IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
Impact Factor: 6.252
Volume 2, Issue 2, April 2022

Signature Verification using Image Processing & Neural Network

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Abstract: *The fact that signatures are widely used as a means of personal verification emphasizes the need for an automated verification system. Verification can be done offline or online depending on the application. The online system uses dynamic signature information collected in at the time the signature is made. Offline systems operate on a digitized image of a signature. We worked on offline verification of the signature using a set of shape-based geometry features. The features used were base tilt angle, aspect ratio, normalized area, center of gravity, number of side points, number of diagonal points and line slope combined with the centroids of the two signature halves image. Before extracting features, it is necessary to pre-process a digitized image to isolate the signature part and remove any existing parasitic noise. The system is initially trained using a database of signatures obtained from signatures that will be verified by the system. For each subject, an average signature is obtained combinations. The above characteristics are taken from his set of authenticator samples signatures. This average signature serves as a sample for verification against the confirmed test signature. In this article, we present how the problem has been addressed in the past decades, analyze recent advances in the field, and potential directions for future research.*

Keywords: Signature Verification

I. Introduction

Signature is a distinguishing feature to identify person through the ages. Signatures have long been used for automatic check payments in the banking industry. When a large number of documents, such as a bank check, need to be authenticated within a limited time, manually verifying the signature of the account holder is often impractical. Signatures provide a secure means of authentication and authorization. An automated signature recognition and verification system is therefore required. This thesis work is carried out in the field of online signature verification system by extracting a special feature that makes signatures difficult to forge. In this thesis, the existing signature verification system has been studied in depth and a model is designed to develop an offline signature verification system.

Handwritten signatures are a particularly important line of this kind of biometrics. This is primarily because is commonly used to identify individuals in the areas of Legal, Legal Administration, and One of the reasons to use it. Overall, the manuscript signing process is without intervention and everyone knows that signatures are used in everyday life.

Biometric fieldwork includes hand shapes, face prints, fingerprints, voiceprints, signatures, and non-retinal vascular analysis. Biometrics are widely used in physical access control applications. Unlike an individual's identification number or PIN, biometrics are like with respect to a person's characteristics. Biometrics uses to improve the level of security and identification. Signature is one of the most popular and most reliable biometrics used to verify a person's ID.

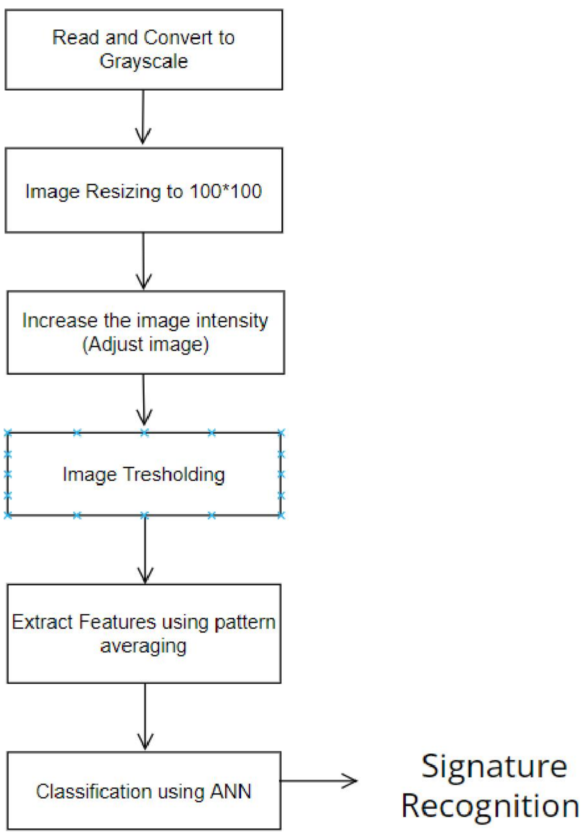
Signature verification approaches fall into two categories, online and offline, depending on how the data is collected. Online data records the movement of the stylus when the signature is created, including position and, in some cases, velocity, acceleration, and pressure as a function of time. The online system uses this information collected during the collection. These dynamic characteristics are unique to each individual, stable enough and repetitive. Offline data is a 2D image of the signature. Processing Offline is complex due to the absence of stable dynamic characteristics. Difficulty also lies in the fact that it is hard to segment signature strokes due to highly stylish and unconventional writing styles. The no repetitive nature of variation of the signatures, because of age, illness, geographic location and perhaps to some extent the emotional state of the person, accentuates the problem. All these coupled together cause large intrapersonal variation. In this research Signatures are processed using a number of techniques, including: Conversion to grayscale, filtering by median filters, and segmentation by canny edge detection. These techniques are performed to improve the quality of the image and extract important features so that only the signature is taken and some of the other features and parts of the image are ignored. At the end of this phase, the images are sent to a new phase, the neural network, where they are classified as different signatures of different people.

