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Offline Writer Independent Handwritten Signature Verification System

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Abstract— ***The signature stands as a pivotal trait of an individual, serving not only as a means of identification but also as a cornerstone for validating official documents. This study aims to explore the potential of geometric features in crafting a robust offline signature verification system employing multiple classifiers with a writer-independent approach. In this endeavor, a writer-independent offline handwritten signature verification model termed the global model, is introduced. Utilizing a Support Vector Machine with a polynomial kernel, the global model is constructed. Two distinct signature databases are employed to assess the classifier's performance, gauged by the Average Error Rate. The findings reveal the efficacy of the Support Vector Machine with geometric features model in effectively discerning between genuine and forged handwritten signatures of the writer.***

Keywords— ***Handwritten Signature, Writer Independent Approach, Writer Dependent Approach, Geometric Features, Support Vector Machine***

I. INTRODUCTION

A person's signature is a recognized biometric characteristic, employed for authenticating official documents and verifying personal identity. Handwritten Signature Verification (HSV) systems play a crucial role in determining the authenticity of signatures and distinguishing between genuine and forged ones. Over the past few decades, various signature verification systems have been explored, broadly categorized into offline and online systems [1]. Online systems utilize optical pens and sensors to capture dynamic handwriting features such as writing speed, pressure distribution, and stroke order during signing. Conversely, offline systems involve collecting signatures on paper and scanning them with optical scanners. Due to the lack of dynamic information, designing offline systems poses challenges, with online approaches generally outperforming them due to the availability of dynamic features [2].

In the development of signature verification systems, forgery sets are typically divided into subsets of random, simple, and skilled forgeries. Random forgery samples consist of genuine signatures from different writers, while simple forgeries involve forgers who only know the genuine writer's name. Skilled forgeries, also known as simulated forgeries, entail forgers who are well-acquainted with the genuine signature and have practiced replicating it extensively [3]. Figure 1 illustrates random, simple, and skilled forgeries alongside genuine signature samples.

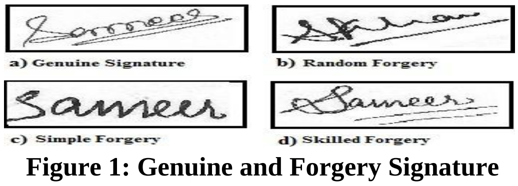

Figure 1: Genuine and Forgery Signature

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The performance evaluation of handwritten signature verification systems revolves around two key metrics: False Rejection Rate (FRR) and False Acceptance Rate (FAR). FRR, also known as type I error, signifies the percentage of genuine signatures erroneously rejected as false, while FAR, or type II error, indicates the percentage of forged signatures erroneously accepted as genuine. Researchers often analyze the Average Error Rate (AER), which is the average of FRR and FAR.

Researchers have explored two primary approaches to offline signature verification systems: writer-dependent (WD) and writer-independent (WI) [2]. In the writer-dependent approach, a distinct model is created for everyone. This model development constitutes a two-class problem, with Class 1 comprising genuine signature samples of a specific writer, and Class 2 containing forgery samples. Conversely, the writer-independent approach focuses on modeling the likelihood distribution between classes and within-class similarities [2].

The writer-dependent approach faces two significant limitations: firstly, it necessitates a large number of genuine signature samples, and secondly, it cannot accommodate new individuals without constructing a new personal model for each. In contrast, the writer-independent approach, also known as the global model, requires only one model to handle all individuals and can incorporate unknown individuals without altering the model. This approach simplifies the signature verification task into a two-class problem, where Class1 encompasses genuine samples from all individuals, and Class2 comprises forgeries (see Figure 2). A major advantage of this approach is its ability to construct a reliable model even with a limited number of genuine signature samples.

