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An Efficient Signature Recognition System Based on Gradient Features and Neural Network Classifier

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Abstract

This paper proposes a novel offline signature recognition system (SRS) based on histogram of oriented gradients (HOG) and fuzzy min max classification (FMMC) methods.
First of all, the signature image required a preprocessing stage, then the Histogram of Oriented Gradients features are adopted to extract features from the training images. It consists of dividing the image into adjacent cells, for each cell histogram of oriented gradients characteristics are calculated.
This technique has been compared with two popular statistical methods such as Loci characteristics and profile projection (PP). The classification is performed using FMMC and it is compared with K nearest neighbors method (KNN). The presented approach achieved a recognition rate of 96% using a diverse signature database.

Keywords: Offline Signature recognition; histogram of oriented gradients; fuzzy min max classification

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1. Introduction

For decades, colossal researches and efforts have been presented for developing algorithms associated to the signature recognition problems. Signature recognition system has involved in difficult tasks such as banking transaction, credit card validation, security system, document verification etc. The handwritten signatures are dependent on various factors; a person’s emotional or mental state, making the signature recognition a challenging problem. There are two types of signature recognition systems: the online type and the offline one. The offline signature recognition system is a complex task than to the online mode [2], so more importance is devoted to the offline signature recognition.

The offline signature recognition performance is highly depended on the features characterizing the image and classification method. Many different features and classifiers have been deployed to challenge the handwritten signature recognition problem.

In [3] modified direction features are extracted from the signature's contour and are used to learn artificial neural network (ANN) and support vector machine (SVM) classifiers, granulometric size distributions are used to extract the local features and KNN is used as classifier [4]. Radon transform is used to feed Hidden Markov Model (HMM) in [1]. Hu and Zernike moments are explored to feed SVM classifier [5]. In [6], the interior stroke distribution and the description of the signature envelope are tested with three types of classifiers: HMM, SVM and KNN. Other studies are used Hough transform as features method and ANN is used for classification [3, 7]. In [2] the curvelet transform is tested with SVM classifier. A series of studies in this area are available in [8, 9, 10, 11].

The complexity and the diversity of the classification problem give rise to many approaches; artificial neural network is one of the more promising methods to pattern recognition [12, 13]. They have been massively used in many recognition problems among them the FMMC which is suited to different type of classes. It consists of creating hyperboxes iteratively and for each iteration three phases are applied: expansion, overlap and contraction.

The rest of this paper is organized as follows: section 2 describes the methodology behind the signature recognition system including preprocessing, feature extraction and classification, the experimental results are presented in section 3. Finally, the conclusions are outlined in section 4.

2. Methodology

This section explains the methodology behind the signature recognition system (SRS). The performance of a SRS depends on how the system can discriminate person signatures. This study requires data acquisition, preprocessing, feature extraction and classification. To evaluate recognition system performance, two statistical features extraction methods and KNN classifier are used for comparison.

2.1. The signature database

For training and testing the recognition system, we use our signature database, because with this type of data, no international database is offered in this context due to the privacy problems. In this paper, a database of about 240 signatures is used. The signatures were taken from 12 persons (20 signatures from each). For training the system, a subset of 120 signatures is used, and the remaining signatures are used for testing.

2.2. Preprocessing

Offline signature recognition may profit from preprocessing steps, to obtain scale and translation invariance and to eliminate distortions and noise; due to scanning hardware or paper background, the purpose of these operations is to improve the efficiency and performance of the signature recognition

The preprocessing stage includes a succession of operations to obtain good results. The principal steps are as follows: conversion the RGB image to grayscale, binarization, noise reduction and cropping.

The signature input image is converted to gray scale which is presented in color, and it is binarized, fixing a threshold value, which the image pixels are compared. Then a filter is applied to the binary image, to reduce noise and eliminate single white or black pixels on black or white background respectively. In order to achieve this, the median filter is applied; each output pixel value is calculated using the median value in a 3-by-3 neighborhood around the corresponding pixel in the input image. The next stage is to only maintain the signature position in image by cropping it.

2.3. Features extraction

The robustness of recognition system depends highly on the choice of the features extraction methods and on their effectiveness in providing the relevant information that characterizes a signature.