II. The Proposed Methodology

These techniques are done in order to enhance the quality of images and to extract the important features in such a way to take only the signature and ignoring the other.

At the end of this phase, the images should be fed to the new phase which is the neural network in which they are classified as different signatures for different individuals. The signature image is first analyzed and processed in the system so that a fractional, noise-free signature is extracted from the original image. The following stages are object extraction and neural classification, where the size of images is reduced while keeping their features intact using sample averaging technique. Once the size of the images was reduced, they were fed into a neural network that propagated their respective targets.

Figure 1 presents a flowchart that illustrates proposed system for the identification of handwritten signature. Figure 2 shows a handwritten signature image from our database that undergoes all the system processes in order finally to be segmented.



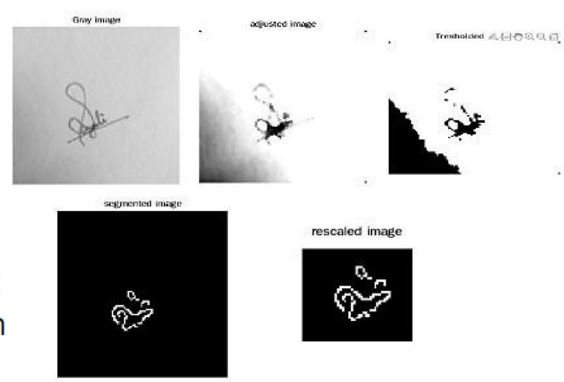


Figure 1: Flowchart of the developed framework

Figure 2: One signature image processed using the developed image processing system

IJARSCT

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2.1 Preprocessing the Data

The purpose of pre-processing is to improve the image data, reduce unwanted distortion, and emphasize some image features that are important for further processing.

Preprocessing consists of three steps: normalization, resampling time, and resampling distance. As you know, the size of a person's signature varies each time they sign a piece of paper or other material. Therefore, here we need to normalize the size to make each person's signature the same size before starting feature extraction. This is to prevent the developed software from tampering with the actual signature just because of the difference in size. Size normalization is done by scaling each character both horizontally and vertically.

2.2 Signature Images Processing

Image has been enhanced for proper identification through a series of images with processing method. These methods make up the completeness of the system in the processing phase.

2.3 RGB to Grayscale Conversion

First, the image is converted from RGB to grayscale, where this conversion is done using the luminance method (Figure 3). This method is a more complex version of the average method. It also averages values from the image matrix, but it forms a weighted average to account for human perception because humans are more sensitive to green than other colors; Green is the most important.

Figure 3: Grayscale conversion Image smoothing using median filtering

Smoothing called Blur, is a picture processing technique used to reduce noise in an image to create a less pixel image and clearer. Most smoothing techniques are based on non-linear low-line filters.

To make a smooth operation, we will apply filters to our images. The most common filter type is linear filters such as Median filters used in our proposed systems. This filter is used to reduce impulsive noise or salt pepper in an image with storing useful features and image edges. Median filtering is a nonlinear process where the output of the pixel being processed is found by calculating the mean of a pixel window surrounding that pixel of interest. In other words, the median filter goes through each element of the image and replaces each pixel with the median of neighboring pixels located in the (multiply) square neighbourhood around the pixel being evaluated. Figure 4 shows the input image after applying the median filter.

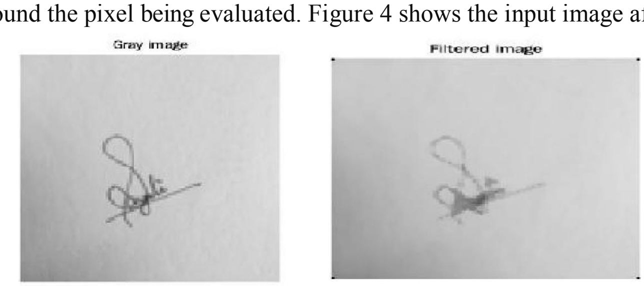

Figure 4: The input signature image after applying median filter

2.4 Adjustment of Image Intensities

In order to increase the intensity of the image and improve its quality, the image will be intensity adjusted. It is an image processing technique that aims to enhance the contrast of an image by increasing the intensity of its pixels. During this operation, the intensity value of each pixel in the input image is transformed using a transfer function to form a contrast adjusted image. The figure below represents the adjustment of an image and its effects in enhancing the image contrast.

