HSV SYSTEM FOR PREDICT THE SIGNATURES ARE FORGED OR NOT BASED ON IMPROVED COMBINATIONAL FEATURES

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***Abstract*—As a behavioral characteristic, handwritten signatures are widely used by financial and government agencies. The emergence of forged signatures causes great property damage to customers. This paper proposes a handwritten signature verification method based on an improved combination feature. According to advanced smart pen technology, when writing a signature, with offline images. Online signature data can be obtained in real time. The first time a combination has been realized from offline and online. Extract and validate the static and dynamic characteristics of the signature Use Support Vector Machine (SVM) or Dynamic Time Warping (DTW). Get two decision scores while getting the validation results. Lastly Propose an accuracy-based SFA method that combines offline and online functions B. Score fusion makes good use of complementarity between classifiers. The results show that different numbers of training patterns are used when conducting experiments with local data.**

***Keywords*— signature verification; support vector machine; dynamic time warping; combined features**

I. INTRODUCTION

Handwritten signatures are very common in life. With the development of machines learning and artificial intelligence is a study of handwritten signature verification It will deepen again..

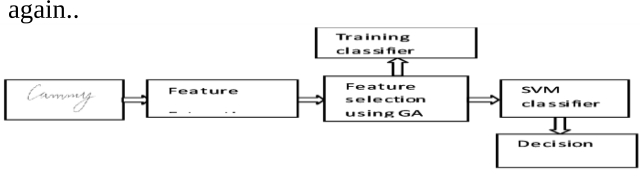


Fig.1 Signature conversion in online

There are two main methods for collecting signature data: offline signature images and online signature data. Offline signature image refers to the handwritten name of the author on the paper, which is then transmitted to the computer through the scanning device to form the signature image, and then verified according to the image features. In fig 1 Online signature refers to verification based on signature tracks, such as coordinates and writing pressure. This article describes a smart pen equipped with a pressure sensor and so on. The camera is used to write names on paper with full dots. When writing signatures, offline images, and online signature data are captured in real time. Signature verification usually involves two phases: training and testing. among them During the training phase, different numbers of actual signatures are used for preprocessing and functionality

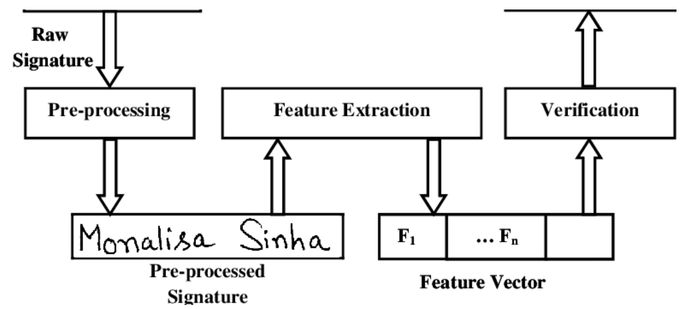


Fig.2.Diagram of signature verification process

Extract it and then put it in a classifier to get the model. In the test phase, the signature is input to the classifier for comparison and the test result is output. In the feature extraction phase, the features of an offline signed image are called static features. These are mainly divided into local functions and global functions. Mainly local function It is divided into a texture function and a gradation function, and the global function is mainly a geometric function . Online signature data functions are called dynamic functions and are primarily. It can be divided into parameter-based functions and function-based functions. It is mainly related to the signing period and the number of upward nibs. Function-based Functions are primarily related to signature trajectories and pressure data. Based on dynamic functions for functional characteristics, better results are usually obtained. There are two main issues with signature verification. One is that there is a big one variations within and between classes. The author's true signature also changes over time, Age and other factors, and counterfeiters also imitate signatures in many trainings. First, we need to extract and select more comprehensive and representative ones. Second, in a real-world scenario, only a small set of real signatures can do this. It's a problem that needs to be resolved for training and even inadequate data. To solve these problems, this paper proposes a method based on score fusion. About accuracy weighting combined with the static function of offline signature image. Dynamic characteristics of online signature data with score fusion. There are two main validation methods:

1. **model-based validation**
2. **distance-based validation**.

The model-based method describes the data distribution primarily by generating a model. B. Hidden Markov Model (HMM), CNN and SVM. Distance-based approach Compare verification signatures with reference signatures primarily using distance measurements According to DTW. This document uses SVM to process offline signed images and DTW to process the Online signature data.

