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Study of Different Soft Computing Techniques Used For Handwritten Signature Recognition

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Abstract
Handwritten signature recognition has witnessed significant advancements in recent years, with a plethora of research focusing on enhancing the verification process. However, despite these efforts, several gaps persist in the verification process of handwritten signatures. This paper delves into the comparative study of various soft computing techniques employed for handwritten signature recognition, acknowledging its pivotal role in computer vision and soft computing domains. Handwritten signatures serve as crucial authentication mechanisms across diverse sectors, emphasizing the importance of selecting efficient soft computing techniques to ensure robust verification and prevent forgeries. This paper presents a comprehensive review spanning the past 15 years, analyzing more than 20 research papers to compare datasets, feature extraction methods, and classification techniques utilized in signature verification. Moreover, it highlights the challenges associated with each approach and provides insights into the advantages and limitations of soft computing techniques employed for signature feature extraction and classification.

Index Terms - Neural Network, Genetic Algorithm, Soft Computing, Computer Vision

Introduction

The verification of handwritten signatures is inherently complex due to variations in writing styles, individual characteristics, and the presence of noise. Consequently, researchers have turned to soft computing techniques, which encompass a range of computational methodologies inspired by biological systems, to address these challenges effectively. The identification and verification of individuals rely on a variety of physical and behavioral characteristics, including fingerprints, facial features, gestures, retinal patterns, and DNA. Handwritten signature, as a behavioral characteristic, serves as a crucial component in personal verification systems. However, unlike other biometric traits, handwritten signatures present a unique challenge due to their inherent complexity. Handwritten signatures exhibit variability even when authored by the same individual, influenced by factors such as physical condition, psychological state, and writing style. This variability poses significant challenges in developing robust verification systems. Despite these challenges, handwritten signatures remain an indispensable biometric trait, offering a convenient and widely accepted means of personal authentication.

The primary objective of this review paper is to provide a comparative summary of recent advancements in the field of handwritten signature verification. Specifically, we aim to analyze and contrast the findings from over 20 research papers, highlighting the methodologies, datasets, and outcomes of various studies. By synthesizing this information, we seek to identify the strengths and weaknesses of existing approaches, thereby shedding light on potential areas for improvement and future research directions.

We can use Soft computing techniques such as neural networks, fuzzy logic, genetic algorithms, and support vector machines offer flexibility and adaptability, making them well-suited for signature recognition tasks. Given the proliferation of research in this field over the past 15 years, it becomes imperative to conduct a comprehensive comparative study to evaluate the efficacy of various soft computing techniques for handwritten signature recognition. Such an analysis can provide valuable insights into the strengths and limitations of different approaches, thereby guiding researchers and practitioners towards selecting the most appropriate techniques for specific applications.

Literature Review

Based on the summaries provided, it seems that the papers referenced cover challenges in signature verification, such as False Rejection Rate and False Acceptance Rate, and identifies types of forgeries. They mentioned outlines the four basic components of a signature verification system: Data acquisition, Pre- Processing, Feature Extraction, and Recognition/Verification. Author provides details the use of Self- Organizing Map (SOM) for feature extraction and Support Vector Machine (SVM) for classification. Specifies the database used for testing, consisting of genuine and forgery samples from 20 individuals.