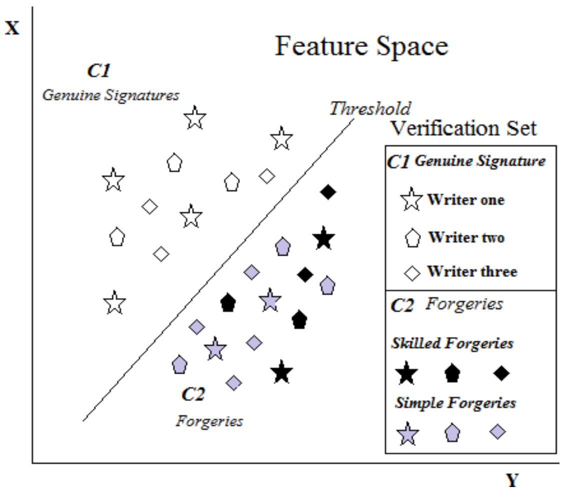

Figure 2: Global Model Signatures Area for Different Writers

Cesar Santos et al. proposed the writer-independent approach for classifying signature samples as either genuine or forged during the development of handwritten signature verification (HSV) systems. Researchers have also tackled the challenge

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of writer-independent HSV using various techniques such as Hidden Markov Models (HMM) [5] [6], machine learning models like Artificial Neural Networks (ANN) [7], Distance Classifier [8] [9], and Support Vector Machines (SVM) [10].

This study aims to construct an offline handwritten signature verification system utilizing the writer-independent approach, a dissimilarity-based method introduced by Cesar Santos et al. Two signature databases are established for evaluation: one comprising samples from 100 writers and the other from 260 writers. Geometric features are extracted from these signature samples to evaluate the performance of the Support Vector Machine with Polynomial Kernel (PSVM).

The remainder of the paper is organized as follows: Section II elucidates the workings of the writer's independent approach. Section III provides details regarding the databases used in the study. Section IV delineates the procedure for feature extraction from signature images. Section V delves into experimental particulars while concluding remarks are presented in Section VI.

I. WRITER INDEPENDENT APPROACH

The writer-independent approach also termed the global approach, is utilized for categorizing offline handwritten signature samples as either genuine or forged. In this methodology, a questioned signature sample (QS) undergoes comparison with reference signature samples RSk (where k ranges from 1 to n), and the degree of dissimilarity is determined using features extracted from both the questioned sample and reference signatures [18], [19]. Based on this dissimilarity measurement, the signature is then classified as either genuine or forged. Various perspectives on proximity, dissimilarity, and similarity concepts are explored in [11, 12, 13]. The notion of dissimilarity representation was introduced by E. Pekalska et al. [13], with the premise that dissimilarities should be significant for objects belonging to different classes and minimal for objects within the same class. To construct the dissimilarity feature vector Di, the disparity between the feature vectors of the reference sample and the questioned sample is computed and forwarded to the classifier to make partial decisions. These partial decisions collectively influence the final decision through fusion strategies (refer to Figure 3).

II. SIGNATURE DATABASE

The current study utilizes two signature databases, namely SDB1 and SDB2. SDB1 comprises signature samples from 100 writers, while SDB2 encompasses samples from 260 writers. Within SDB1, 60 writers' signatures are allocated for training and 40 for testing, whereas in SDB2, 160 writers' signatures are assigned for training and 100 for testing. The signatures are collected from undergraduate and postgraduate students of an educational institution across two sessions conducted once every fifteen days over the course of a month. A standard A4 size paper is employed for signature collection, subsequently scanned at 600 dpi gray level.

During each session, each writer produces 20 genuine signatures. Additionally, for each genuine writer, four students are chosen to create forgeries. Each forger generates 5 signatures for simple forgeries and 5 for simulated forgeries, resulting in a total of 20 simple and 20 simulated forgeries per genuine writer. Simple forgeries are crafted with only knowledge of the writer's name, while simulated forgeries involve extensive practice with genuine signatures.

In this study, a dissimilarity-based approach is adopted, where classifiers are trained with positive (genuine) and negative (forgery) samples. Positive samples are generated by computing dissimilarity vectors among 6 genuine samples per writer, yielding 15 distinct combinations for SDB1 and 2400 for SDB2. Random forgery samples are exclusively utilized to form negative sample sets. For SDB1, negative samples are generated from dissimilarity vectors computed from the first four genuine samples of the first five writers and the first four genuine samples of randomly selected 50 writers from the remaining training set, totaling 1000 negative samples. Similarly, for SDB2, negative samples are generated from dissimilarity vectors computed from the first four genuine samples of the first five writers and the first four genuine samples of randomly selected 140 writers from the remaining training set, resulting in 2800 negative samples.

