Signature Recognition Using Zernike and Invariant Movement

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Abstract

Nowadays, the human signature plays an important role in biometric authorization. Signature verification can be performed online or offline. With the help of modern computers, signatures are treated as images and recognized with the technique of computer vision and neural network. Signature detection is a very challenging active research because of the possible signature appearance variation in illumination, occlusions, etc. Although there are many research papers in signature recognition, there are a lot of gaps to implement the robust signature recognition system. In this paper, offline signature recognition and verification is proposed. In our system, there are two main portions: feature extraction and classification. The features are extracted using invariant central movement and modified Zernike movement as there are a large amount of variation in size, translation, rotation and shearing parameters in a signature. Multilayer perceptron neural network is applied to recognize signatures.

Keywords: Biometric Authorization, Computer Vision, Signature Detection, Back Propagation, Neural Network

1. Introduction

The more and more advanced the electronic medium is, computers play an essential role in processing, storing and transmitting the information. The computer vision system is targeted to achieve a reasonable visual recognition ability that is comparable to the human. Since there needs to be dealt with the possible appearance variation that are caused by change in occlusions, facial features, illumination, etc., the signature detection system is a popular research field. To tackle the incomplete or uncertain data, the back propagation is the best technique to mimic human reasoning more precisely. The significant attribute of a person is the human signature and therefore the signature is used for authorization purpose. Although there are many research papers for signature recognition, there are still gaps in many places. So, in this paper, off-line signature recognition is proposed. Signature can be written in various ways. Some signatures can be written with flourishes. As human assume signatures as the artistic handwriting objects, most of the signatures can be unreadable. In this paper, a signature is treated as an image. And, it can be recognized with the help of computer vision and artificial neural network technique.

The efficiency of office and business has been dramatically increased by computer technology and people depend on electronics more than ever before. Students are daily handling and processing unfathomable amounts of information in their routines regarding diagnostic investigation, treatment and patient care. That overwhelming amount of student records are generated an how this information is efficiently processed have become a brittleness of office automation and electronic business. Although there are different medical records for different students, computers are more capable than before, and signature detection for student records has become possible. Our system has two main portions: (a) training signatures, and (b) verification and recognition of given signature. Recognition is finding the identification of the signature owner. Verification is the assessment whether the signature is genuine or forgery [1].

2. Related Work

In 2018, Aristanto and Solichin [2] proposed the signature recognition with the approach of Zernike moment and support vector machine (SVM). They tested 23 employees and achieve the accuracy of 88%. Unfortunately, the system cannot recognize if the signature is written in low pen color.

In 2016, Rahmi et. al. [3] presented the off-line signature recognition with the help of back-propagation neural network. The accuracy obtains the recognition rate of 63%. They found that the accuracy is greated influenced on the image preprocessing phase.

Similarly, Inan and Sekeroglu [4] presented the off-line signature recognition with the technique of back-propagation neural network by the time 2019. They tested the system with 27 persons and achieve the recognition rate of 86.3%.

Almost all pattern recognition schemes have been proposed with the supervised learning approach. All these papers do not consider too much computation and geometry. Our system also takes advantage of artificial neural network (ANN). ANN for signature recognition utilizes the information theory approach in that the pertinent information is extracted from a signature image. In addition, ANN is used for recognition. Neural network is popular in recognition since it can learn from observed data.

3. Signature Recognition

Signature recognition is a part of pattern recognition. Pattern recognition studies the operation and design to recognize patterns in data. Signature recognition is an easy task for humans. In automatic signature recognition, the useful features are extracted from an image, and these features are applied into a useful representation to perform some classification on them. Automatic signature recognition is related to sub-disciplines such as cluster analysis, discriminant analysis, error estimation and feature extraction. Almost all off-line signature recognition and verification systems utilize image processing and feature extraction [5].

ANN is a little different from traditional computing techniques to deal with problems. Therefore, it is widely used in many areas such as pattern recognition (image recognition, fingerprint detection…). The general is ANN and particular technique that fits this role is a multilayer feed forward perceptron with back propagation learning rule.

