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ADeep Study on the Performance of the Spatial Density Distribution Method to Recognize Handwritten Signatures

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Abstract

A signature is a special identifier that confirms a person's identity and distinguishes him or her from others. The main goal of this paper is to present a deep study of the spatial density distribution method and the effect of a mass-based segmentation algorithm on its performance while it is being used to recognize handwritten signatures in an offline mode. The methodology of the algorithm is based on dividing the image of the signature into tiles that reflect the shape and geometry of the signature, and then extracting five spatial features from each of these tiles. Features include the mass of each tile, the relative mean, and the relative standard deviation for the vertical and horizontal projections of that tile. In the classification stage, four measurements of the Euclidean distance were used. While the accuracy rates for 4854 samples drawn from five different evaluated standard datasets ranged from 92.24% to 100%.

Keywords: Image Processing, Signature Recognition, Handwritten Signature, Signature Identification, Spatial Density.

دراسة عميقة لأداء طريقة توزيع الكثافة المكانية للتعرف على التواقيع المكتوبة بخط اليد

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الخلاصة

التوقيع هو معرّف خاص يؤكد هوية الشخص ويميّز بينه او بينها والآخرين. الهدف الرئيسي من هذه المقالة هو لتقديم دراسة معمّقة لطريقة توزيع الكثافة المكانية وتأثير خوارزمية التجزئة المرتكزة على الكتلة على أدائها عندَ استعمالها للتعرف على التوقيعات المكتوبة بخط اليد ضمن النمط اللا آني. طريقة الخوارزمية مبنية على تقسيم صورة التوقيع إلى بلاطات تعكس شكل التوقيع وهندسته، ثم استخراج خمسة خصائص من هذه البلاطات. تشتمل الخصائص على: كتلة البلاطة والمتوسط النسبي والانحراف المعياري النسبي للإسقاطات الرأسية والأفقية لتلك القطعة. في مرحلة التصنيف تم استعمال أربع قياسات للمسافة الإقليدية. بينما تراوحت معدلات الدقة لـ 4854 عينة مأخوذة من خمس مجموعات بيانات قياسية مختلفة تم تقييمها من 92.24٪ إلى 100٪.

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1. Introduction

A signature is a human sign that is written by the hand of a person himself and may contain symbols, curves, letters, or groups of letters that are used to imply the name of the writer, who is generally referred to as a signatory or a signer [1–4]. In general, it shows an individual characteristic of a person and is

a personal attribute for authentication [3], [5]. Signatures have many applications and they are used in wide areas such as financial transactions, banking systems, cheques, insurance, access control, document authentication, signing contracts, work documents, petitions, corporations, hospitals, administrative issues, forensics cases, notary public, employees' attendance, exams, and signing of certifications [6–12].

The modern electronic workflow and the telecommunication network have increased the need to deal with handwritten signatures in an automatic manner using certain systems [13]. In general, handwritten signature systems are divided into two types: recognition and verification [9]. A signature recognition system aims to determine a writer's identity among a set of writers, with an operation usually referred to as a "one to many" comparison operation. While a signature verification system aims to tell whether a questioned signature truly belongs to a person or not, in an operation that is usually known as a "one-to-one" comparison operation [10],[14].

The automatic handwritten signature systems are classified into two modes based on the data acquisition technique. The first mode is known as "offline" or "static mode", where the features are extracted from the signature after it has been acquired and stored as a two-dimensional (2D) digital image using a camera or a scanner. The second mode is called "online" or "dynamic mode," where features are directly extracted at the time when the signature is being created or singed [15–17].

The main goal of this paper is to study the effect of a mass-based segmentation algorithm on the spatial density distribution method through the implementation of a handwritten signature recognition system in an offline mode. Usually, recognition using the offline mode rather than the online mode is considered to be more difficult in implementation due to the following considerations: when utilizing the online mode, information such as speed, signing pressure, and digital pen orientation is recorded, making the recognition process easier, while when using the offline mode, these types of data are missed [18], [19]. On the other hand, the lack of dynamic information in the static mode complicates the process of implementation of these systems [20], [21]. Another challenge arises from the fact that the signature for the same person may be varied and affected by many factors such as age, gender, illness, psychological factors like fatigue, stress, or emotional state of the signer; the physical condition of the signer, like whether he is standing or sitting on a chair; lightning conditions; signing period; writing instrument; direction and inclination of signing; signature box size; and purpose of signing [22–24]

In general, offline systems are preferred over online, because the signer need not be present at the time of signing, which means that the features of his or her signature could be extracted at any time [12], [18]. In contrast to online systems, offline systems are considered inexpensive as they digitize the signature into a 2D image after scanning the paper or using a digital camera. While the online systems need special electronic devices to capture the signature information in real-time, such as tablets, touch screen monitors, digital ink, stylus, a digital pen with pressure sensor and personal digital assistants (PDA) {Formatting Citation}, that's led to the online mode systems becoming unnatural to the users [5].

