Offline Handwritten Signature Recognition based on SURF features using SVMs

ABSTRACT

Biometric recognition for human identification plays a key role in the rapid development of computer vision and pattern recognition research areas. The biometrics, refers to the automatic identification of a person based behavioural characteristics, physiological properties or traits. Signature recognition is one such human identification method, and can be performed either in offline or online mode. The signature is used in various documents, such as attendance sheets, application forms, bank cheques, and credit card transactions. Therefore, the ability to recognise signatures accurately, effortlessly, and in a timely manner would make a compelling case for this form of identification to be preferred. This paper proposes a classification approach to recognise and verify handwritten signatures using Speeded-up robust features (SURF) and multiclass support vector machine (SVMs) techniques. Experiments have been carried out with our dataset of 1600 samples and a recognition rate in excess of 95% was obtained.

Keywords: Handwritten Signature Recognition; SVM; SURF; SIFT

1. INTRODUCTION

The offline handwritten signature verification is the important part of the biometrics. Biometrics method of authentication offers several advantages over traditional methods. Various biometric traits are being used for real-time recognition, the most popular being face, iris and fingerprint. However, there are biometric systems that are based on retinal scan, voice, signature and hand geometry. The offline signature verification is considered as a behavioural characteristic based biometric trait in the field of security and prevention of forgery. The verification defines the process in which a signature is tested to decide whether a particular signature truly belongs to a person. There are two major methods for signature verification. One is an on-line method to measure the sequential data such as handwriting and pen pressure with a special device. The other is an off-line method that uses an optical scanner to obtain handwriting data written on a paper.

In this paper, we propose handwritten signature recognition system using support vector machines to recognize signatures. In this approach, the features that are considered in the recognition are: SIFT and SURF. We consider images of signatures with different writers.

Following this introductory section, the rest of the paper is organised as follows. Section 2 summarises the related work in handwritten signature recognition, whereas section 3 describes the background of SIFT, SURF, K-means and SVM. The proposed methodology is presented in Section 4. Section 5 briefly describes our own dataset. Experimental setup and testing results are presented in section 6. Finally, section 7 concludes this paper with future extension.

2. RELATED WORK

In [1], the authors have proposed an off-line handwritten signature verification system. They use Static Signature Verification (SSV) system consists of rigorous pre-processing and feature extraction followed by a classifier. SSV is implemented with four stages includes, pre-processing, feature extraction, classification and decision-making. Pre-processor processes the raw signature samples to make them usable by the feature-extracting unit. Feature extractor extracts the features that might be useful in classifying the signatures as authentic or fake. Classifier uses an Artificial Neural Network (ANN) with Error Back Propagation (EBP) algorithm to attain a certain result, based on which a decision can be made on the signature given as input. Decision-making is done with a general idea of the classification unit. This method may be further improved by rigorous evaluation and a feedback network, which needs to be considered to limit the possibility of over training of the neural network.

In [2], the authors have proposed an off-line signature verification system based on Discrete Wavelet Transform for Arabic and Persian signatures. Arabic and Persian signatures have commonality in shapes, fine and general details. Moreover, both have unique general features that distinguish them from other signatures. This system is based on Discrete Wavelet Transform (DWT) to extract common features to aid the verification step.

In [3], the authors have proposed an off-line handwritten signature verification system. While evaluating the signature verification system here two parameters are evaluated as Vertical Projection Profile (VPP) and Horizontal Projection Profile (HPP). When perform testing it has been noted that VPP is more reliable than testing done based on HPP. VPP provides a more reliable result on tests like false acceptance, false rejection and failure result rather than HPP.

In [4], the authors have proposed an off-line signature identification system using fuse multiple classifiers. From the signature images, global and local features are extracted and the signatures are verified with the help of Gaussian empirical rule, Euclidean and Mahalanobis distance based classifiers. SVM is used to fuse matching scores of these matchers. Finally, recognition of query signatures is done by comparing it with all signatures of the database.

In this paper [5] skilled forgery detection is focused. It emphasizes on the extraction of the critical regions which are more prone to mistakes and matches them following a modular graph matching approach. The technique is robust and takes care of the inevitable intra- personal variations. In Traditional graph matching methods, they use the whole image and each pixel is compared with every other pixel in the other image, thus incurring a large computational overhead. In this method they identify isolated, smaller critical portions of the signature images. These critical regions contribute significantly to the shape of the original image and therefore serve as accurate model of the signature. These critical regions are utilized as a basis for graph matching, thus reducing the computational overhead by a large amount.