II. RELATED WORKS

A. Signature feature extraction

Current status of research on algorithms for extracting signature verification functions. It mainly extracts characteristic texture features, geometric features, and dynamic features. Pfizer et al. Propose automatic recognition technology based on multi-level function Fusion and optimal feature selection [1] and calculated 22 Gray Level co-occurrence.The Matrix (GLCM) function and eight geometric functions, geometric functions were used to characterize the shape of the signature, such as: B. Textures expressed in GLCM such as edges and faces. Information such as each signature was changed, and the High Priority Index Feature (HPFI) was adopted to combine these functions and propose a function-based selection process. What is the best function for Skewness Kurtosis Controlled PCA (SKCPCA)? Selected to separate the signature into a fake signature and a real signature. The proposed system is Validated using MCYT, GPDS, and CEDAR datasets and compared to existing methods FAR and FRR were significantly improved, with FAR at 2.66%, 9.17% and 3.34%. The downside was that the deleted features could affect the feature selection process. System performance and removed features may have given better results with other data put. Bhunia et al. Proposed a signature verification method based on the author . Uses two different types of texture features, discrete wavelet features and local quantization . Pattern (LQP) function to extract two types of transformations based on signature [2] Photo. Use a Oneclass Support Vector Machine (OCSVM) for each signature creator. Establish two independent signature models for LQP and wavelet features. Get two different validation results for each signature creator, Scores of two OCS VMs based on the averaging method to get the final validation Score. Equal error rates by testing GPDS, MCYT, and CEDAR datasets (EER) was 12.06%, 11.46% and 7.59%, respectively, confirming the generality. Method. Ghanimetal. Extract various functions and they System detection function. Calculated features include an alignment histogram Geometric features such as gradient (HOG) and length distribution, gradient distribution, etc. entropy. Based on the application of various machine learning classification methods: The bagging tree, random forest (RF), SVM, and system were tested on the UTSig dataset. Experimental results show that SVM is superior to other classifiers. The correct answer rate is 94% [3]. Hadjadjetal. Oriented using local ternary pattern (LTP) Basic Image Feature (oBIF)Texture Descriptor for Extracting Features [4] and Projecting Signature image to the feature space. Once the signature check is submitted, Reliability was assessed by combining the decisions from the two SVMs technology Accuracy tested with ICDAR 2011 Dutch and Chinese signature datasets. The rates were 97.74% and 75.98%, respectively. To solve and improve existing challenges in signature verification System verification ability, Okawa et al. Proposed a new feature extraction method. It uses a combination strategy to combine the recognized Fisher vector with the KAZE function. Forming new functions from foreground and background images [5], MCYT75 records were found to have a lower error rate than existing signatures Verification procedure. Alai et al. Propose a handwritten signature verification method Based on spacing symbol representation and fuzzy similarity. In the feature extraction phase, features of the local binary pattern (LBP) are extracted from the signature image [6]. This method has been tested on a GPDS dataset. The number of training samples For 8 and above, the proposed method has a higher error rate. Akbarieal. Proposed A global method that treats a signature image as a waveform that decomposes the image Using a set of wavelet subbands at a particular level, the decomposed image expands as follows: Obtain the waveform and quantize the waveform to generate a feature vector [7]. Good results were obtained for bo-th the MCYT and CEDAR datasets. Gyimahetal.suggestion Improved handwritten signature verification system that combines GLCM and images Area characteristics [8]. FAR by testing methods in SVM using various kernel functions Was 2.50 and FRR was 0.14. Sharifetal based on the idea of optimal feature selection. Proposed a new trait selection method that uses a genetic algorithm to find a match Enter the feature vector, then the SVM classifier [9]. By experiment with 3 datasets From CEDAR, MCYT, and GPDS, the system received 8.9, 17.2, and 9.41 FARs, respectively. Parziale et al. Proposed the concept of stability. By finding the most stable part of Signature, this part is the most similar part and was introduced in DTW. Verification by distance measurement [10]. Zoisetal. Proposed a new grid-based template Matching schemes, the essence of which was to effectively encode geometric structures Sign through the grid template and divide the subset appropriately. Validity Detected in 4 datasets [11].

B. Signature classification

Current status of research on algorithms for checking handwritten signatures Domestic and foreign classifiers that mainly use neural networks and SVMs. Portman et al. Learned visual cues directly using the Convolution Neutral Network (CNN) Signature images had a significant impact on GPDS datasets using EER It decreased from 6.97% to 1.72% [12]. Luize et al. Suggested to solve this problem with a fix Network structure by learning fixed size features using spatial pyramid pooling. From the variable signature [13]. Better results were obtained with the GPDS dataset. Or Experimental results have shown that it is possible to use higher resolution signature images. Increase performance. Laietal. I used a monitored CNN to learn to distinguish between features. Levels are divided into shallow and deep features. Also, they too proposed a location-based twin neural network to learn more distinctive features. room. Good results have been obtained with different datasets [14]. Aliketal. Proposed A new CNN structure [15] called the Large Scale Signature Network (LS2Net) Problems with large training examples with batch normalization. LS2Net has arrived. High precision for MCYT, CEDAR and GPDS datasets. Experiments showed this batch Normalization has contributed significantly to performance.

Zhengetal..Applicable rank Support for vector machines (Rank SVM) to resolve signature verification task [16]. This The signature dataset are used to differentiate the signature sets.

Photograph edit distance and a deep neural community shape signature verification version. They believed that the structur characteristic version and the statistical characteristic version have been absolutely distinctive and feature complementary advantages. On the MCYT and GPDS information units, it to turned into proved that combining structural fashions and the statistical fashions can appreciably enhance overall and to performance and gain from their complementary feature of characteristics [17]. In view of the incapability to acquire the professional forged signatures at some stage in the schooling process, Sm et al. solved the trouble with the aid of using the checking the distinctive loss capabilities of CNN and met the substantial necessities for generalization of handwritten the signature verification [18]. Cauchy Schwarz divergence and hinge loss, they have been blended into a dynamic multi-loss function, and proposed a brand new integration framework. for the usage of them in CNN on the identical time. The task Soleimani et al. proposed a Deep Multitask Metric . The end Learning(DMML) category approach for handwritten tasks signature verification. DMML in particular used the thoughts of multi-venture mastering and switch mastering. The signs Experiments had proved that DMML had higher overall and performance in verifying signature authenticity, professional forgery and random forgery [19]. Okawa proposed using and Local Stability-Weighted Dynamic Time Warping(LS-DTW) approach to affirm on line signatures. Experiments on and to process MCYT-a hundred and SVC2004 on line signature information units had done desirable results, successfully]. enhancing the velocity and accuracy of online signatures. Numerous signature features and classification methods are .used in the literature.This white paper focuses on the signs of combination and comparison of features and the realization of complementarity between classifiers. To improve the sign method of handwritten signature verification .We propose a score fusion method based on accuracy (SFA) to realize an combination of functions.