3.1. Back Propagation Algorithm

A back propagation network is the kind of supervised learning. It can be performed in two different modes, training (or learning) and testing. A set of examples are given to the network during learning. The flow diagram of back propagation algorithm is shown in figure 1.

The neural network training is the kind of the supervised training. The patterns and the desired output for each pattern are sequentially given to the recognizer. The recognizer takes the pattern as input and generates an output. If the predicted output pattern is different from the desired pattern, the internal weights that are negatively contributed to the output are updated according to the learning rule of the back propagation algorithm. In this way, its accuracy is increased from the initial state to a final state. In the initial state, random weights are assigned and are stored in the weight matrix form. The network's output is compared with the expected target value. This value is known as the error value. The weights are modified by propagating the network. In the final state, the classifier is capable of producing correct (or almost correct) output. The performance of the network is assessed by using the sigmoid function.

4. The Proposed Solution

The software development of signature recognition using propagation for student record system is mainly described. Step by step implementation, software flow chart and detail using are also expressed.

4.1. Data Acquisition

In this section, sample signatures of each person are collected in the digital image format. The signatures are collected form 20 people, 10 signatures for one person. 7 signatures for one person are taken for training and so the total number of training signatures is 140 signatures. For the testing purpose, 3 signatures for one person are taken and so the total number of testing signatures is 60 signatures. Signatures must be scanned in gray. The 140 signatures are stored in a database which is later used for training.

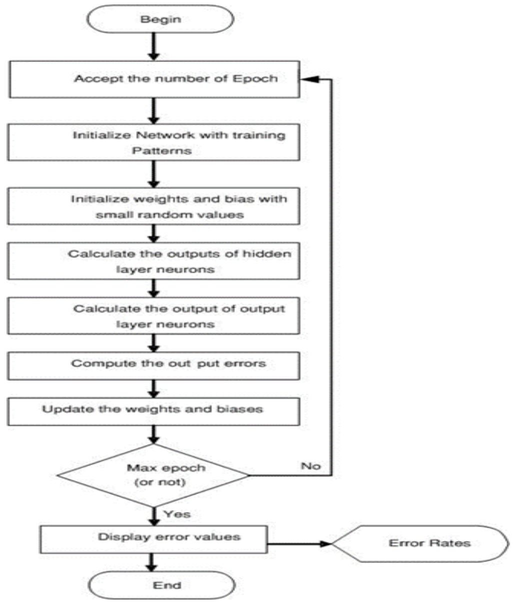

Figure 1. Flow diagram of back propagation

4.2. Preprocessing

In this section, signatures are preprocessed so that they are standard for feature extraction. There are four main steps. They are background elimination, noise reduction, width normalization, and skeletonization. A brief description of the image (signature) preprocessing step is shown as follows:

1. The images' dimensions are deducted to 300×340 pixels.
2. The minimized images with the format of RGB (Red, green and blue) are changed into gray-level coded images.
3. The gray level of 90 is determined as the threshold value. The gray levels under 90 are modified to gray level of 0 and the gray level over 90 to 255.
4. Lastly, the gray-level coded images are converted to the binary images so that it can use pixels with value of 0 and 1.

4.3. Feature Extraction

In a signature recognition system, the effective feature extraction methods greatly influence to obtain a high recognition performance. The input of the training phase is the extracted features of this phase. Various feature extraction algorithms to extract conventional global features of signatures and new features. To minimize intra-class pattern variations and maximize the inter-class variations, the proposed new features are Hu's Invariant central movement to normalize scale and translation, and modified Zernike movement to normalize rotation.

4.3.1. Invariant Central Movement

An image's movement order (u +v) is composed of binary pixels B(x, y) [6], [7] as shown in (1).

$$m_{u,y} = \sum_x \sum_y X^u Y^v B(x,y) \qquad (1)$$

$u, v = 0,1,2,3 \ldots$

The image center of the mass (x, y) and body are A is calculated as (2).

$$\bar{x} = \frac{m_{10}}{m_{00}} \bar{y} = \frac{m_{01}}{m_{00}} \quad (2)$$

The translation invariant movement (the central movement) is calculated as (3)

$$\mu_{uv} = \sum_x \sum_y \overline{X - (X)^u} \; \overline{(Y)^v \, B(x, y)} \quad (3)$$