The importance of this research comes from the fact that signatures are widely spread and, thus, the use of a handwritten recognition system would be very helpful, especially for indexing, searching, and archiving. There is much literature dealing with offline signature verification topics rather than offline signature recognition [10]. Furthermore, due to its uniqueness, the signature is a popular, easy, and inexpensive identification and authentication method that is widely accepted by the public and official organizations [25].

2. Previous Related Works

Over the past decades, many researchers have suggested different methodologies and algorithms for recognizing signatures. Most of these methodologies follow a general structure of three basic stages: pre-processing, feature extraction, and classification [26]. In this section, the authors explore different methodologies presented in the literature and outline the contribution of their proposed method.

N.N. Kamal and L. George [7] converted the true color image into a grey image, then into a binary one, and normalized its dimension by zero-padding to make both of the two dimensions of the image equal. To extract the features, the image is subdivided into overlapped sub-images, then the centroids of two binary vectors, the vertical vector and the horizontal one, are extracted. Four different Euclidean distances are used for classification. The number of samples was 928, and the accuracy rate reached 94.8275%.

B. Hadjadji *et al*. [14] pre-process the image using a local iterative threshold, then the image is divided into cells through an equi-space or equi-mass grid. After that, each sub-image is normalized to the size of N×N. A wrapping Curvelet transform is performed on the grid over the signature image to generate the required training features vector. For each writer in the database, a One-Class classifier based on Principal Component Analysis (OC-PCA) is created. A questioned signature is assigned to its corresponding writer as the best match between the trained features vector and the OC-PCA. In the classification phase, a Fuzzy Integral (FI) based on Choquet is used. The total number of the used genuine samples of two standard datasets is 8520, and the successful identification rate reaches 97.99% and 94.96%.

P. Chauhan *et al*. [22] pre-process the image by converting it to a greyscaled one, resizing it, and then converting it to a binary image. For the feature extraction process, five parameters are computed for the image: eccentricity, convex area, entropy, standard deviation, and orientation. For the classification process, a backpropagation artificial neural network (ANN) is used. From a figure documented in the researchers' paper, one can predict that three different databases are used, with recognition rates ranging between 80% and 85%, and the number of used samples is not stated.

In the work of T. S. Gunawan *et al*. [3] the pre-processing stage includes: cropping the colored image, resizing it to 206×128 pixels, and converting it to a greyscaled one. For the feature extraction stage, two filters are used: the Canny edge detector and the Average filter. Feed-forward ANN is used as a classifier for 250 samples collected from 50 people, 150 of which are used as training samples and the remaining 100 as testing samples. The performance with Canny reached 100%.

T. Marušić *et al*. [10] in their work for pre-processing, the signature image is: binarized using a local adaptive technique; denoised with a mean filter; cropped, rotated, and submitted to morphological operations of dilation and erosion; normalized to 384 pixels with the keeping of a fixed aspect ratio; and finally, the image is skeletonized. At the feature extraction stage, three kinds of features are extracted from the image: 16 different global features, such as aspect ratio, horizontal and vertical center of gravity. Also, local features are extracted from 18 equal blocks like area, horizontal projection, and vertical projection. Besides that, the SIFT operator is used to gain image features. The Radial Basis function (RBF) gives better results in classification than Support Vector Machines (SVM) or Multilayer Perceptron (MLP). The 450 samples used for training give an accuracy rate of 98%, while the 150 samples for testing give an 88.97% success rate.

M.R. Deore and S.M Handore [16] pre-process the image by converting it to a greyscaled one, denoising it with a median filter, the Otsu method is used for thresholding, then thinning, boundary detection, and cropping, followed by scaling to a specific size is done. For the feature extraction stage, the Discrete Wavelet Transform (DWT) is utilized. For classification, backpropagation and (PCA) are used to reduce the wavelet coefficients. ANN is used for classification. The number of samples used and the accuracy rate are not specified.

K. Daqrouq *et al*. [9] first converted the image into a binary one, then resized it to a fixed size of 80 ×250, with these steps considered part of the pre-processing stage. Then Wavelet Packet transform (WPT) and DWT were used for the feature extraction phase. The entropy value was applied over the extracted data from these transforms. Probabilistic NN is used for classification. WPT is considered a better way to evaluate the identifying of two different datasets, A and B, with samples totaling 21,600 and 300, respectively. Success rates reached 92%.

R. Sa-Ardship and K.Woraratpanya [11] emphasized their efforts to improve recognition rates during the preprocessing stage. This includes image binarization and completion, cropping, resizing to a fixed dimension of 250×300, Polar-Scale Normalization (PSN), and Adaptive Variance Reduction (AVR). The last one is applied to normalize signatures based on the ratio of standard deviation and mean of images. For feature extraction, 22 Histograms of Oriented Gradients (HOG) are implemented over a cell of size 6×6 pixels. Feed Forward ANN is used as a classification method. Seven different datasets were used for four languages. The number of samples was 5739, and the average recognition rate reached 98.39%.