III. PROPOSED SYSTEM

A. Outline

Figure 3 shows the implementation process of the signature verification procedure. The first is data collection. The offline image of the signature and the online data are acquired at the same time via the smart pen, and the quality of the signature data is as follows. It has been enhanced by pretreatment and feature extraction to ensure the accuracy of the validation results. For offline images and online data, SVM and DTW were used for validation. And I got two scores, Score1 and Score2.Finally, the result of offline and merge Online functionality is acquired via SFA. The online data contains six columns, namely X coordinate, Y coordinate, whether the stroke starts or not, whether the stroke ends or not, and pressure. Table1lists the signature data of the two authors. Each signature has a corresponding offline image and online data. The online curve in the table is obtained based on the X coordinate of the signature data. The abscissa of the graph represents time, and the ordinate represents the change of the X coordinate or Y coordinate of the online signature over time during the writing process. The red curve represents the real signature and the blue curve represents forged signatures, it is obvious that there is a big difference in the curve. The data will be processed, verified and fused separately in the subsequent steps.

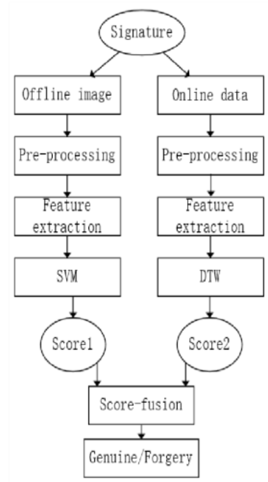


Fig 3. System Overview

B. Data Acquisition

In this paper, sign using a smart pen with a camera and pressure sensor .The signature can be obtained in real time. In total, signatures were collected from 20 authors. Paper filled with small dots. When writing signatures, pictures, tracks In total, it includes 30 genuine signatures and 30 counterfeit signatures for each author. 1200 sig natures. The fake signature used in this article is to find a couple of experimenters. This includes 30 real signatures and subsequent signatures, as well as 30 fake signatures after pre-training to get the author, for a total of fake signatures. .. The paper data is set to be used by a few of this experimenter, and the article is entirely composed of Chinese signatures, but the experimental methods used can be extensive. Real signature, and run fake after pre-training, Applies to other languages. All signature data collected includes both offline signatures Fake signatures are reliable and practical. The dataset used in this article. Images and online signature data. Compiling this dataset itself is a bold attempt. We want to achieve more Chinese scientific signatures and more reliable ones, but experimental verification by combining signature methods has been applied to data applied online and images in other offline languages. can Y coordinate, whether the stroke starts, whether the stroke ends, and pressure, images and online signature data. The creation of this dataset itself is a bold proof Table 1 shows the signature dates of the two authors. Each signature has a corresponding signature. We would like to achieve more scientific and reliable signature verification jointly. Offline images and online data. The online curve in the table is the result of X Adjustment of signature data. The horizontal axis of the graph represents time, the vertical axis is the coordinates, the change in the y-coordinate of the x-coordinate, whether the y-coordinate dash starts at the time of writing, and that ends one character of the time dash during writing and writing.

Represents. The red list of curve signatures represents the actual data for signature 2, and the author represents blue. Each curve signature represents a fake signature, and it is clear that there are significant differences between the curves. Corresponding offline images and online data. The online curve in the table .The data is processed, validated, and merged individually in subsequent steps. Based on the X coordinate of the signature data, signatures of online data and offline images.The online data contains 6 columns. Adaptation of signature data. The horizontal and vertical axes of the graph display show the time course of the X and Y coordinates of the signature during the writing process. The red curve represents the actuals and the blue curve represents the fake signature. It is clear that there is a large data on the curve. The data is processed, validated, and merged individually in substeps.

