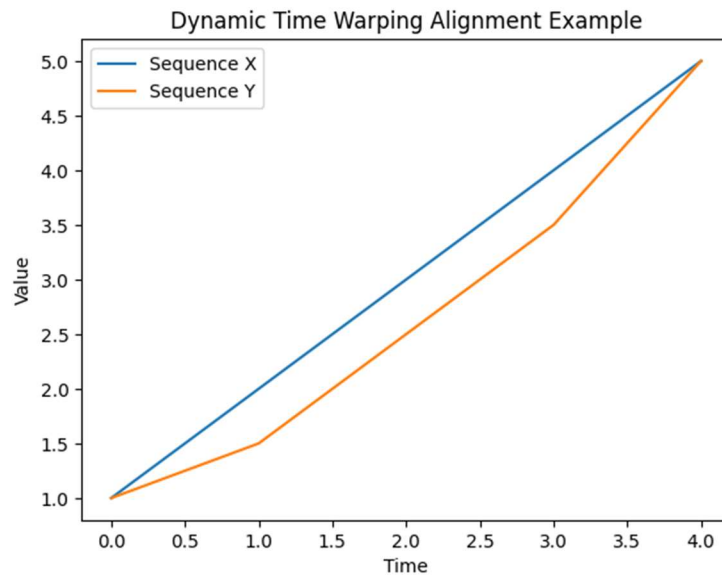


Figure 3. Alignment of Two Time Series using Dynamic Time Warping

Time Y ↑

-
-
-
-
-
-

-----→ Time X

7. Experimental Results



Table 1. Performance Comparison of Signature Verification Methods

Method Used	Accuracy (%)	FAR	FRR
MLP	88.5	Medium	Medium
Proposed CBR-DTW	94.2	Low	Low

The comparative analysis shows that the proposed CBR-DTW approach achieves higher accuracy than the MLP-based model. Additionally, it records lower False Acceptance Rate (FAR) and False Rejection Rate (FRR), indicating improved handling of temporal variations in handwritten signatures. These results support the applicability of the proposed method in practical biometric verification scenarios.

8. Discussion

The results suggest that the integration of Case-Based Reasoning with Dynamic Time Warping improves verification performance. DTW assists in aligning temporal sequences and reducing inconsistencies caused by variations in writing patterns. At the same time, the system adapts by incorporating new samples into its case repository, which helps lower FAR and FRR and improves performance on unseen signatures. Compared to traditional machine learning models, the framework offers enhanced adaptability and reliability.

9. Conclusion

This study presents an integrated approach combining Case-Based Reasoning and Dynamic Time Warping for handwritten signature authentication. The framework effectively addresses challenges related to temporal variation and intra-class differences. The results demonstrate improvements in both accuracy and reliability, indicating its suitability for real-world biometric applications.

10. Future Scope

- **Convolutional Neural Networks (CNNs)**
- Deployment in mobile authentication systems
- Extension to multi-modal biometric systems

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