P. Patil *et al*. [17], besides converting the image to what is so-called a binary image, it is rotated and cropped, submitted to the mean filter, and resized to 512 ×512 after being pre-processed. HOG is the method used to acquire the image features, in which the image is divided into 16×16 blocks, where each block consists of four cells of 8×8 pixels with 50% overlap between blocks. The three main steps of HOG are gradient computation, gradient voting, and normalization computation. Feedforward backpropagation NN is utilized for classification. A dataset of 240 samples was exploited in this system, and the successful recognition rate reached 96.87%.

M. Taşkiran and Z.G. Çam, [19] convert the true colored image into a binary one, remove its noise through 3×3 filter, resize it to 80×150 pixels of cropped images. All the previous steps are included as a pre-processing stage. For feature extraction, the HOG algorithm is used. PCA is used for feature reduction. Different methods are tested for classification, such as MLP, RBF, and General Regression Neural Network (GRNN), which is considered a branch of Feed Forward NN. The total number of samples reached 600 samples, in which half of them were used for training and the other half were used for testing. The best classification accuracy reached 98.33% when the GRNN algorithm is used.

D. Suryani *et al*. [4] pre-process the image by converting the colored image to greyscale, binary, removing its border, and extracting the bounded box. For feature extraction, the moment is used, followed by min-max normalization, which is used to generate a vector of values of 0's and 1's. Then the algorithm of the Fuzzy Kohonen Clustering Network (FKCN) is applied to obtain clusters of invariant moments. For classification, the signature is identified by finding the minimum distance from the center of the class using Euclidian distance. In total, 80 samples are used in this system. The attained accuracy rate reached 70%.

P. Kiran *et al*. [27] after converting the RGB image into a grey one, resize it to 256×256, correct its intensity using gamma, correct the threshold, then use the Canny edge detector for the purpose of segmenting the signatures, resize the gained images to 64× 64 and use backpropagation NN for classification. The total number of samples is 100. The highest rate of recognition obtained was 93%.

Ghosh R. [28]: for the pre-processing step, resize the image to 128×128 and correct its skewness. Four features extracted from the signature image include: changing the path direction, path slop, path waviness, and center of mass. Classification is done using Recurrent NN based deep learning, where two models are used: long-short term memory (LSTM) and bidirectional LSTM. The author compared his work with convolutional NN. Six datasets are used, with the highest achieved recognition rate reaching 99.94%.

The basic limitation found in the existing methods is that many of the authors of these previous works of literature used a very limited number of samples to train, evaluate, and test their systems, such as Gunawan *et al*. [3], Suryani *et al*. [4], Patil *et al*. [17], and Kiran *et al.* [27]. Because it is well known that using a limited number of samples to train any identification system will lead to low recognition rates. In addition to that, there are many cases where the authors did not mention the types of datasets or the number of samples they used to train their proposed system, such as Chauhan *et al*. [22]. While Deore and Handore [16] did not even document the success rate their system reached, on the other hand, the authors of the proposed method solved this problem by using a sufficient number of samples to train and test the proposed recognition system, where five distinct standard datasets with a total number of samples reached 4854 signatures from 224 signers, which is considered a huge number of signatures when compared to the surveyed approaches.

The following are some of the distinctions between the suggested approach and previous traditional methods. In the pre-processing stage, there is no need to resize the image of the signature to a pre-defined size, and since the signature shape may come across the image vertically, horizontally, or diagonally, the resizing may change the shape of the signature, which will affect the features that are extracted from the digital image. Instead of resizing, only cropping is adopted, because cropping retains the shape of the cropped object and eliminates the unnecessary pixels from the image.

The other limitation found in the previous work is that the features that are extracted from the digital image do not utilize and reflect the shape of the signature, as in Chauhan *et al*. [22], where the proof is that the used features give low recognition rates. Also, some authors used general transformations which may not adopt the nature of the signature, such as Gunawan *et al*. [3], who depend on edge detectors only, and Deore and Handore [16], who use the DWT and Daqrouq *et al*. [9], beside DWT, who depend on WPT, Hadjadji *et al*. [14], who perform the Wrapping Curvelet transform, while the HOG is adopted by Taşkiran and Çam [19], Patil *et al*. [17], and Sa-Ardship and Woraratpanya [11].

The proposed algorithm adopts a segmentation method that reflects the geometrical properties of the shape of the signature and uses a feature extraction method that utilizes the distribution of pixels of the signature over the digital image, while a fixed-size block is used by Kamal and George [7].

In general, many of the authors of previous works, such as Chauhan *et al*. [22], Daqrouq *et al*. [9], and many others, have tested their algorithms using a single classifier, i.e. ANN, which is a difficult tool to implement, but the suggested system employs four versions of Euclidean distance measurements, which are regarded as simple to implement, reproducible, and efficient classification methods in their function.