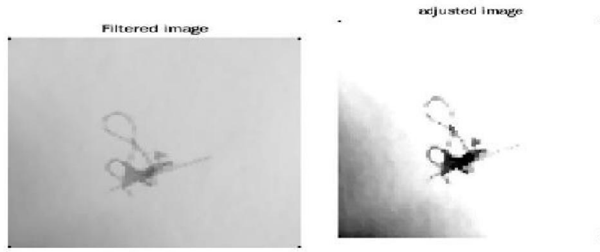

Figure 5: Adjusted image intensities

As can be seen, the signature is clearer and extracted after applying this technique. We can see from the image above that the image adjustment has a great effect on improving the contrast and brightness of the image, so it is clearer and its features are brighter and show. This helps in detecting edges and image features in the subsequent process.

2.5 Thresholding

Threshold is the separation of an image region into two regions. An area corresponds to the foreground area; in which it contains the objects of interest to us. The remaining area is the background, corresponding to unnecessary objects. This provides image segmentation based on different visual intensities and discontinuous intensities in the foreground and background regions. The input to this method is usually a grayscale or color image, while the output is a binary image representing the segmentation. Black pixels for the background and white pixels for the foreground. The segmentation achieved by a single parameter is called the intensity threshold. This is determined by analyzing the histogram of the image representing the intensity distribution of the image. During thresholding, each pixel is compared to this threshold value. If the value of a pixel is higher than this threshold, it is considered a foreground (white) pixel. If the pixel value is lower than this threshold value, the pixel is considered as background pixels (black).

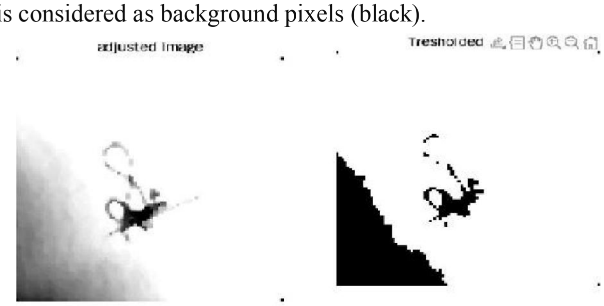

Figure 6: Illustrates a signature image that undergoes thresholding

2.6 Canny Edged Based Segmentation

Segmentation can be defined as grouping parts of an image into multiple regions. The purpose of such image processing is to represent some important and necessary regions of the image, such as tumor, face, etc.

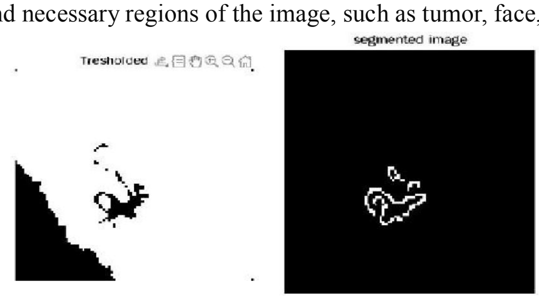

Figure 7: Segmented signature using Canny edge detection

Pixel contour is associated with certain magnitude changes or discontinuities; therefore, edge detection is the process of identifying these sharp intensity contrast points (i.e. discontinuities) in an image. The classical Sobel and Prewitt edge detection operators use 3 × 3 kernels that are matched against the original image to compute approximate values of the derivatives, one for the horizontal changes and one for the horizontal changes. verticals. In this proposed system, we detected edges using intelligent operators. This technique is the most commonly used method for detecting image edges and segments. Canny edge finder is considered as one of the best edge finder currently in use detector as it provides good noise immunity and detects true edges or intensity discontinuities while keeping errors to a minimum.

2.7 Feature Extraction and Rescaling using Pattern Averaging

Pixel contour is associated with certain magnitude changes or discontinuities; therefore, edge detection is the process of identifying these sharp intensity contrast points (i.e. discontinuities) in an image. The classical Sobel and Prewitt edge detection operators use 3 × 3 kernels that are matched against the original image to compute approximate values of the derivatives, one for the horizontal changes and one for the horizontal changes verticals. In this proposed system, we detected edges using intelligent operators. This technique is the most commonly used method for detecting image edges and segments. Canny edge finder is considered as one of the best edge finder currently in use detector as it provides good noise immunity and detects true edges or intensity discontinuities while keeping errors to a minimum. Below in Figure 8: is shown some of processed rescaled images.