Lastly, the normalized central movement, the translation and scale invariant, is derived as follows:

$$n_{uv} = \frac{\mu_{uv}}{(\mu_{uv})^k} \quad (4)$$

Where

$K = 1 + (u + v)/2 \; for \; u + v \geq 2$

4.3.2. Zernike Movement

The polynomials of Zernike movement are a set of complex polynomials which form a complete orthogonal set over the interior of the unit circle [8]. Zernike polynomial form is illustrated in (5)

$$V_{nm}(p, \theta) = V_{nm}(p, \theta) = R_{nm}(p) \exp(jm\theta) \quad (5)$$

Where,

$j = \sqrt{(-1)}, \; n \geq 0, n - |m| \; iseven \; |m| \leq n$

ρ = the vector length between the origin and the point (x, y),

θ = the angle between the vector and the x-axis in the counter-clockwise direction and the radial polynomial.

The movements are the projections of the image function onto this orthogonal basic function. For a digital image, the Zernike movement order with repetition m is calculated as (6).

$$A_{nm} = \frac{n+1}{\pi} \sum_x \sum_y B(x, y) [V_{nm\,(\rho,\theta)}] \quad (6)$$

To compute the Zernike movements for the underlying image, the pixels of the image are mapped to the unit circle x2+y2≤1 by assuming the image's geometrical center as the original and scaling its bounding rectangle into the unit circle.

The image's pixels are mapped to unit circle to compute the movements for the underlying image. Because of the Zernike's orthogonality nature, the original image's parts in the unit circle can be estimated with its Zernike movements A_{nm}up to the given order n_{max} as follows.

$$\hat{B}(x, y) = \sum_{n=0}^{n_{max}} \sum_m A_{nm} V_{nm}(\rho, \theta) \quad (7)$$

From the Zernike movements, the orthogonality property allows to reconstruct image with the additional information content of each individual order moment. In addition, the moments of a rotated image are the same as those of original image that gets hold of a phase shift upon rotation. As a result, the moments' magnitudes are the underlying image's rotation invariant features. The image shifting and scaling into the unit circle are allowed to get the translation and scale-invariance.

4.4. Training and Classification

The resulted extracted features are put into the database. The human signature is highly rely on the varying factors such as the physical and practical condition such as the tip of the pen used for signature, the psychological or mental condition, signatures taken at different times, etc. Since two signatures from the same person can be never same, we also have to take into account of a high degree of variation. This variation is also considered to achieve the good accuracy rate in detecting forged signatures.

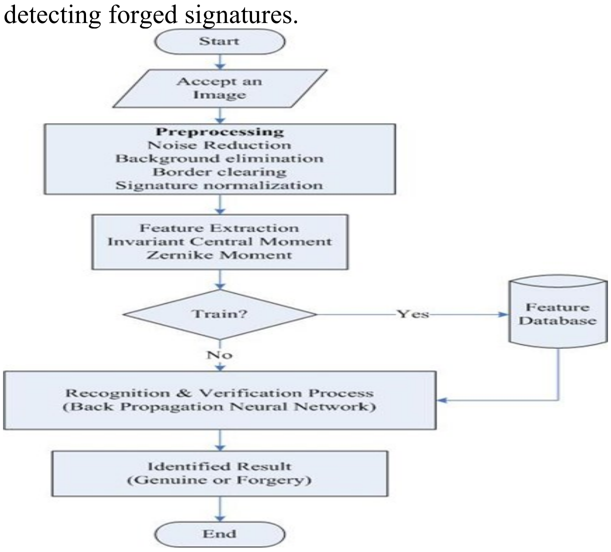

Figure 2. Flow diagram of the system

5. Implementation

The proposed system's flow diagram is illustrated in figure 2. Our system is divided into the two main steps: signature detection and neural network creation.