3. The Used datasets

Five different standard datasets are used to train and evaluate the performance of the proposed method: SigComp2009 which is also known as (ICDAR 2009), SigComp2011, SigWiComp2013, SigWIcomp2015 and UTSig.

The formats of samples of the used datasets come in two forms: Portable Network Graphics (PNG) and Tagged Image File Format (TIFF), and since Bitmap (BMP) is a non-compressed format and compatible with the Microsoft Windows operating system, all the samples of the digital images are converted to a BMP format with a color depth of 24 bits per pixel. The tool that is used to perform this task is called “Ashampoo Photo Commander” version 11.0.3. Note that the image samples differ in their dimensions and in their illumination conditions. More details about the dataset used are shown in Table 1. In the dataset SigComp2009, there are some discarded samples from the training and testing processes of the proposed system because these samples do not belong to any class.

Table 1- Brief information about the used datasets

Dataset Name	Number of persons (i.e. Classes)	Number of samples per class	Total number of samples	Dimensions of samples		Original format	Used format
				from	to		
SigComp2009	78	70 classes *12 samples and 8 classes 11* samples	928	400×588	1813×904	PNG	BMP
SigComp2011	10	9 classes *24 Samples, except one class of 23 Samples	239	229×221	958×383	PNG	
SigWiComp2013	11	42 Samples per class	462	307×117	597×178	PNG	
SigWIcomp2015	10	12 Samples per class	120	946×276	1069×296	TIFF	
UTSig sample	115	27 Samples per class	3105	284×650	1825×822	TIFF	
Total	224			4854			

4. Proposed methodology

The basic motivation behind creating an automatic offline recognition system for handwritten human signatures is that the signature is a public sign that is accepted by people and is increasingly used in the modern workflow of telecommunication and daily treatments. Also, the offline recognition systems are inexpensive if they are compared with online or any other identification systems that may need special instruments.

As early cited in the related work section, the major stages of any identification system include pre-processing stage, a feature extraction stage, and a classification stage. Figure 1. depicts the general layout of the proposed system.

The distinction of the proposed method over the previous methods is that it is a size-independent method, meaning that for pre-processing there is no need to resize the image of the signature to a pre-defined size, because resizing the image to a fixed size may cause the signature to change its properties and affect the feature extraction stage.

The novelty of the proposed system is that it extracts five different statistical features from image segments that reflect the geometrical shape and the spatial distribution of the signature pixels in the digital image. The classification is based on Euclidean distance measurement. This effective combination of steps has not previously been used in any existing signature recognition system. The following subsections provide more details about the proposed method:

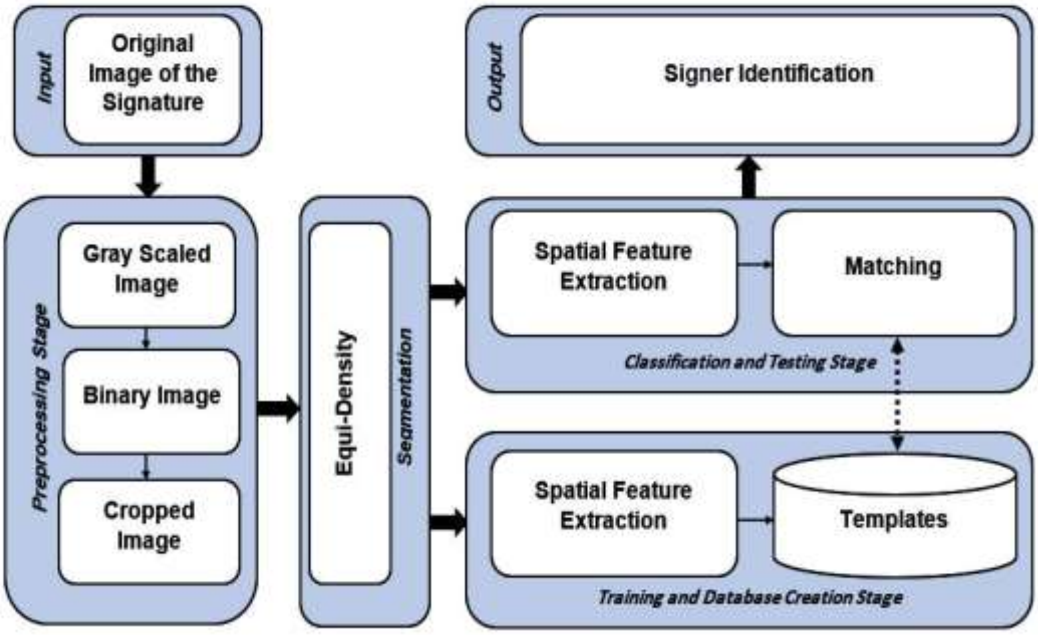

Figure 1-The General layout of the proposed system

4.1 Pre-Processing stage

The process of reducing unwanted information is known as pre-processing [11], which is a crucial part of any identification system because successful implementation of it will lead to better recognition rates. For the presented system, this stage consists of three basic steps. The first step includes converting the image of the signature to a grayscale one.