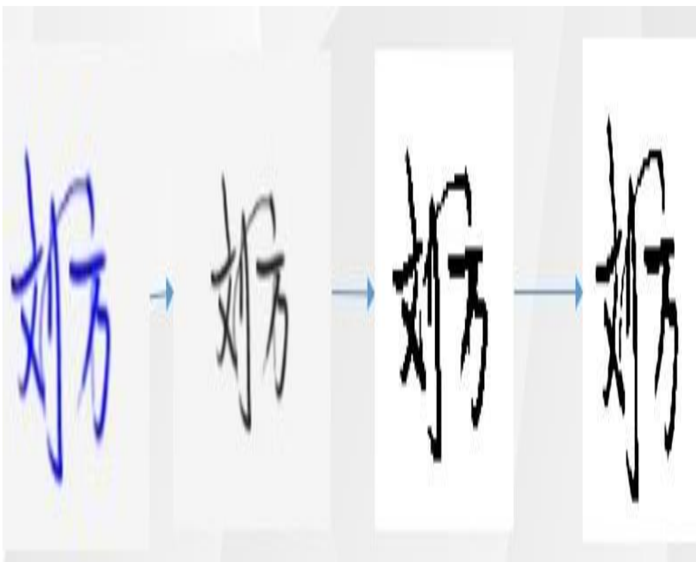


Fig 4: Orginal signature

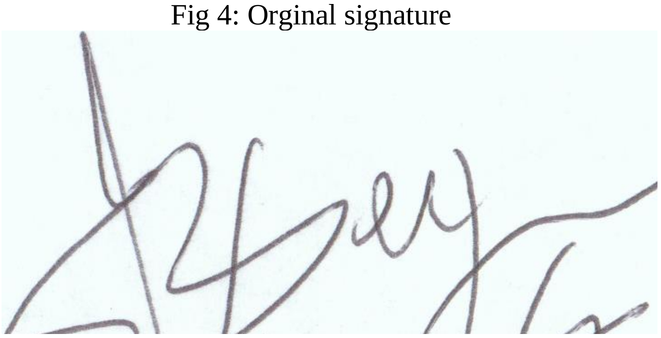


Fig 4 : Forged signature

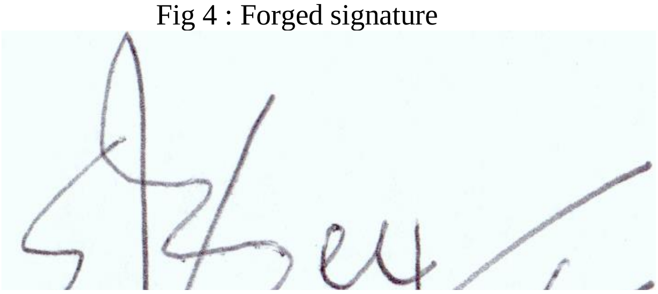
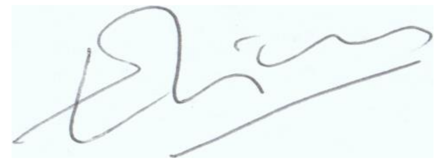


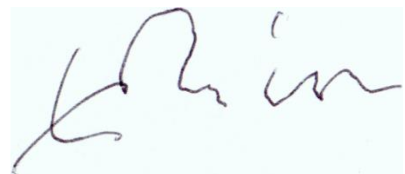
Table 1 Signature Data

Offline image



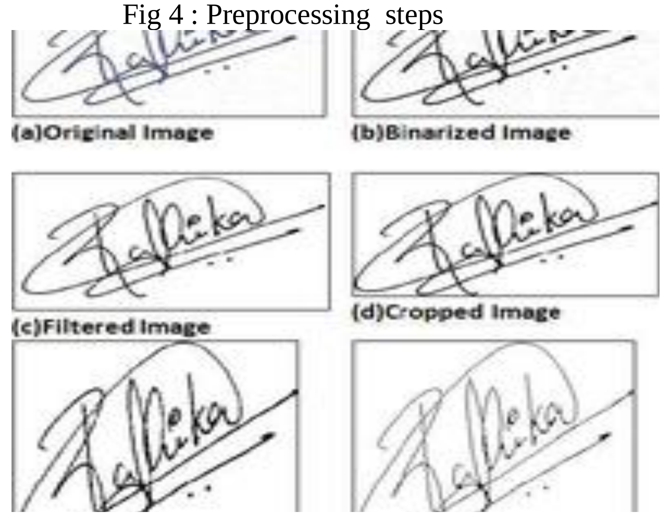
Writer1 Real

Online data

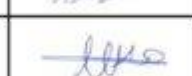
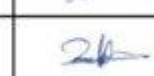