3. BACKGROUND

3.1 Feature extraction

3.1.1 SIFT

The SIFT [12] algorithm can be used to generate the following set of image features:

Step 1: Scale-space extrema detection:

> The first stage of computation searches over all scales locations. It is implemented efficiently by using a difference-of-Gaussian function to identify potential interest points that are invariant to scale and orientation.

Step 2: Key point localization:

> At each candidate location, a detailed model is fit to determine location and scale. Key points are selected based on measures of their stability.

Step 3: Orientation assignment:

> One or more orientations are assigned to each key point location based on local image gradient directions. All future operations are performed on image data that has been transformed relative to the assigned orientation, scale, and location for each feature, thereby providing invariance to these transformations.

Step 4: Key point descriptor:

> The local image gradients are measured at the selected scale in the region around each key point. These are transformed into a representation that allows for significant levels of local shape distortion and change in illumination.

3.1.1 Speeded-UP Robust Features (SURF)

The SURF [11] algorithm is yet another descriptor which is partly inspired by SIFT. SURF will detect landmark points (features/interesting points) in an image, and describe the points by a vector which is robust against (a little bit) rotation scaling and noise. It can be used in the same way as SIFT which is patented.

The SURF algorithm can used to generate the following set of image landmark points: A structure with the information about the Landmark points, the landmark position, the scale of the detected landmark, the laplacian of the landmark neighbourhood, orientation in radians and the descriptor for corresponding point matching.

The detection of interest points is selected by relying on the determinant of the Hessian matrix where the determinant is maximum. SURF locates features using an approximation to the determinant of the Hessian matrix, chosen for its stability and repeatability, as well as its speed.

3.2 Cluster

3.2.1 K-means

Given a matrix $X \in \Re^{N \times d}$ (representing N points - rows - described with respect to d features - columns), then K-means clustering [10] aims to partition the N points into K disjoint sets or clusters by minimising an objective function, which is the squared error function, that minimises the within-group sum of squared errors:

$$dist_{ij} = \left\| X_i^{(j)} - C_j \right\|^2$$

$$X_{opt} = \sum_{j=1}^{K} \sum_{i=1}^{N} dist_{ij}$$

where $dist_{ij}$ is a chosen distance measure between a data point $X_i^{(j)}$ and the cluster centre C_j, is an indicator of the distance of the N data points from their respective cluster centres. K-means is a Gaussian mixture model with isotropic covariance matrix the algorithm is expectation-maximization (EM) algorithm for maximum likelihood estimation.

3.3 Classification

3.3.1 Support Vector Machines

SVM is a supervised learning technique based on a statistical learning theory that can be used for pattern classification [6]. In general SVMs outperform other classifiers in their generalisation performance. A linear SVM finds the hyperplane leaving the largest possible fraction of points of the same class on the same side, while maximising the distance of either class from the hyperplane. SVMs were originally developed for solving binary classification problems and then binary SVMs have also been extended to solve the problem of multi-class pattern classification. For multi-class classification the one-versus-all (OVA), one-versus-one (OVO), directed acyclic graph (DAG) [7] and unbalanced decision tree (UDT) [8] techniques can be used.

4. METHODOLOGY

In this section, the proposed handwritten signature recognition system is described in details. The system consists of pre-processing, feature extraction and classification. The block diagram of signature recognition consists of various steps as shown in Fig.1.

4.1 Pre-processing

The steps in pre-processing involve binarization, noise removal and boundary extraction.

4.1.1 Binarization

Binarization is the process of converting a gray scale image into binary image using Otsu's method.

4.1.2 Noise removal

Noise can be removed by applying median filters and some techniques [13] to the binarised image.

4.1.3 Boundary extraction

Each handwritten signature image is enclosed in a tight fit rectangular boundary. The portion of the handwritten signature image outside this boundary is discarded using horizontal and vertical projection technique [9].

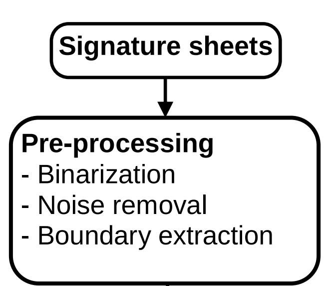

Fig. 1. Flow chart indicating boundary extraction procedure

4.2 Feature extraction

Features are extracted from pre-processing signature images.