- G. Pirlo, V. Cuccovillo, D. Impedovo, P. Mignone developed on-line signature verification technique. They Focused on online signature verification and employs a multi-domain strategy for classification and utilized Dynamic Time Warping (DTW) for evaluating the genuineness of signature segments. They Conducted experimental evaluation using the SUSIG database.
- In this paper Hemanta Saikia, Kanak Chandra Sarma had mentioned different approaches and issues related to offline signature verification systems. Likely provides insights into the state-of-the-art techniques and challenges in the field.
- In this paper author proposed an offline signature verification and recognition system using the Pixel Matching Technique (PMT) and compares it with ANN back-propagation and SVM techniques. Likely provides experimental results to demonstrate the performance of the proposed method.
- In this study, the author explores the efficacy of pre-trained Convolutional Neural Networks (CNN) in feature extraction from genuine and forged signatures. The extracted features are then subjected to classification using Support Vector Machine (SVM), Naive Bayes (NB), and k-Nearest Neighbors (KNN) algorithms. The performance of these classifiers is evaluated based on metrics such as run time, classification error, classification loss, and accuracy using a test-set comprising genuine and forged signature images. The
- Experiments are conducted on the UTSig dataset, and the results are analyzed to assess the effectiveness of each classifier in the verification phase. This study contributes to understanding the comparative performance of different classification algorithms in the context of handwritten signature recognition, providing valuable insights for the development of robust signature verification systems.
- In this paper, Author implemented a machine-learning single-layered Neural Network model (SOM) for signature Detection by collecting multiple users' signatures. They utilized SVM for classification and evaluates performance using FAR and FRR metrics.
- This study focuses on the development and comparison of three algorithms based on the principles of ART-1, ART-2, and Auto-AMN for offline signature verification. The objective is to achieve high accuracy while minimizing time consumption, considering signature verification as a bi-objective optimization problem.

Key points from this study include:

i. Algorithm Development: Three algorithms based on ART-1, ART-2, and Auto-AMN principles were developed for signature verification.

ii. Parallel Implementation: Parallel methods were proposed for all three algorithms to distribute computation work across multiple processors, aiming to achieve results in minimal CPU time.

The performances of ART-1, ART-2, and Auto-AMN were compared. The study revealed the following results:

a) ART-1 achieved 99.89% accuracy with a time consumption of 8.37 seconds in serial and 2.28 seconds in parallel execution.

b) ART-2 achieved 99.99% accuracy with a time consumption of 5.86 seconds in serial and 1.58 seconds in parallel execution on a quad-core processor.

c) Auto-AMN achieved a detection accuracy of 75.68% with a time consumption of 9.58 seconds in serial and 2.98 seconds in parallel.

Parameter Settings: For ART-1 and ART-2, the number of cluster unit's 'm' was set to 20. The error threshold was set to 5% for decision-making in the case of AMN. Overall, the study demonstrates the effectiveness of ART-1 and ART-2 algorithms in achieving high accuracy with reduced time consumption, especially when executed in parallel. However, Auto-AMN, despite having lower accuracy, also benefits from parallel execution in terms of time efficiency. These findings contribute to advancing the state-of-the-art in offline signature verification algorithms and provide insights into optimizing performance for real-world applications.

In this research study, the author employs the Artificial Neural Network (ANN) algorithm with Back Propagation for signature recognition. A notable aspect of this study is the development of a mechanism to adaptively adjust the learning rate, aimed at enhancing the accuracy of the system. The primary objective of the study is to assess the effectiveness of the Back Propagation algorithm in recognizing signatures. By Conducting recognition experiments on a number of signatures, the study aims to evaluate the appropriateness of using Back Propagation for this task.

The testing results are obtained using specific parameters:

- Learning rate: 0.64
- Number of iterations: 100

The study reports an accuracy value of 63% based on these parameters. This accuracy value reflects the performance of the ANN algorithm with Back Propagation in recognizing signatures under the specified conditions. Overall, the study contributes to the understanding of the applicability and performance of Back Propagation in signature recognition tasks. It highlights the importance of parameter tuning, such as adjusting the learning rate, in optimizing the accuracy of the recognition system. Further experimentation and optimization may be necessary to improve the recognition accuracy and enhance the effectiveness of the signature recognition system.

The author introduces a novel fuzzy approach to offline handwritten signature recognition. The solution involves characteristic feature extraction, which begins with finding the signature's centre of gravity. Then, a series of lines are drawn through this centre at various angles, and the cross points of these lines with the signature sample are identified. These cross points are then grouped and sorted to form structures, from which a fuzzy model termed the "fuzzy signature" is created. During the verification phase, the level of conformity between an input sample and the fuzzy signature is calculated.One notable aspect of this approach is its extension in feature extraction and the introduction of the fuzzy model, which had not been previously employed. Moreover, the solution ensures that the information stored within the verification system cannot be used to recreate the original signatures collected during the enrolment phase, enhancing storage safety, particularly in large databases where security is paramount. Additionally, the approach is highly flexible, allowing for the intuitive extension of fuzzy sets through the incorporation of dynamic features, thereby enabling it to function as an online method.