Writer 2 Forged

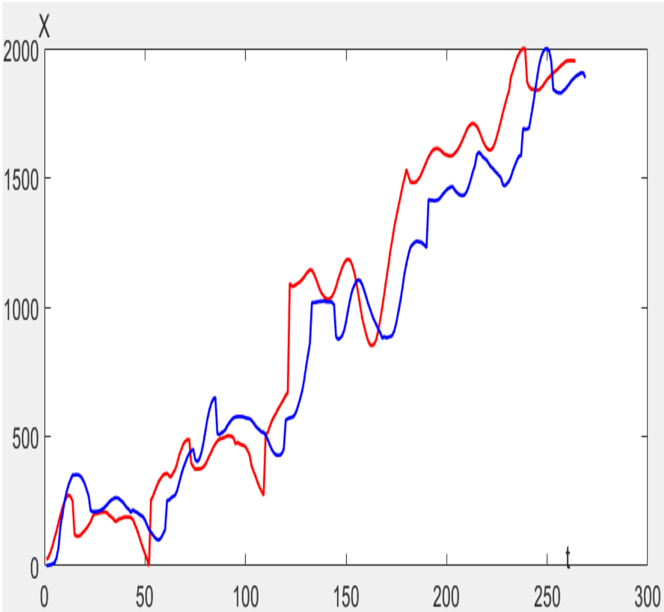
Fig 4 : Preprocessing steps



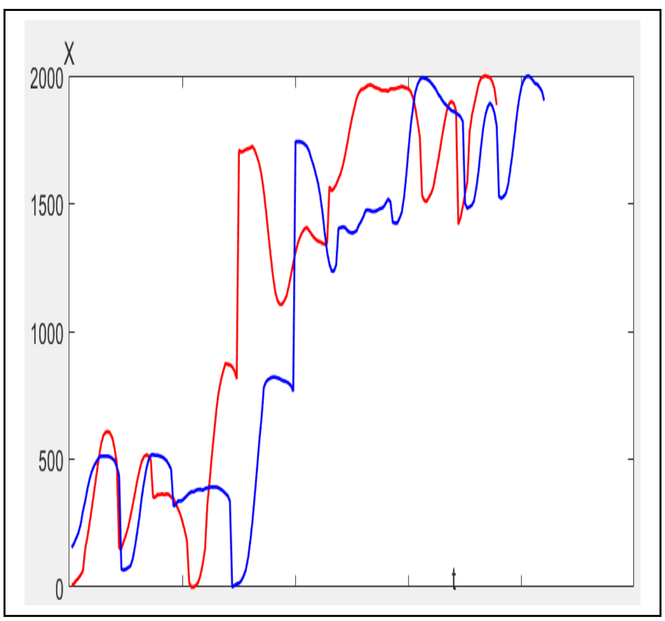
First result after preprocessing

1		93%	2		94%
3		89%	4		97%
5		99%	6		98%
7		94%	8		99%
9		98%	10		93%

Offline



Online



Let f (x, y) be the signature image, (x1, y1) and (x2, y2) be the two points in the image, let the distance bed, and let the horizontal axis of the angle and coordinates between the two points be θ, f (x1). , Y1) = i, f (x2, y2) = j. In this way you can get the matrix P (i, j, d, θ) with different distances and angles. This task analyzes the position of the gray space horizontally, vertically, from bottom left to top right, and from bottom right to top left. That is, θ = 0, 45, 90, 135. At the same time, this task uses four parameters to reflect the status of the matrix. That is, contrast, correlation, energy, and uniformity, as shown below

$$Con = \sum_i \sum_j (i-j)^2 P(i,j)$$

$$Corr = \left[\sum_i \sum_j ((ij)P(i,j) - \mu x \mu y\right] / \sigma x \sigma y$$

$$Ene = \sum_i \sum_j P(i,j)^2$$

$$Hom = \sum_i \sum_j P(i,j)/(1+|i-j|)$$

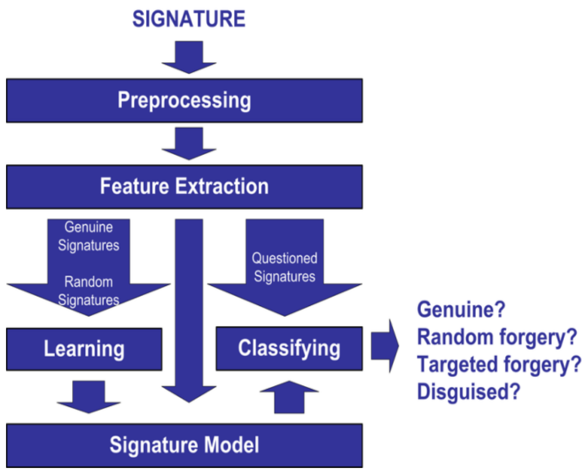


Fig 4 .Signature processing

D. Feature extraction

The feature extraction stage involves extracting static and dynamic features of the signature.

a) *Static Features*

For offline signature images, the texture and geometric features of the signature are extracted. The texture function is used to represent the local information of the image, and the geometric function is used to represent the global information of the image. The feature vector obtained by combining the two can completely and accurately represent the content of the image. In this paper, we use GLCM and HOG to extract image texture features. GLCM You can get the interval and the change in grayscale. This is the basis for the analysis of local patterns and placement rules for images. HOG is used to calculate directional statistics for local image gradients. The main idea is segment the signature image, calculate the gradient values in each direction on a cell-by-cell basis, and accumulate them to form a histogram. In this paper, the cell size is set to 2020. The formula is: Where Gx (x, y), Gy (x, y), and H (x, y) represent the horizontal gradient, the vertical gradient, and the pixel value of the pixel (x, y), respectively. image.

$$Gx(x,y) = H(x+1,y) - H(x-1,y)$$

$$Gy(x,y) = H(x,y+1) - H(x,y-1)$$

$$G(x,y) = \sqrt{Gx(x,y)^2 + Gy(x,y)^2}$$

$$\alpha(x,y) = cot\left(\frac{Gy(x,y)}{Gx(x,y)}\right)$$

In addition, nine geometric features used to represent the global are extracted. Image information. The equations are in Table 2. Where d is the distance from point x1 to x2. Subsequent testing processes evaluate the effectiveness of each static feature.

Table 2. Overview of geometric features.

Feature	Formula
Area	$\sum_{i=1}^{n}\sum_{j=1}^{m} A[i,j]$
MajorAxisLength	$x1 + x2$
MinorAxisLength	$\sqrt{(x1+x2)^2 - d}$
Perimeter	$2l + 2w$
Extent	$\frac{Area}{BoundingBox}$
Solidity	$\frac{Area}{ConvexArea}$

b) Dynamic Features

Dynamic functions have the characteristics of time limits, movements, and angular fluctuations. They tend to have a stronger personal style compared to static traits. The combination of static and dynamic features can effectively improve the accuracy and reliability of signature verification. This white paper uses smart pen technology Offline and on line information on the identical time, and sooner or later combines static and dynamic functions thru SF-A. In addition to the horizontal and vertical coordinates and strain information contained within side the on line information, the dynamic functions used on this paper additionally extract 4 different dynamic functions, particularly velocity, acceleration, attitude and radius of curvature [21], as proven in Table3.

Table 3. Dynamic features.