5.1. Signature Detection

The first step of this software development is to collect or to create the image database. The signature images are collected by scanning. Skin color detection plays an important role in signature detection. There are many techniques in locating skin color regions from the input image. These techniques apply the HSV or YIQ formats although the format of the input color image is the RGB format. Since RGB components are sensitive to the lighting conditions, it has the failure in the signature detection if the changes occur in the lighting condition. So, the system apply the YCbCr component that is the one of existing C# function to minimize the computation time. The luminance information is obtained from the Y component, the chrominance information from the Cb and Cr. So, the luminance information can easily be de-embedded. Every pixel is used to classify skin or non-skin according to color components in the skin color detection process. With the mean and standard deviation of Cb an Cr components, it is determined to obtain the detection window for skin color.

Next, individual regions are separated according to the three steps. Firstly, black isolated holes are filled up to get rid of the white isolated regions that are smaller than the minimum signature area in the training images. The threshold is set 170 pixels as the same as the traditional. Secondly, the Roberts Cross Edge detection algorithm is applied to split some integrated regions into individual signatures. The Roberts Cross operator is used to highlight regions of high spatial gradients of the edge as it comports 2D spatial gradient measurement on an image. The highlighted regions are changed into black lines and eroded to connect crossly separated pixels. A different method of signature template is then resorted to decide what differentiate a signature from its features. Deciding to change all gray scale images to black-and-white images, edge extraction algorithm is applied to extract the important features and combine these features to get a signature's template. Result signature image after detection is shown in the following figure 3.

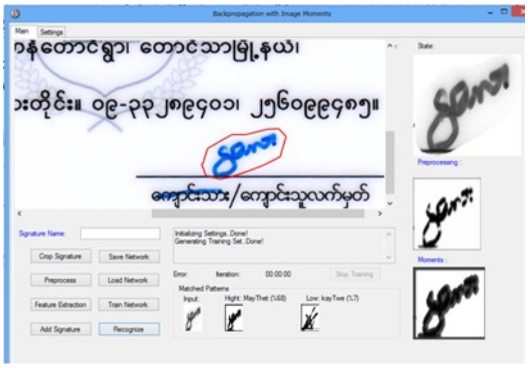

Figure 3. Signature detection window

In image preprocessing step, the normalization of the image size, the histogram equalization and gray scale conversion are performed. After performing this module, every signature of 100*100 pixels that can distribute the intensity of signature images is obtained to achieve a high signature recognition performance. These signatures are put into a signature library of the system to perform training.

5.2. Neural Network Creation

After signature detection and adding signatures to library (patterns folder), we have to input the neural network. The system uses feed forward neural network. Since neural network is formed with simple elements that are operated in parallel, the number of neurons in each network layer is needed to input for training network. Although it has to be fixed the number of neuron output layers of neural network, the number of input layers and number of hidden layers can be changed as shown in figure 4. In training, all the bitmap (*.bmp) images must be located in one (input) folder and each image must be named the target (or output). In testing, all the classes must be trained first and there is a folder named "PATTERNS".

In training, the learning rules must be applied to classify the correct output. The sigmoid function is utilized to approximate the output of each layer in the network. A network training function is utilized to modify weight and bias values according to gradient descent momentum and an adaptive learning rate. The training parameter is defined as follows:

- Number of input neurons = 200
- Number of hidden layers = 3 layers
- Number of each hidden-layer neurons = 123 neurons
- Number of output neurons = 13
- Type of transfer function in each layer = sigmoid
- Performance Function = Sum square error
- Performance Goal =0.01
- Maximum number of iteration to train =10000
- Maximum epochs = 1500

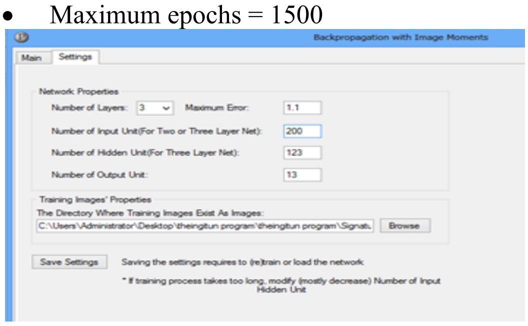

Figure 4. Setting tab page of back propagation form

As soon as the user opens the system, splash screen will appear. After the splash screen has shown, the system can display the main form. In the main form, there are two menus;

- Application menu: To create neural network image library and search hospital records for input image.
- Help menu: To show about this system.