Author utilized special domain features such as high-intensity variation points and cross-over points extracted from genuine as well as test signatures. These features likely serve as distinctive characteristics for signature recognition, contributing to the effectiveness of the verification system.

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Working

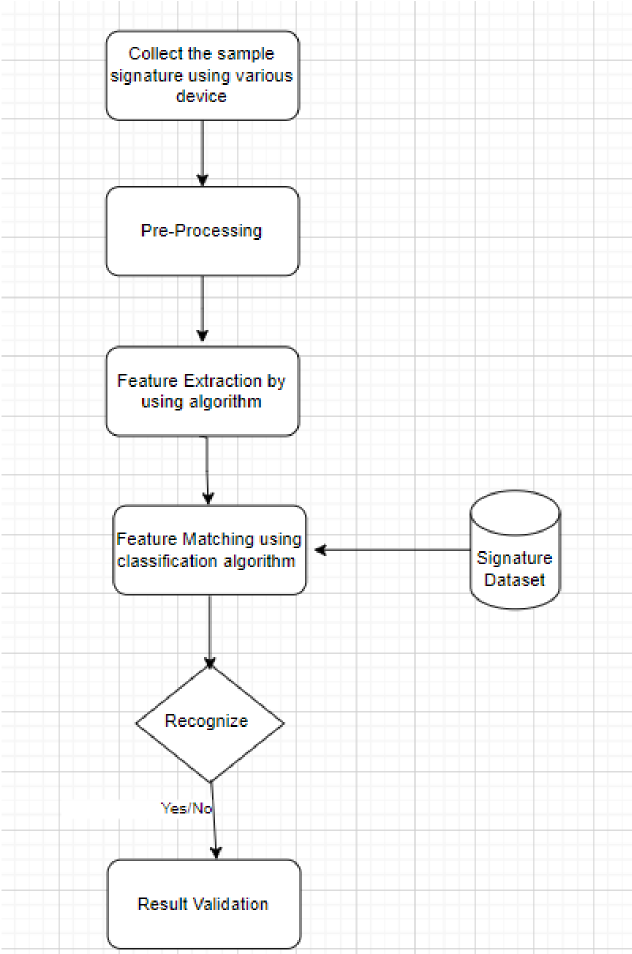
Implementation of different Stages used for signature verification are as follows:

a) Data acquisition: - In offline signature verification systems, data is collected using off-line acquisition devices such as cameras or optical scanners. These devices capture the signature image and convert it into a digital format.

b) Pre-processing the input signatures: - Pre-processing involves improving the quality of the signature data after acquisition. This includes various operations such as converting colour images to grayscale, removing noise, thresholding, morphological operations, cropping, binarization, and normalizing signature size.

c) Extraction of special features: - Feature extraction techniques for handwritten signatures can be categorized into global and local features:
   i. Global feature techniques compute features from the entire signature, often focusing on geometric characteristics, wavelet coefficients, and Fourier coefficients.
   ii. Local feature techniques compute features from specific regions within the signature, including texture features and gradient features.

d) Classification: - The classification stage involves comparing the extracted features with template signatures stored in the database to determine the class of the tested signature.
   i. Decision-making regarding the authenticity of the signature is known as verification, typically treated as a two-class classification problem.
   ii. Verification: Verification Includes following methods:
      - Model-based verification: Describes the data distribution by generating models such as convolutional neural networks (CNN), hidden Markov models (HMM), and support vector machines (SVM).
      - Distance-based verification: Utilizes distance measures for comparing the test signature with reference signatures, often employing dynamic time warping (DTW) for comparison.