In this context, we will focus more particularly on HOG structural features. In order to evaluate and prioritize this technique; we compare it with two statistical methods; Loci and PP. We use these techniques because of their robustness and their great utility in pattern recognition.

Histogram of Oriented Gradients (HOG)

HOG features are proposed by Dalal and Triggs [15], they capture local details and are robust to illumination changes [24]. Several steps to calculate HOG features are organized as follows:

First of all, the horizontal and vertical gradients, g_x, g_y are calculated for every pixel, and then they are used to compute the gradient magnitude g and gradient direction θ using the following formula:

$$g = \sqrt{g_x^2 + g_y^2} \tag{1}$$

$$\theta = \arctan g \frac{g_y}{g_x} \tag{2}$$

In this paper, the signature image is normalized with the size 128 × 64. The signature image is divided into no overlapping rectangular cells 8×8 pixel cells, resulting in a 16×8 cell grid. Each pixel inside the cell participates to build a histogram of a nine bin.

In order to reduce the effect of contrast changes, the normalization is carried out on feature histograms grouped in blocks. The created blocks have a size of 2×2 cells.

The signature image is automatically divided into 7 × 15 blocks, therefore 105 blocks are created. Each block contains 4 cells, each cell in turn contains 9-bin histograms of 4cells. The dimension of attribute vector per block is 4*9=36. The final attribute vector is the concatenation of the histograms of all cells in a block for all blocks.

The purpose of this approach is to produce pertinent information and non-redundant features [25].

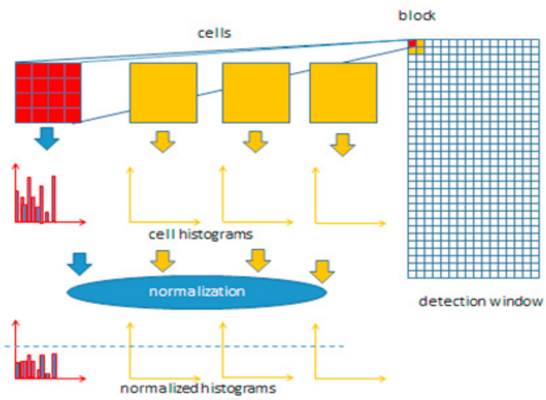

Fig.1. HOG feature extraction framework

Profile projection (PP)

Profile projection method provides global features, widely used in pattern recognition [16]. It consists of presenting the edges of the image as a vector by computing the number of background pixels between each side of the image until the first pixel presenting the image.

Loci features

Loci features method has proposed by Gluksman in 1967 [17, 18, 19]. This technique has been extensively used because of its robustness to style and font changes. This method consist of scanning of all the image background pixels, for each background pixel a loci number is calculated, which is the number of transitions in the four horizontal and vertical directions. The attribute vector components are constituted by the frequency of occurrence of loci numbers. The number of transition for each background pixels is limited to two.

2.4. Classification

Fuzzy Min-Max classification (FMMC)

Principle

FMMC is proposed by Simpson in 1993 [20], it contains three layers, input, output and hidden layers. The input layer contains a number of neurons which is equal to the dimension of the attribute vector N. The number on hidden neurons changes with the creation of prototypes P. The number of output neurons is equal to the number of signature classes k.

The synaptic weights between input and hidden layers are formed by two matrices V and W characterizing the different created prototypes in the hidden layer. The synaptic weights connecting the hidden and output layers are created by a Z matrix characterizing the classes of different prototypes [22].

Each hyperbox B_j created in the hidden layer, defined by its min point $V_j=(v_{jn})_{1\leq n\leq N}$ and its max point $W_j=(w_{jn})_{1\leq n\leq N}$.

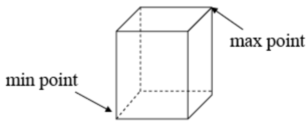

Fig.2. A hyperbox in $\Re^3$

The learning process consists of selecting an input image $O_i=(a_{i1},a_{i2},\ldots,a_{iN})$ and finding the nearest hyperbox B_j providing the highest degree of membership $b_j(O_i)$ [20,21,22] to include the image.

$$b_j(O_i)=\frac{1}{2N}\sum_{n=1}^{N}[\max(0,1-\max(0,\gamma\min(1,a_{in}-w_{jn})))+\max(0,1-\max(0,\gamma\min(1,v_{jn}-a_{in})))] \tag{3}$$

For each training input image three steps are devoted which are; expansion overlapping and contraction. These phases are supervised by two parameters; the vigilance factor θ and the sensitivity γ [22].