In this section, if the user wants to search hospital records of a person that has been already saved, the upload photo and search button can be used. First user need to click and choose image to open the image. When user click search button, the application will search and display recognition image as shown in figure 5. The system will display nearest two image from signature library. The name of the photo can be chosen form name combo box. After searching signature image from signature net, user need to type national registration card number in the NRC text box to get detail information of the image. If the person is new or the name of the person is incorrect, user need to train and save image from Back propagation form.

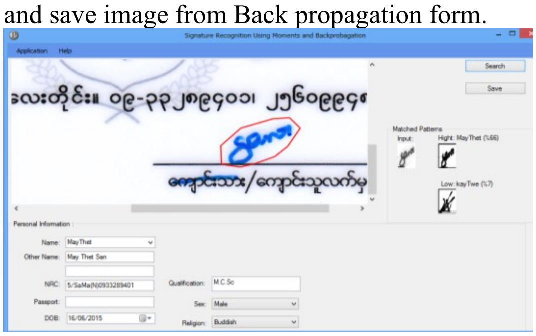

Figure 5. Main tab of back propagation form

In this window, there are five buttons and one link button for user selection

- Upload Photo link button – to open the image file for testing or searching records
- Search Button – to search signature and record from signature database

- Save Button-to save updated data or new personal data for image
- Browse Button – to upload hospital record file of a person (only micro soft word 2007 format)
- Add Button – to save updated hospital data or new hospital data of a person
- Open - to open hospital record from the Detail Records combo box

When user click New Signature from Application menu, back propagation form will display as shown in figure 4. In this section, user can add new signature and create neural network structure and train. When upload photo link button, file open browser will display and user can open an image. Signature can be cropped from an image by clicking the signature detect button. If the image is new patient or person, user need to type in the name text box and add signature to image library. In the form, user can train images and save trained network and test. After neural network setting from settings page, user can train the network by clicking the train network button. User needs to save network for recognition process and searching hospital records after the training.

In this tab page, there are seven buttons and one link button for user selection

- Upload Photo link button – to open the image file for testing or searching records
- Signature Detect Button – to crop signature from image and to apply preprocessing such as color segmentation, gray scale filter, histogram normalization and equalization
- Add Signature Button-to save person signature to signature library
- Save Network Button – to save trained neural network
- Load Network Button – to load trained neural network
- Train Network Button- to train neural network with back propagation
- Recognize - to test signature image
- Stop Training Button- to stop network training process

Figure 4 shows the settings tab page of the back propagation form for creating network. After setting for network, user needs to save settings by clicking save settings button. In this tab page, there are two buttons for network settings.

- Browse button – to choose the image library path for create and to get output target images
- Save Settings Button – to save neural network settings for neurons and layers (maximum 3 layers, input, hidden and output)

6. Result and Analysis

The system is implemented on the platform of window 10 x64-based processor with the installed memory of 4.00GB. The processor is Intel ® Core™ i5-4200U CPU @ 1.60 GHz 2.30 GHz.

To evaluate the system, all the signatures must be scanned. The signature images can be in the various dimension because all signatures must be deducted to 300×340 pixels in the image preprocessed images. The system is evaluated with the 20 persons, 10 signatures for one person. For the testing purpose, 3 signatures are taken for one person and therefore 60 signatures are tested.

Accuracy is evaluated with the following equation:

$$Accuracy = \frac{Number\ of\ correctly\ tested\ signatures}{Total\ number\ of\ tested\ signatures} \qquad (8)$$

Out of 60 signatures, 50 signatures are correctly verified and the remaining cannot be detected. So, the current system achieves 83.3% recognition rate.

7. Conclusion

The system is implemented by separating the signature from its background and performing the original image's normalization and digitization and applying moment invariants and some global properties to the neural network. As the computer technology is developing with time, there can be new methods for signature recognition. Therefore, the system could be extended to be motion image recognition system which can be used authentication, data entry (banking environment) and process automation (security). Currently, we take advantage of the back-propagation algorithm to implement the offline signature recognition system. And the system could be extended to be online recognition system. The dimensions of the input matrix need to be adjusted for performance. The system performance can be better by increasing the feature vector dimensions and higher the resolution.

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