Overall, the signature recognition system progresses from data acquisition and pre-processing to feature extraction and classification, with the ultimate goal of accurately verifying the authenticity of handwritten signatures. Each stage plays a crucial role in ensuring the system's effectiveness in real-world applications.

This paper presents a comparative analysis of the most common soft computing techniques utilized for feature extraction and classification in the context of handwritten signature recognition. The study focuses on evaluating the effectiveness of various feature extraction methods and classification techniques through a systematic comparison. The results of this comparison are presented in tabular format, highlighting key performance metrics such as accuracy, precision, recall, and computational efficiency. By synthesizing findings from multiple studies and experiments, this comparative analysis provides valuable insights into the strengths and limitations of different soft computing approaches for feature extraction and classification in handwritten signature recognition systems. These insights can guide researchers and practitioners in selecting appropriate techniques for enhancing the accuracy and efficiency of signature recognition systems in practical applications.

Comparative Analysis

Table 4.1: Study of different feature extraction techniques used in previous research papers.

Feature Extraction Method	Classification Method	Author	Used Dataset	Result	Issued
Global and local features selected using genetic algorithm	Support vector machine (SVM) classifier	Sharif et al. [11]	(A) CEDAR (B) MCYT (C) GPDS	(A) AER for CEDAR is 4.67%. (B) AER for MCYT is 5.0%. (C) AER for GPDS is 3.75%.	In this feature extraction technique, We observed High error rate
Histogram of	Generalized	Tas¸kiran	Collected	Accuracy is equal	Here we

oriented gradients (HOG) features	regression neural networks (GRNN) algorithm	and Çam [12]	signature images at Yildiz technical university from 15 person, 40 sample from each.	to 98.33%	observed large implementation costs and processing time
Fine-tuned CNN was used as signature features extraction technique	Support vector machine (SVM) classifier	Bonde et al. [13]	(A)GPDS (B)MYCT-75 (C) UTSig	(A) Accuracy for GPDS is 92.03 (B) Accuracy for MYCT-75 is 90.78 (C) Accuracy for UTSig is 85.46.	We noted accuracy rate is low in standard database Comparative to other feature extraction techniques.
Histogram of oriented gradients (HOG) features	Fuzzy min max classification (FMMC) method	Melhaoui and Benchaou [14]	Collected dataset from 12 person, 20 signature from each	Recognition rate is equal to 96%.	The recognition rate depends highly on the choice of the sensitivity parameter which regulates how fast the membership Value decreased
Convolutional neural network (CNN)	Support vector machine (SVM) classifier	Mersa et al.[15]	(A) GPDS-Synthetic (B) MYCT-75 (C) UTSig	(A) GPDS-Synthetic EER is 6.81%. (B) MYCT EER is 3.98%. (C) UTsig EER is 9.80%.	Deep networks need rich and plentiful training data, which is rare in signature datasets
Moment invariant features	Efficient fuzzy Kohonen clustering network (FKCN) algorithm.	Suryani et al[16]	They use 80 samples of signatures obtained from 8 persons.	Accuracy is equal to 70%.	In this feature extraction technique we found that the accuracy of the training data is smaller than the accuracy of the test data
Circlet transform (CT), Statistical properties was calculated by the gray level co-occurrence matrices (GLCM)	k-Nearest neighbour (k-NN), Support vector machine (SVM) classifier	Foroozandeh et al. [17]	(A)GPDS-Synthetic (B)MYCT-75 (C) UTSig	(A) EER with GPDS-synthetic is 5.67. (B) EER with MYCT-75 is 7 when r = 1 and 8.20 when r =10. (C) EER with UTSig is	The proposed method did not outperform on MYCT-75 dataset

				6.72.	
Histogram of template (HOT) feature	Support vector machine (SVM) classifier	Serdouk et al. [18]	(A) CEDAR (B)MYCT-75	(A) For CEDAR AER is 1.03% (B) For MCYT-75 AER is 6.40%	Here problems occur when Highlight strokes orientation in handwritten signatures appears then accuracy suddenly dropped.
Ridgelet transform and grid features	Support vector machine (SVM) classifier	Nemmour and Chibani [19]	CEDAR dataset	EER is equal to 4.18	The system can achieve higher accuracies but requires larger runtime
Contourlet transform (CT) based directional code Co-occurrence matrix (DCCM) technique.	Writer-independent decision thresholding	Hamadene and Chibani [20]	(A) CEDAR (B)GPDS	(A) For CEDAR AER is 2.10. (B) For GPDS AER is 18.42	The verification step is performed using only the feature dissimilarity measure .