The second step involves obtaining the binary image. The pixels of the binary image are obtained from the converted grey image pixels (white or black) by comparing them to a threshold value. Since the samples of the images in the datasets vary with their illumination conditions, different threshold values are used to binarize the images. Table 2 explains the different threshold values that are used with each dataset. In the preprocessing step, the third step includes cropping the binary image to reduce its size.

Table 2-The threshold values that were used for binarization

Dataset name	Threshold values
SigComp2009	128
SigComp2011	200
SigWiComp2013	180
SigWIcomp2015	128
UTSig	128

4.2 Equi-Density segmentation method

In this system, the cropped binary image of the handwritten signature is divided into several areas. These areas reflect the geometrical features of the signature; in other words, they depend on the shape of the signature and the distribution of the density of pixels over the image area. Each area, i.e. image tile, in the divided image will hold the same number of pixels, i.e. the same mass. Figure 2 shows examples of equi-density segmentation.

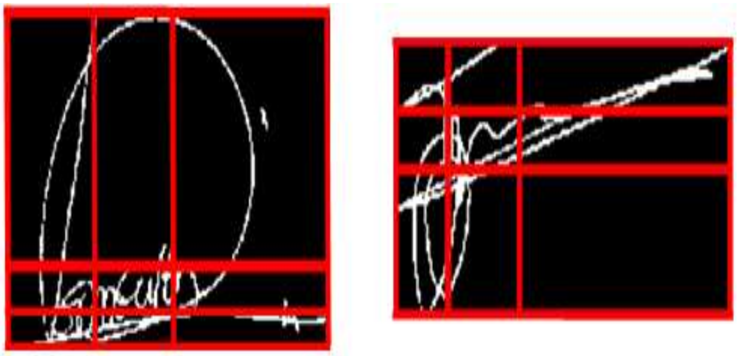

Figure 2- Dividing the binary cropped image into a 3×3 area using equi-density method

4.3 Features extraction

Since the signature is a geometrical shape, then the extracted features should reflect the spatial distribution of its pixels. In the proposed system, two projection arrays of one dimension (1D), namely, a horizontal projection array and a vertical projection array, are determined for each tile of the digital binary image. Then, from each segmented tile, five unique features that represent the signature's spatial properties are extracted:

- The first feature is the density, or total mass, which refers to the total number of objects' pixels in a single tile, divided by the area of that tile.
- The second feature is the relative mean value of the horizontal projection vector.
- The third feature is the standard deviation of the horizontal projection vector.
- The fourth feature is the relative mean of the vertical projection array.
- The last feature is the standard deviation of the vertical projection array.
- The density is extracted from the entire tile while the relative mean and the relative standard deviation are extracted from the projection vectors: the vertical and the horizontal. Figure 3 describes an example of the five statistical features extracted from a single image tile.

Note that the word "relative" refers to the division of the summation of the values by the height or the width of the tile, not the height or the width of the entire image.
The total number of features obtained from each signature image is calculated using Eq. (1).

$$No.\ of\ Featues = N \times M \times 5 \quad (1)$$

Where N is the number of tiles along the width of the image, while M is the number of segments along with the image height, and the number 5 refers to features extracted from each tile. Procedure 1 clarifies the steps of the proposed image segmentation and feature extraction methods.

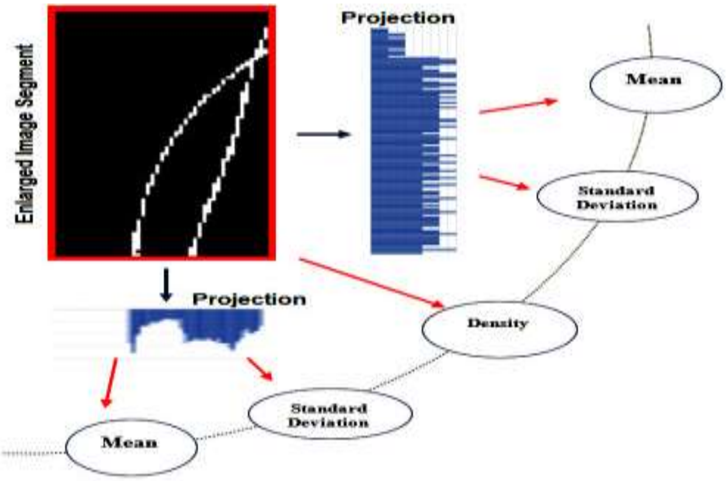

Figure 3-An enlarged image tile with the five features extracted from it.