In total, 1900 dissimilarity vectors for SDB1 and 5200 for SDB2 are utilized to train PSVM. The number of required genuine and forgery samples of signatures depends on the number of references used for the questioned signature during the testing process. In the current approach, forgery and genuine signature samples from writers not included in the training process are used for testing.

III.. FEATURE EXTRACTION

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In this study, ten distinct features are utilized to form the geometric feature vector, namely: signature area, mean, standard deviation, number of connected components, perimeter of the signature image, number of horizontal edges, number of vertical edges, number of edge points, number of lines (both horizontal and vertical), and number of branch points. A detailed description of each of the ten features used in the geometric feature vector for signature analysis is given below.

1. Signature Area: The signature area refers to the total area covered by the signature on the document or image. It provides a measure of the spatial extent of the signature.
2. Mean: In this context, mean refers to the average value of pixel intensities within the signature region. It provides insight into the overall brightness or darkness of the signature.
3. Standard Deviation: Standard deviation measures the dispersion or spread of pixel intensities within the signature area. A higher standard deviation indicates greater variability in pixel intensities, suggesting more complexity or detail in the signature.
4. Number of Connected Components: Connected components are distinct

regions within the signature image that are connected by adjacent pixels. Counting the number of connected components helps characterize the complexity or structure of the signature.

5. Perimeter of the Signature Image: The perimeter is the boundary or outline of the signature. Measuring the perimeter provides information about the shape and complexity of the signature.
6. Number of Horizontal Edges: Horizontal edges refer to transitions in pixel intensity values along horizontal lines within the signature. Counting the number of horizontal edges helps quantify the horizontal structure or texture of the signature.
7. Number of Vertical Edges: Similarly, vertical edges denote transitions in pixel intensity values along vertical lines within the signature. Counting the number of vertical edges provides insight into the vertical structure or texture of the signature.
8. Number of Edge Points: Edge points are the pixels where significant changes in intensity occur, indicating boundaries or transitions within the signature. Counting the number of edge points helps assess the overall sharpness or clarity of the signature.
9. Number of Lines (Horizontal and Vertical): Lines represent prominent straight segments within the signature, either horizontally or vertically oriented. Counting the number of horizontal and vertical lines helps characterize the overall structure and organization of the signature.
10. Number of Branch Points: Branch points are locations within the signature where multiple edges intersect or diverge. Counting the number of branch points provides insight into the complexity and branching structure of the signature.
11. These features collectively capture various aspects of the signature's size, shape, texture, and complexity, facilitating its analysis and classification in signature verification systems.
12. To derive the geometric feature vector from a pre-processed signature image sized 256 x 512, the following steps are undertaken:
13. Global Feature Extraction: Ten features are extracted from the entire signature image, constituting the global features.
14. Local Feature Extraction: The signature image is partitioned into four equal segments, and the same ten features are extracted from each segment to obtain local features.

As a result, a total of 10 global and 40 local features are extracted from the signature image, culminating in a geometric feature vector with a length of 50.

IV. EXPERIMENTAL DETAILS

In this study, the training of classifiers excludes simple and simulated forgery signature samples, focusing solely on genuine and random forgery samples. This approach is chosen because simple and skilled forgery samples may not be readily available during system development for many applications. Two scenarios, labeled Scenario I for SDB1 and Scenario II for SDB2, are employed to assess the performance of PSVM classifiers using geometric feature vectors. Table 1 provides the time required (in seconds) for training the PSVM classifiers with geometric features.

MATLAB is utilized to conduct the experiments. The experiments are conducted with varying numbers of reference signatures (RS), specifically 3, 5, 7, 9, 11, 13, and 15.