Feature	Definition
Velocity (v)	$\sqrt{xi^2 + yi^2}$
Acceleration (α)	$\sqrt{vi^2 + (vi * \theta i)^2}$
Angle (θ)	$\arctan(yi/xi)$
Radius of curvature (ρ)	$\log(vi/\theta i)$

E. SVM

An SVM is a class of generalized linear classifiers that classify data in a supervised learning manner, the decision boundaries of which are the hyperplanes of the maximum margins resolved for the training sample. This document uses SVMs to classify offline images and RBF kernel functions to get the image classification results. Positive samples in the training phase are trained with different numbers of actual signatures. This paper uses the same number of real signatures from other authors for training, as training in real-world situations does not allow you to get fake signatures. This provides a new way to solve the small sample problem. The test set consists of the author's actual signature and the forged signature. When you get the offline verification results, you can see that the SVMs are categorized according to the distance from the sample to the hyperplane. In the real world, this is represented by a score. If the score is less than 0, it is considered a genuine signature, and if the score is greater than 0, it is considered a counterfeit signature. Derivate the score and record it as Score1 to lay the foundation for the following complex functions .

F. DTW

DTW is an ordinary optimization problem. It makes use of a time warp characteristic that satisfies sure situations to explain the time correspondence among the take a look at template and the reference template, and solves the warp characteristic similar to the minimal cumulative distance whilst the 2 templates match. This paper makes use of DTW to categorise on line signature records. We use one-of-a-kind quantities of actual signature records for schooling, and use their suggest to acquire the Gaussian distribution of the reference template, after which evaluate the Gaussian distribution of the take a look at template with it to get the diploma of similarity, denoted via way of means of Score2. Due to the one-of-a-kind quantity of schooling samples, the edge for judging the authenticity of the signature is likewise one-of-a-kind. For the following function combination,

it's far important to make sure that Score2 and Score1 have the identical judgment standard. We normalize the edge of the web signature records, that is, subtract the edge itself. Finally, whilst Score2 is much less than 0, it's far judged as a actual signature, and whilst Score2 is extra than 0, it's far judged as a cast signature.

$$G \quad Score\,2(xi) - thre < 0$$

-

$$F \quad Score2(xi) - thre > 0$$

G. SF-A

For offline images and online data of the same signature, different verification results may be obtained by using SVM and DTW. For example, for one of the offline images and online data with a real signature, the offline image is judged as a real signature by SVM, and the online data is judged as a forged signature by DTW, so there is a certain complementarity among them, and fusion with weights is required. At present, the commonly used fusion methods are mainly divided into three categories, namely, fusion based on class labels, fusion based on class ranking, and fusion based on probability output. The third type is more applicable to the situation in this paper. For two decision scores, the commonly used method is to use the Sigmoid function in logistic regression to predict the output result, and find the best weight for the two decision scores through the gradient descent method and increasing the number of iterations. If the result is greater than 0.5, it is considered a genuine signature, and if it is less than 0.5, it is considered a forged signature. Finally, the most suitable straight line for data partitioning is found to complete the classification. In the experimental phase, SFL is used to represent a score fusion method based on logistic regression. The SFA proposed in this white paper is based on the classification accuracy of SVM and DTW and uses weighted averages and logistic regression to assign weights to scores 1 and 2, respectively. Determining merging is a combination of the static and dynamic characteristics of a signature. Suppose the accuracy of SVM is Accuracy1, the weight of Score1 is defined as w1. The accuracy of DTW is Accuracy2, and the weight of Score2 is defined as w2. Then the weights of w1 and w2 are defined as follows. It can be seen from the definition that the higher the accuracy of the classifier, the weight also bigger. Xi represents the ith signature. Final Score obtained from SFA is compared to 0. If it is less than 0, it is considered a genuine signature, and if it is greater than 0, it is considered a forged signature. By assigning weights to each classifier based on accuracy, also known as confidence, and merging the scores, you can increase the reliability of the results you get and achieve a higher degree of complementarity for the classifiers.

$$\text{sigmoid}(x) = 1\ 1 + e{-}x$$
$$w1 = Accuracy1/(Accuracy1 + Accuracy2)$$
$$w2 = Accuracy2/(Accuracy1 + Accuracy2)$$
$$Final\_Score(xi) = w1 * Score1(xi) + w2 * Score2(xi)$$
$$i = 1 \ldots 1200$$

$$Final\_Dec = (\ G\ Final\_Score(xi) < 0\ F\ Final\_Score(xi) > 0$$
$$i = 1 \ldots 1200$$

For offline images and online data of the same signature, different verification results may be obtained by using SVM and DTW. As far as SF-L and SF-A are concerned, the SF-A proposed in this paper has achieved the best results under different training samples by weighting the verification accuracy of the classifier. As far as SF-L and SF-A are concerned, the SF-A proposed in this paper has achieved the best results under different training samples by weighting the verification accuracy of the classifier.far as SF-L and SF-A are concerned, the SF-A proposed in this paper has achieved the best results under different training samples by weighting the verification accuracy of the classifier. In order to verify the effectiveness of the proposed method, we conducted experiments on a local data set. By using different numbers of training samples, two classifiers were used to experiment and compare different signature features. Experimental results show that the use of SF-A fusion of static and dynamic features has achieved the greatest accuracy and the lowest FAR and FRR, which can effectively verify handwritten signatures. This paper proposes a handwritten signature verification method based on improved combined features to meet the requirements of the current high-precision system. We use smart pens to obtain the offline image and online data of the signature at the same time, and perform preprocessing and feature extraction on them respectively. Then we use SVM and DTW for offline images and online data respectively to get verification results and decision scores, and propose the SF-A method to achieve the purpose of combining static and dynamic features by fusing decision scores. In order to solve these challenges, this paper proposes a score fusion method based on accuracy weighting, which combines the static features of offline signature images and the dynamic features of online signature data through score fusion. Specifically, the image and data are preprocessed and feature extracted respectively, and then the images and data are verified by SVM and DTW respectively. Through the two classifiers, we can get the verification results and decision scores of offline signature and online signature. It can be seen from the definition that the higher the accuracy of the classifier, the weight also bigger. Xi represents the ith signature. Final Score obtained from SFA is compared to 0. If it is less than 0, it is considered a genuine signature, and if it is greater than 0, it is considered a forged signature. By assigning weights to each classifier based on accuracy, also known as confidence, and merging the scores, you can increase the reliability of the results you get and achieve a higher degree of complementarity for the classifiers. A total of 20 authors' signatures were collected, including 30 authentic signatures and 30 forged signatures for each author, a total of 1200 signatures. The forged signature used in this paper is to find 2~3 experimenters, provide the real signature, and then perform the forgery after pre-training to obtain the forgery .The forged signature is reliable and practical. The data set used in this article is entirely composed of Chinese signatures, but the experimental methods used can be widely applied to other languages. Each signature data collected includes both offline signature image and online signature data.