Table 4.2: Study of different Offline Dataset comparison

Dataset name	Language	No. of signers	Genuine	Forge	Total
CEDAR [18]	Belongs to versatile cultural backgrounds	55	24	24	2640
MCYT-75 [18]	Spanish	75	15	15	2250
GPDS-syntheses [11]	Computer-generated dataset		24	30	4000

Table 4.2 display different dataset with the no. of Signatures collected by different author for research and signature languages.

Table 4.3: Comparison between the most used classifiers with their benefits and Limitation.

Logistic Regression	• Simple and fast to implement. • Outputs can be interpreted as probabilities. • Suitable for binary classification tasks.	• Assumes a linear relationship between features and the log-odds of the response. • May not perform well with highly non-linear data. Sensitive to outliers.
Support vector machine (SVM)	• Versatile, as different kernel functions can be used to handle non-linear data. • Robust against overfitting, especially in high-dimensional spaces.	• Computationally expensive, especially with large datasets. • Requires careful selection of kernel and regularization parameters. • Can be sensitive to the choice of the kernel function and its parameters.
Dynamic time warping (DTW)	• Robust to temporal distortions: DTW can handle time-series data that are stretched or compressed in time, making it suitable for analyzing	• Computational complexity: DTW has a time and memory complexity that depends on the lengths of the sequences being compared. It can be

	sequences with variable lengths or speeds • Non-linear alignment: DTW finds the optimal alignment between two sequences by warping them in time, allowing it to capture non-linear relationships and patterns in the data. • Versatility: DTW can be applied to various types of time-series data, including speech recognition, gesture recognition, financial time series, and biomedical signal processing. • No assumption of linearity: Unlike some other methods, DTW does not assume linearity or stationarity in the data, making it suitable for analyzing complex and non-linear time-seriespatterns.	computationally expensive, especially for long sequences or large datasets. • Sensitivity to noise and outliers: DTW may produce suboptimal alignments in the presence of noise or outliers in the data, potentially leading to inaccurate similarity measurements. • Parameter sensitivity: DTW requires setting parameters such as the warping window size, which can significantly affect its performance. Selecting appropriate parameter values can be challenging and may require experimentation. • Memory requirements: Storing the entire distance matrix for computing DTW can consume a large amount of memory, especially for long time-series data. • Not suitable for high- dimensional data: While DTW is effective for analyzing one-dimensional time-series data, it may not perform well with high- dimensional time-series or multivariate time-series data.
Random Forests	• Reduces overfitting compared to individual decision trees. • Can handle large datasets with high dimensionality. • Provides an estimate of feature importance.	• More complex than individual decision trees, harder to interpret. • Can be computationally expensive, especially with a large number of trees. • May not perform well with noisy data.
K-nearest neighbour (KNN)	• Simple and intuitive. • No training phase, making it easy to implement. • Non-parametric, can handle complex decision boundaries.	• Computationally expensive during testing, as it requires calculating distances to all training examples. • Memory-intensive, especially with large datasets. • Performance can degrade with high-dimensional data due to the curse of dimensionality.
Neural Networks	• Can learn complex patterns and relationships in data. • Highly flexible architecture, suitable for various tasks. • Can handle large datasets with high dimensionality.	• Requires a large amount of data for training. • Computationally expensive, especially with deep architectures. • Prone to overfitting, requires careful regularization and tuning.
Decision Trees	• Easy to understand and interpret. • Can handle both numerical and categorical data. • Implicitly performs feature selection.	• Prone to overfitting, especially with complex trees. • Can be unstable, small variations in the data can result in different trees. • Not well-suited for capturing complex relationships in the data.