Procedure. 1. Image segmentation and feature extraction using spatial density distribution method

Input: Cropped Binary Image.
Output: Image Features

Begin
- **Step1** - Determine Nx // the number of tiles along the Width of the image
  - Determine Ny // the number of tiles along the Height of the image
- **Step2** Redim feat (Nx, Ny) // Preserve a features array
- **Step3** For every pixel in the cropped image of the signature Loop
  - Calculate Den // the sum of all image pixels
  - End Loop
- **Step4** - Mx= Den/Nx // Determine the number of pixels in each tile
  - My=Den/Ny
- **Step5** For every column in the cropped image of the signature Loop
  - Find the sum of image pixels
  - if sum = Mx Then
    - Register the x value
  - End If
  - Register a cell width Tx
  - End Loop
- **Step6** For every row in the image Loop
  - Find the sum of image pixels
  - if sum = My Then
    - Register the y value
  - End If
  - End Loop
  - Register a cell Height Ty
- **Step7** For every Nx cell in the image Loop
  - Get the X1 of the cell
  - X2= X1+Tx

```
        For every Ny cell in the image Loop
            Get the Y1 of the cell
            Y2= Y1+Ty
            For every pixel, a tile starts with (X1, Y1) and ends with (X2, Y2) Loop
                - Compute CellDen // the 1st feature which is the Cell's Density
                - Compute the relative mean of the vertical projection of the cell //
                  2nd Feature
                - Compute the standard deviation of the vertical projection of the cell
                  // 3rd Feature
                - Compute the relative mean of the horizontal projection of the cell //
                  4th Feature
                - Compute the standard deviation of the horizontal projection of the
                  cell // 5th Feature
            End Loop
        End Loop
    End Loop
End
```

As a part of the training operation, two template vectors are produced for each of the five statistical spatial features: the mean template vector and the standard deviation template vector. These vectors are created for all image classes in the used datasets.

4.4 Classification and Matching Methods

The template vectors that have been created are utilized for matching and categorization. Matching is done by utilizing a distance measurement to determine the shortest distance between the features that are extracted from an input signature image and the values contained in the template vectors [1]. In the proposed system, the equations (2-5) have been prepared to classify criteria that include the use of four different forms of Euclidean distance measurements.

$$Sm_{i,j} = \sum_{I=1}^{N} \left(\frac{f_i - \mu_j}{\sigma_j} \right)^2 \tag{2}$$

$$Sm_{i,j} = \sum_{I=1}^{N} \left| \frac{f_i - \mu_j}{\sigma_j} \right| \tag{3}$$

$$Sm_{i,j} = \sum_{I=1}^{N} \left| f_i - \mu_j \right| \tag{4}$$

$$Sm_{i,j} = \sum_{I=1}^{N} \left(f_i - \mu_j \right)^2 \tag{5}$$

Where *Sm* reflects the similarity measurement; which is the sum value of the differences between the i_{th} value of a feature f extracted from the image query and a j_{th} mean value μ or the standard deviation value σ of a template vector for all image classes N.

Any recognition system needs training. To accomplish the training task, template vectors are created, where two-thirds of the image samples of each class are used to create the template vectors. It is worth noting that three test modes are created for each of the five datasets. For all three of these assessments, the signature image is divided into several tiles ranging from 2 to 20 tiles per image dimension, which means that the total number of tiles for an image equals to N×N tiles. Also, in each test for every dataset, the equations (2-5) are examined, while the accuracy rate is calculated using Eq. (6).

$$Accuracy\ Rate = \frac{Passed\ Samples}{Number\ of\ Tested\ Samples} \times 100\% \qquad (6)$$

The three conducted tests include the “Trained Part” test. This is the first test, and it examines the samples of dataset classes that are involved in the creation of the database templates’ vectors. For the datasets (SigComp2009, SigComp2011, SigWiComp2013, SigWIcomp2015, and UTSig), the outcomes for this test were 100%, 100%, 100%, 100%, and 97,56%, respectively.

The second test is the "Untrained Part" test, which examines all the remaining samples in each group that were not included in the training procedure. The outcomes for this test were (95.39%, 100%, 100%, 100%, and 89.44%) for SigComp2009, SigComp2011, SigWiComp2013, SigWIcomp2015, and UTSig, respectively.

The third test is the comprehensive test, where all classes of samples are tested. Figure 4 shows the outcomes for this test.