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

Since this article aims to achieve a combination of offline images and online data, it is still difficult to get a public dataset that can contain offline images and the corresponding online data at the same time. Therefore, this task will use offline images and online data collected from 1200 signatures for the experiment. Use FAR, FRR, AER, and accuracy as metrics. FAR is the percentage of fake signatures used in the test that are determined to be genuine. FRR refers to the percentage of genuine signatures used for testing that are determined to be fake signatures. AER is the average of FRR and FAR. accuracy refers to the verification accuracy, that is, whether the prediction result matches the actual situation. Current deep learning techniques can achieve excellent signature verification effects, but they require a large amount of data to perform experiments and are not very practical. Given the actual application, I think it is necessary to solve a small example in a real situation. By studying small sampling problems, most scholars choose samples within 10 for training. 10 samples usually give the best experimental results. For 1200 signatures, this paper selected 3, 5, 8, and 10 actual signature samples for training and experimented and compared various characteristics. For offline signature training sets, we randomly selected 3, 5, 8, and 10 actual signature training sets. Randomly select one author's signature as a positive sample for SVM training and the same number as the real signatures of other authors as a negative sample to resolve situations where fake training signatures cannot be obtained in real-world situations. In the online signature training set, 3, 5, 8, and 10 actual signatures are randomly selected as the enrollment sample to get the first Gaussian distribution, and the remaining signatures are selected as the test sample for the second Gaussian. The distribution has been acquired. We compared the similarities to see if it was true. Each experiment was repeated 10 times to ensure the accuracy of the results.

i. Results

Table 4 shows the experimental results of two classifiers using different features under a local dataset. After obtaining results using different numbers of training samples, the SFA results proposed in this article to combine dynamic and static features by score fusion are better than using functional validation and logistic regression alone. Also turned out to be excellent. Figure 3-6 shows the sample split between SFA and SFL. The improved weighted line can better separate real and forged signatures than the original method.

Table 4. The result of three training samples.

Method	Features	FAR	FRR	AER	Accuracy
SVM	GLCM	16.83%	20.83%	18.83%	81.17%
	HOG	24.83%	21.83%	23.33%	76.67%
	GLCM + HOG	12.17%	17.50%	14.83%	85.17%
	Geometric	37.83%	28.00%	32.92%	67.08%
	Texture + Geometric	13.00%	17.50%	15.25%	84.75%
DTW		11.17%	10.50%	10.84%	89.17%
SF-L		7.17%	7.67%	7.42%	92.58%
SF-A		6.67%	7.17%	6.92%	93.08%

Table 5. The result of five training samples.

Method	Features	FAR	FRR	AER	Accuracy
SVM	GLCM	14.50%	13.17%	13.83%	86.17%
	HOG	11.83%	19.33%	15.58%	84.42%
	GLCM + HOG	6.67%	12.33%	9.50%	90.50%
	Geometric	29.17%	26.50%	27.83%	72.17%
	Texture + Geometric	6.33%	12.17%	9.25%	90.75%
DTW		9.83%	9.33%	9.58%	90.42%
SF-L		5.33%	5.50%	5.42%	94.58%
SF-A		5.33%	4.83%	5.08%	94.92%

Table 6. The result of eight training samples.

Method	Features	FAR	FRR	AER	Accuracy
SVM	GLCM	10.83%	10.67%	10.75%	89.25%
	HOG	8.17%	8.17%	8.17%	91.83%
	GLCM + HOG	5.50%	5.83%	5.67%	94.33%
	Geometric	20.00%	27.33%	23.67%	76.33%
	Texture + Geometric	5.67%	5.83%	5.75%	94.25%
DTW		8.00%	7.50%	7.75%	92.25%
SF-L		3.67%	1.83%	2.75%	97.25%
SF-A		2.17%	3.17%	2.67%	97.33%

Table 7. The result of ten training samples.