Pseudocode of the feature extraction techniques for handwritten signature images is given in Algorithm 1.

Algorithm 1: Feature extraction

Input: Set of images of Signature
Output: Feature vectors (SIFT and SURF)
Step 1: Selecting Training images from the image database.
Step 2: Collect all the SIFT / SURF features from the images in 1.
Step 3: Cluster these descriptors using k - means into k number of clusters where k is a number you set. The centers of these clusters are the "visual words" i.e. representative features in the database of images.
Step 4: For every image in the database, for each SIFT / SURF features in the image, the training set (also known as training histogram) is created by find the indices of the minimum value of the image and the closest cluster center (using Euclidean distance) in the codebook/dictionary.
Step 5: The testing set (also known as testing histogram) is also generated by using the testing images as 4.
Step 6: Finally, the initial matching is done by finding the minimum value of the Euclidean distances of the corresponding training and testing features.
Step 7: End of program

4.3 Classification

We used the one-versus-all (OVA) SVMs for the classification of Handwritten signatures. The implementation of multi-class classifiers was performed using the SVMs package.

5. DATASET

A collection of 40 signatures from each of 40 classes attended was gathered yielding a total of 1600 signatures our data set.

6. RESULTS

We estimate the generalized accuracy using different kernel parameters γ and cost parameters C. A range of values of C = [2^0, 2^1 ... 2^{12}] and γ = [2^{-10}, 2^{-9} ... 2^2] have been experimented with, in finding the optimal values for these parameters.

In our first experiment, we used 50% of the data for training, and the other 50% for testing. For each pair of (C, γ), the validation performance was measured by splitting the initial training set into 70% for training (*train*) and the remaining 30% for validation (*val*). Then we tuned the parameter pair of (C, γ) on a grid-based search using the *train*-*val* set. The recognition rate was evaluated using the following formula:

$$\text{Recognition rate} = \frac{\text{Total number of correctly recognised signatures}}{\text{Total number of signatures}}$$

The following table (Table 1) shows how the accuracy varies with the chosen K- Value in the K-means algorithm.

TABLE 1: SIFT EXPERIMENTS

Value (k)	5	10	15	20	25	30	35	40
Accuracy	68	58	47.12	38.75	31.75	28.75	23.5	22.5

From the above Table 1 the SIFT algorithm's accuracy considerably degrades when increasing the K-Values. The accuracy reaches its maximum when K takes the value 5.
Result: K = 5, Accuracy = 68 %

TABLE 2: SURF EXPERIMENTS

Value (k)	5	10	15	20	25	30	35	40
Accuracy	86.5	88.87	86.5	84	82.5	82.37	80.37	81.37

From the above Table 2, it can be seen that the SURF algorithm's accuracy decreases and increases with the K-Values. The accuracy becomes its maximum when K takes the value 10.
Result: K = 10, Accuracy = 88.87 %

In our second experiment, the experimental setup was 10-fold cross validation.
Accuracy = 96.87% for SURF features
We evaluated our proposed approach on the overall dataset. Our approach yields a recognition rate of 96.87%.

7. DISCUSSION AND CONCLUSION

In this paper, we presented a comparative experiment of SIFT and SURF based offline signature recognition algorithms. From the experimental results, it was found that the level of efficiency of the SURF algorithm was much higher than that of the SIFT algorithm. From the initial test it was revealed that SURF features provide better accuracy than SIFT features, the best training and testing data sets obtained from the SURF experiment is used in the SVM testing and prediction.
In conclusion, the future work of this research is to compare the level of efficiency and performance with the G-SURF (Gabor filter based features with SURF features), ORB (Oriented BRIEF, very fast binary descriptor based on BRIEF) and, FAST (Features from Accelerated Segment Test) based algorithms.

Furthermore, better performance of the classifier may be achieved by trying different kernel functions, different pre-processing techniques, different distance measure and different classifiers. Further better training and testing sets can also be obtained by automatically shuffling the training and testing sets into some predefine rates.

We need to integrate the designs presented in this research to have a fully-fledged software for signature recognition and verification in the future. Furthermore, many areas of study related to invariant features and various distance measures are still open.

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