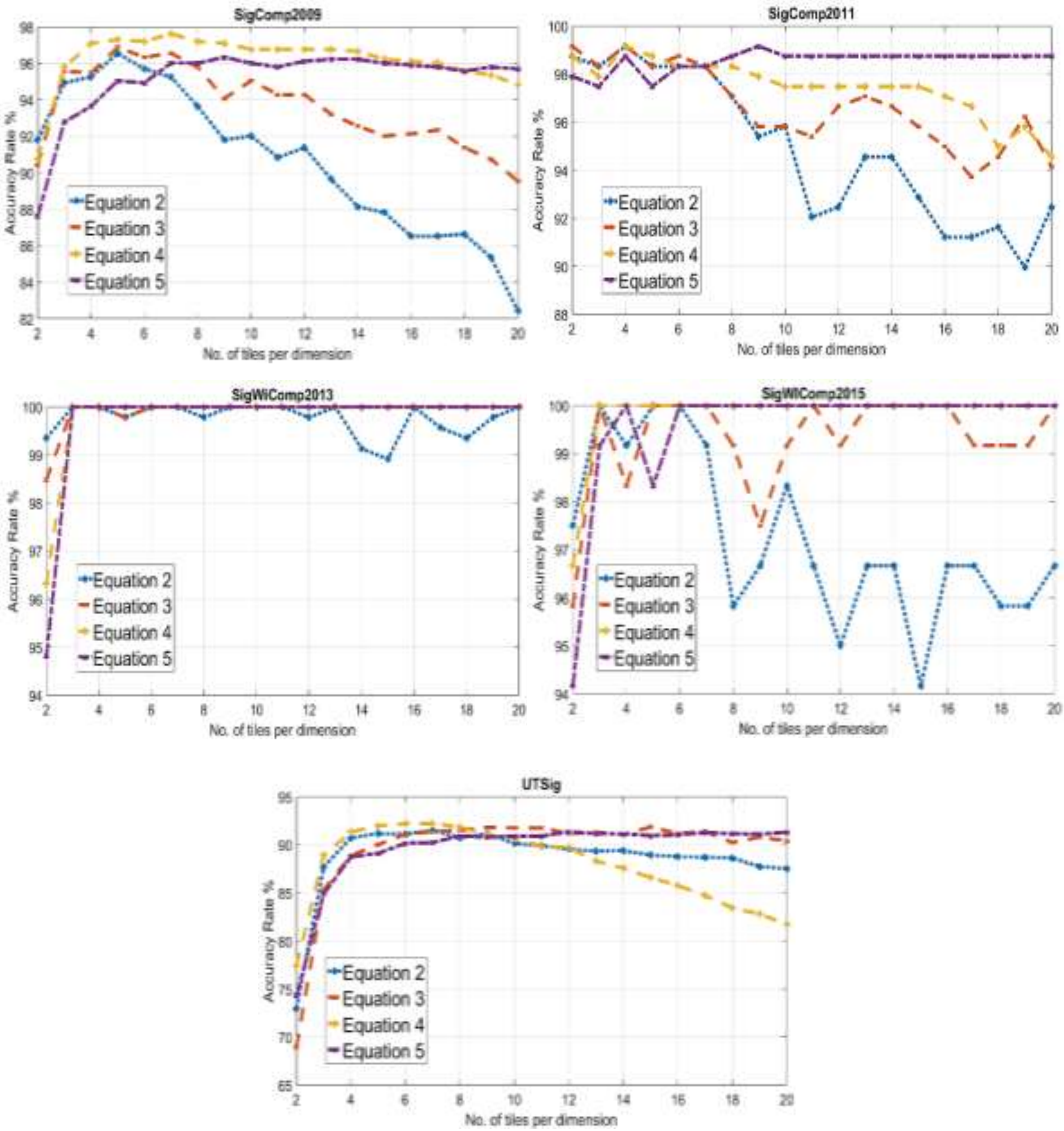

Figure 4-The results of the “comprehensive tests” for the five tested datasets.

5. Results and Discussions

The hardware and software frameworks are used to implement the proposed algorithm, also the results are discussed and clarified in this section.

This system was implemented through the visual basic software environment. The tests were conducted on a PC running 32-bit Windows 7. The used CPU is an Intel Core i3, with 6 Gigabytes of memory (RAM). Also, the presented system works properly on the 64-bit Windows 10 operating system environment. Graphics were made using MATLAB 2016Ra and Excel 2016.

Based on the acquired results from the “Comprehensive” test, which includes the trained and untrained samples, the recognition rates for the datasets: SigComp2009, SigComp2011, SigWiComp2013, SigWIcomp2015, and UTSig are: 97.62931%, 99.16318%, 100%, 100%,

and 92.23833%, respectively. The low rate reached almost 92% in the dataset of UTSig because of the huge variation of its intra-classes.
One can notice that the four Euclidean distance measurements give very encouraging accuracy rates. However, to determine the best criteria among the four tested equations, the frequency of the appearance of each equation in the five highest gained accuracy in each test is calculated as shown in Figure 5.