This range is chosen to accommodate fusion strategies such as median, mean, majority voting, max, and min, which typically perform optimally with an odd number of partial decisions. Among these strategies, mean fusion yields the most promising results in this study. Table 2 and Table 3 present the performance of the classifiers (CF)

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using geometric features, as measured by Average Error Rate (AER), for Scenario I and Scenario II, respectively.

Table 1: Elapsed Time (in seconds) for Classifiers in Training using Geometric Features

Database	Classifier Used	Elapsed Time
SDB1	PSVM	1.7511
SDB2	PSVM	4.4995

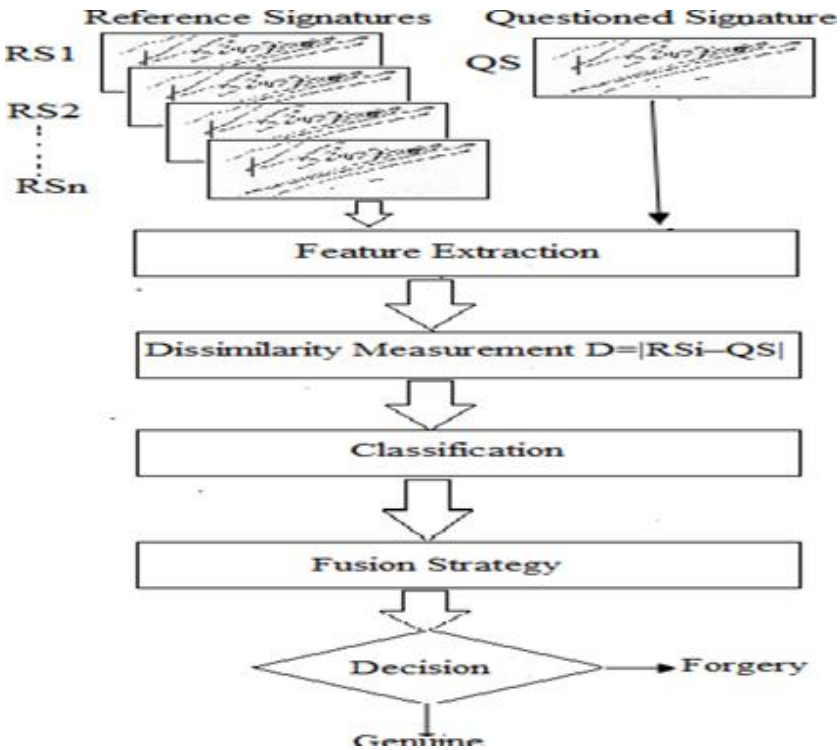

Figure 3: Writer Independent Approach for Offline Signature Verification System

Table 2: Classifier Performance for Scenario-I using Geometric Features in Terms of AER

S.No.	Reference Signatures	AER
1	3	9.375
2	5	9.375
3	7	9.375
4	9	9.375
5	11	9.375
6	13	9.500
7	15	12.500

Table 3: Classifier Performance for Scenario-II using Geometric Features in Terms of AER

S.No.	Reference Signatures	AER
1	3	5.250
2	5	7.250
3	7	6.750
4	9	7.500
5	11	7.000
6	13	7.250
7	15	7.500

In this approach, writers involved in the training phase are excluded from the testing process. The experiments are conducted on a system with a Core 2 Dual processor and 4 GB RAM configuration. The elapsed time (in seconds) for both training and testing of classifiers is recorded. It's important to note that the elapsed time may vary based on the specific system configuration employed.

V. CONCLUSION

This study focuses on evaluating the performance of PSVM classifiers utilizing geometric feature sets across two handwritten signature databases. The primary goal is to propose an effective global offline handwritten signature verification system.

The findings demonstrate that the PSVM classifier, when combined with geometric features, effectively distinguishes between genuine and forged signatures of the writer. Additionally, experimental results indicate that the classifiers perform better on the SDB2 database compared to SDB1.

Based on these observations, it can be inferred that enhancing the system's accuracy, as measured by the Average Error Rate (AER), could be achieved by expanding the number of users included in both the training and testing processes.

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