K Nearest Neighbors (KNN)

KNN is proposed by Cover et al. It has been widely used in pattern recognition for its simplicity and its efficiency [14]. KNN is a method which is based on the nearest neighbor principle; it is based on the fact that only the closest object influences on the classification result [22]. In order to get better results, KNN use the Manhattan distance between the attribute vector of the test image and all attribute vectors of learning images and then attribute the test image class to the first closest neighbor class.

3. Results and discussions

Following the previous analysis, to classify the unidentified signature image to the appropriate person, the image passes through the preprocessing and the feature extraction stages. The attribute vector is applied to the classifier; kNN or FMMC. In this present paper, we compared our proposed system (HOG+FMMC) with two statistical methods; PP and Loci features, to prioritize HOG method and we use kNN classifier to prioritize FMMC.

The performance of any signature recognition system is typically described by calculating the recognition rate (R.R). We start our first experimental simulations by computing recognition rate using different features extraction methods to feed FMMC classifier. FMMC method is supervised by two parameters; the vigilance factor θ and the sensitivity γ. The first results are obtained by varying θ with fixed γ, $\gamma=0.1$

Table 1. R.R using different features extraction methods by FMMC with the varying θ

θ	R.R by HOG	R.R by profile projection	R.R by Loci
0.0001	96%	78.5%	92%
0.0009	96%	73%	93%
0.001	96%	73%	92%
0.1	92.5%	73%	85%

Table 1 shows that the R.R obtained by HOG method outperforms all types of features for every θ value. Moreover, the recognition rate depends on the choice of the vigilance factor θ which control the size of created hyperboxes. When θ is small, a several hyperboxes will be created which can only contain a small number of objects, therefore, we have a very good precision and higher recognition rate.
The second results are obtained by varying the γ with fixed θ, $\theta= 10^{-4}$.

Table 2. R.R using different features extraction methods by FMMC with the varying γ

γ	R.R by HOG	R.R by Profile projection	R.R by Loci
0.1	96%	78.5%	92%
0.6	96%	78%	92%
1	96%	78%	92%
7	96%	77%	91%
11	95%	77%	90%
12	93%	75%	90%

Table 2 shows that the recognition rate obtained by HOG outperforms all feature extraction methods, and, the recognition rate depends highly on the choice of the sensitivity parameter which regulates how fast the membership value decreases when an input pattern is separated from the hyperbox core.

The recognition rate 96% was not improved using values less than 1 which is the best value for this parameter (decreasing parameter γ increases the hyperboxes sensitivity).

Table3 shows the recognition rates of signatures images, using kNN and FMMC for different features.

Table 3. R.R of signature images using kNN and FMMC.

Features extraction methods	R.R by kNN	R.R by FMMC
Loci	88%	93%
Profile projection (PP)	79%	78.5%
HOG	95%	96%

From Table3, we notice that the FMMC method outperforms the kNN, which proves that the learning process of FMMC is more efficient. On the other hand the results obtained by HOG method are higher, more particularly with the *FMMC* where the recognition rate achieved is 96%.

HOG descriptor capture local details and give more information for the attribute vector which has been able to differentiate between signature images.

This result confirms that the local features are more precise than the global ones. The global features such as: profile projection and Loci characteristics represent signature image as a whole but the local ones consist of dividing the image into a small regions and describing them to extract more information from its.

4. Conclusion

In this paper we have presented a new approach for recognizing offline signature, this process takes into account the robustness of the two processes: extraction and classification methods. HOG characteristics are used as features extraction method and FMMC as classification method.

The signature image is initially preprocessed. It is divided into adjacent cells and for each cell 9 bin histogram of oriented gradients is calculated, then overlapping blocks are formed, each block contains 2x2cells, so a 36 points feature vector are collected and normalized. The resulting HOG feature vector serves as the descriptor for the image and is used to feed FMMC. The proposed technique was compared with PP and Loci to evaluate HOG method and it was compared with kNN to prioritize FMMC. The proposed system has achieved good results; a 96 % was obtained.

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