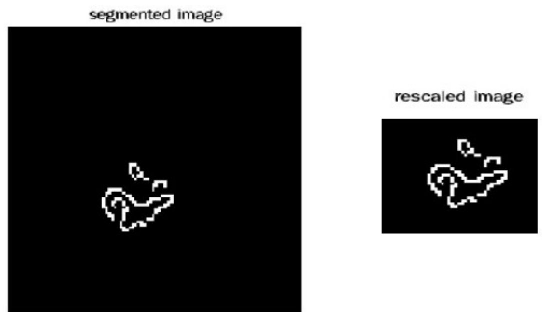

Figure 8: Rescaled image using pattern averaging

2.8 Data Training

The network was simulated and trained using Matlab software and tools. Due to its simplicity and sufficient number of images, the backpropagation algorithm was used as a learning method. The database contains 100 images. 60% of the magicians were used for training and 40% were used for testing**.**

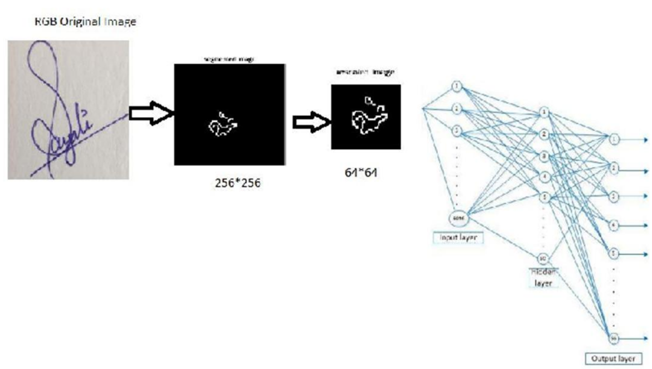

Figure 9: BPNN1 with 50 neurons

The figure above shows the proposed neural network architecture for the signature detection task. The input layer of the BPNN network consists of 4096 neurons because each image is rescaled to a 64x64 bitmap using pattern averaging

The hidden layer is made up of 50 neurons, but the output layer has 56 neurons because there are only 56 different signature classes. Figure 39 shows the network when 20 hidden neurons are used.

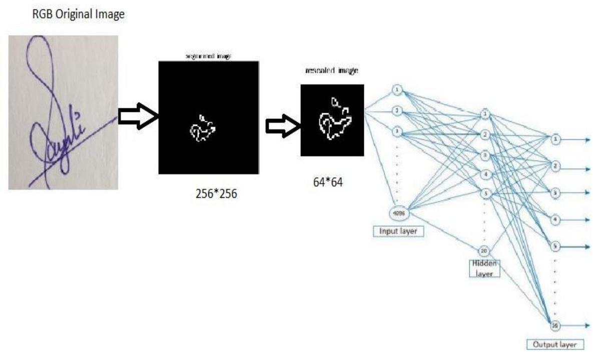

Figure 10: BPNN2 with 20 hidden neurons

Table 1 shows the input parameters used for network training. You can see that the network ran with a learning rate of 0.05, a count of 0.37, a minimum error of 0.001, and a maximum of 7000 iterations.

Parameter	BPNN1	BPNN2
No. of neurons in Input layer	4096	4096
No. of neurons in Output layer	56	56
No. of neurons in hidden layer	50	50
Maximum iteration number	1000	1000
Learning rate	0.05	0.05
Momentum rate	0.37	0.37
Error	0.001	0.001
Activation Function	Sigmoid	Sigmoid

Table 1: Training input parameters of the network

2.9 Performance

After the convergence of the network, the testing phase takes place. In this phase we evaluate the ability of the proposed system to recognize some signatures that were seen before but with different shift translations, illuminations, and different handwritings. The system was tested on matlab software. 40 diff signature images were used in testing the developed and trained network. The result of both testing and training phase is included in the following table2

Signature	Image Sets	No. of image	Recognition rate of BPNN1	Recognition rate of BPNN2
100	Training Set	60	97%	96%
	Training Set	40	87%	86%
All Signature images	Both Sets	100	92%	91%

Table 2: Recognition of the developed system

III. Conclusion

Marks or signatures are exceptional examples of handwriting, including exceptional letters and phrases. Many signatures can be ambiguous. They are a kind of stunning handwritten objects. However, text or signatures can be treated as images and can be recognized using computer vision and fake nervous system strategies. Letters or signatures are exceptional examples of handwriting, including exceptional letters and phrases. Many signatures can be ambiguous. They are a kind of stunning handwritten objects. However, text or signatures can be treated as images and can be recognized using computer vision and fake nervous system strategies.

So this research has helped us learn more and more about the signature identification and verification. This study builds on the various signature identification/verification studies done for this paper, making it possible to prepare and plan a signature verification system. signature has been designed and presented in this paper.

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