The choice of classifier depends on factors such as the nature of the data, the size of the dataset, computational resources available, and the specific requirements of the problem at hand.

Table 4.4: Study of different feature extraction techniques used by previous author for signature verification.

Method	Example	Pros	Cons
Histogram of Oriented Gradients (HOG)	HOG features were used by Jain et al. (2004) in their work on offline signature verification.	• Captures gradient information effectively, useful for capturing edge and texture information. • Robust to changes in illumination and background.	• May be sensitive to noise and clutter in the image. • Computationally intensive, especially for large images.
Local Binary Patterns (LBP)	LBP features were employed by Le et al. (2016) for offline signature verification	• Simple and computationally efficient. • Insensitive to changes in illumination.	• Limited in capturing global structure and context. • Not effective for capturing fine texture details.
Scale-Invariant Feature Transform(SIFT)	SIFT features were utilized by Nanni et al. (2009) for online signature verification.	• Robust to changes in scale, rotation, and translation. • Captures distinctive local features	• Computationally expensive, especially for large data sets. • Requires careful parameter tuning.
Speeded-Up Robust Features (SURF)	SURF features were used by Ferrer et al. (2007) for offline signature verification	• Faster computation compared to SIFT. • Robust to changes in scale and rotation.	• Less distinctive compared to SIFT. • Sensitivity to changes in viewpoint
Gabor Filters	Gabor features were employed by Hollingsworth and Bowyer (2008) for offline signature verification.	• Effective in capturing texture and shape information. • Tuneable to different frequencies and orientations	• Computationally expensive, especially for large filter banks. • Sensitive to noise and artifacts.
Discrete Wavelet Transform (DWT)	DWT features were used by Toselli et al. (2007) for online signature verification.	• Multiresolution representation captures both global and local features. • Efficient in capturing texture and shape variations.	• Selection of wavelet basis functions can affect performance. • Requires careful selection of decomposition levels.
Principal Component Analysis (PCA)	PCA features were employed by Houmani et al. (2014) for offline signature verification.	• Dimensionality reduction facilitates efficient feature representation. • Removes redundant information and noise.	• Assumes linear relationships between variables. • May lose discriminative information in high-dimensional data.

Table 4.4 displayed feature extraction techniques used by previous author for signature verification and we find out the gaps as well as advantages of those techniques used in signature verification.

Conclusion

We concluded that:

a. The proposed mechanism for signature recognition represents a significant advancement over previous methods. Instead of verifying a single signature input at a time, the system now processes multiple inputs simultaneously for verification. By doing so, we aim to assess both the false acceptance rate and false rejection rate, providing a more comprehensive evaluation of the recognition system's performance.
b. Despite the availability of various algorithms for handwritten signature recognition, the problem of high false acceptance and rejection rates persists. To address this challenge, we employ soft computing tools, particularly Convolutional Autoencoder. Soft computing offers adaptability and uncertainty handling, making it a suitable approach for signature recognition tasks.
c. In Convolutional Autoencoder, different signature samples from the same individual are passed as inputs, and the model predicts the authenticity of the signature based on learned knowledge. Through the training process, the model learns from the collected signature samples, enabling it to accurately predict outcomes for new signature inputs.
d. The supervised learning process involves collecting data to create a signature dataset and training the model through image classification. Additionally, measures such as employing the MD5 algorithm are taken to protect the collected data from potential threats posed by hackers.
e. Overall, the proposed approach leverages advanced techniques in soft computing and deep learning to enhance handwritten signature recognition accuracy while addressing security concerns associated with data storage and protection. Further research and experimentation in this direction are warranted to refine and optimize the recognition system for real-world applications.

Data Availability Statement (DAS)

Data available within the article or its supplementary materials: -
We confirmed that the data supporting the findings of this study are available within the article [and/or] its supplementary materials.

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