Method	Features	FAR	FRR	AER	Accuracy
SVM	GLCM	8.83%	10.50%	4.83%	90.33%
	HOG	7.00%	6.33%	6.67%	93.33%
	Geometric	16.83%	25.33%	21.08%	78.92%
	GLCM + HOG	4.83%	5.83%	5.33%	94.67%
	Texture + Geometric	4.17%	5.50%	4.83%	95.17%
DTW		7.67%	7.50%	7.59%	92.42%
SF-L		2.50%	2.33%	2.42%	97.58%
SF-A		1.00%	3.33%	2.17%	97.83%

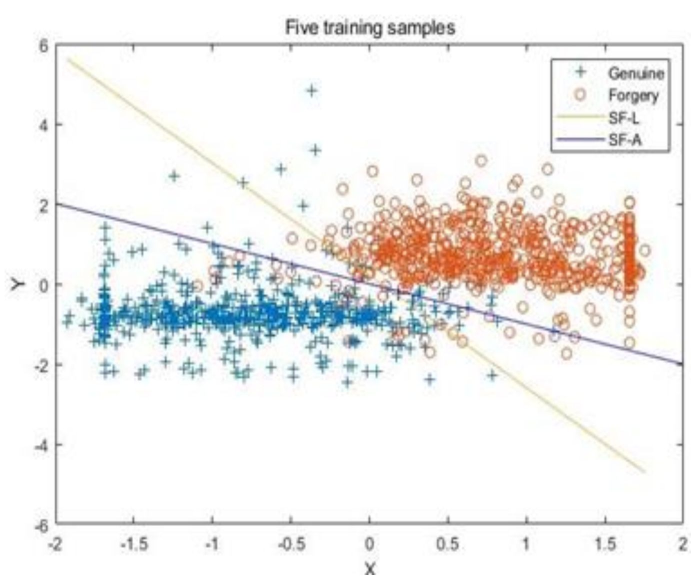


Figure 5 .Sample distribution when using 5 different samples

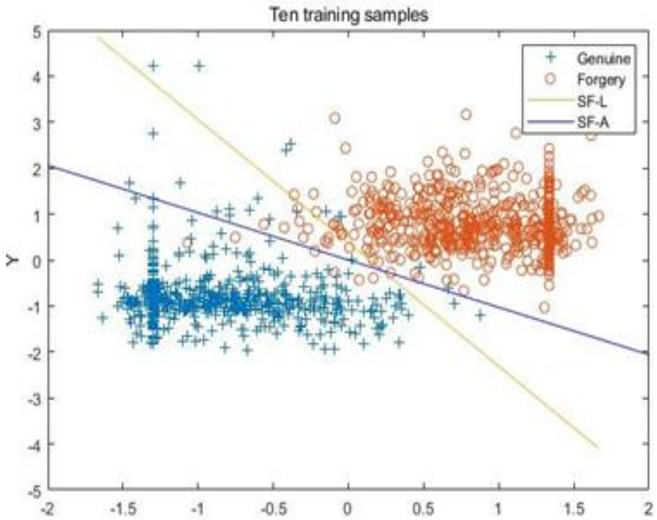


Figure 6. Sample distribution when using 10 different samples

ii. Comparative analysis

Experimental results show that using SFA to combine static and dynamic features for handwritten signature verification is effective. By observing the experimental results of each function, for offline images, the effect of using GLCM is better than HOG when the number of samples is 3 and 5, and the number of samples is 8. I found out. 10, HOG is better than GLCM. Overall, texture features work better than geometric features that may be related to the dimensions of the feature vector. The feature vector dimension of the geometric feature becomes smaller. However, the result of combining geometric and texture features can usually improve the accuracy of the inspection. In addition, the texture function represents the local texture information of the offline image, and the geometric function represents the global information of the image, which reduces FAR and FRR. The combined feature vectors should be more representative and reliable. From the point of view of score fusion, i. H. Combining static and dynamic functions, both SFL and SFA experimental results are superior to static or dynamic function-only experimental results, and the two fusion methods complement between the two classifiers. Shows that you can improve your performance. With respect to SFL and SFA, the SFA proposed in this paper achieved the best results among the various training patterns by weighting the validation accuracy of the classifier. In particular, the FAR index improvement is more important, and in certain cases the FAR requirements are often higher. Therefore, we can conclude that the proposed SFA can effectively improve the efficiency of handwritten signature verification field known as Educational Data Mining (EDM). It happens because of the increase in educational resources and data that can be explored to learn how a student learned. Researchers also investigated the factors that influence learning outcomes [33] Table 6 show the accuracy result for the Generalized Linear (GL), Deep Learning (DL), and Decision Tree (DT) with runtime accuracy.

IV. CONCLUSION

This paper proposes a handwritten signature verification method based on a complex function that has been improved to meet the needs of current high-precision systems. Use the smart pen to get the offline image of the signature and the online data at the same time and perform preprocessing or feature extraction on them. Next, SFA to achieve the purpose of combining static and dynamic functions by using SVM and DTW for offline images and online data to obtain validation results and decision scores and merging the decision scores. I will propose a method. Experiments were performed on local datasets to verify the effectiveness of the proposed method. Two classifiers were used to experiment and compare different signature features using different numbers of training samples. Experimental results show that by using the SFA fusion of static and dynamic features, we have achieved the highest accuracy and lowest FAR and FRR that can effectively verify handwritten signatures. This paper contributes to the fusion of scores and the combination of functions. SFA makes good use of the complementarity of the results of each classifier to achieve a higher accuracy rate. At the same time, this paper uses smart pen technology to combine offline images with online data for the first time. Finally, in the SVM training phase, the actual signatures of other authors are used as a negative sample of training. This provides new ideas for small training problem examples. In contrast to deep learning methods, the proposed method is more interpretable and widely applicable. In future work, the dataset will be continuously exaggerated to check the universality of the method. For example, collect signatures in different languages and compare the validation effects of the proposed procedure in different languages. Publish the dataset used so that more researchers and institutions can experiment and compare. At the same time, we will investigate the signature features in more detail and find the most representative signature feature vector. We will continue to explore ways to get the best validation results with a minimal training set.

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