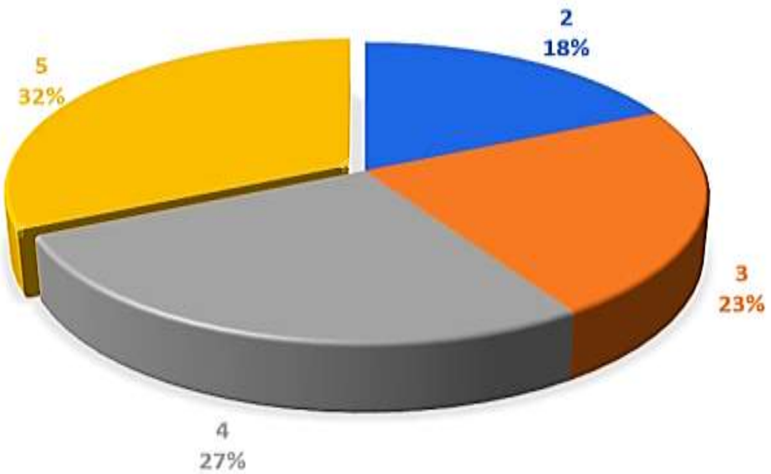

Figure 5 - The frequency of distance measures amongst the five highest attainerecognition rates for each of the tested datasets for the three test modes. The numbers (2-5) refer to the number of distance measure equations.

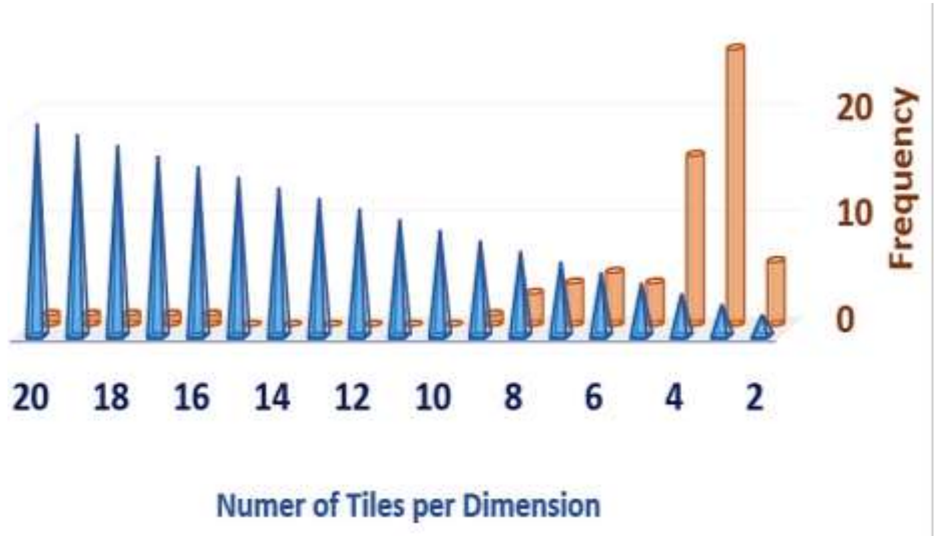

Figure 6-The frequency refers to the repetition of a “number of tiles per dimension” appears in the five highest attained recognition rates in the comprehensive test mode amongst the five datasets.

It appears that the most frequent distance measurement that stands out amongst the five highest attained rates of each test for the tested datasets is Eq. (5). While the most frequent number of tiles per dimension that appears amongst the five highest attained rates for each dataset for the conducted tests is three tiles per dimension, as shown in Figure 6.
In general, since different systems use different signature databases, it is difficult to compare the performance of different signature identification systems [29]. However, Table 3 summarizes a comparison among surveyed literature where methodologies, datasets, and results gained are documented based on what is stated in this literature.

From this table, one can note that both the proposed system and the one created by Kamal and George [7] use the same dataset of SigComp2009, but the proposed system gives a higher accuracy rate with 97.62931% rather than 94.83%, where their segmentation method uses equal-sized blocks rather than density-based or mass-based segmentation methods. The presented system gives a higher accuracy rate than Chauhan *et al*. [22] that reaches 69%, 83%, and 75%, because they depend on global features while the presented system is based on features that reflect the geometry and the shape of the signature. In addition to the type of features, Suryani *et al.* [4] gain 70% as they train their system with a limited number of samples, reaching 80 samples, and Marušić *et al*. [10] reach 88.97% for the untrained samples, where they use 150 samples only, and even though they use local features, the segmentation method to equal-sized blocks rather than equal-density blocks like the one used in this paper, leads to a lower recognition rate. Daqrouq *et al*. [9] even train their system with a sufficient number of samples but obtain 92% because they use a transformation applied globally on a fixed image size. Kalera *et al*. [29] got 93.18% and 93.33%. In general, the results from the “Trained-Part” test of the proposed system outperform the state-of-the-art systems and confirm the validity of the proposed method.

6. Conclusion

This paper demonstrates the performance of the spatial density distribution method in an offline system to recognize signatures. The proposed method is size-independent (i.e., there is no need for image resizing). Firstly, the image is segmented by the equi-density segmentation method, with no need to implement overlapping between the segments. Then five different spatial statistical features are extracted from the image tiles. The features include the density of the image tile, the relative mean and the relative standard deviation of the horizontal projection of the tile, and the relative mean and the relative standard deviation of the vertical projection of that tile. To evaluate the proposed method, five different standard datasets are trained and tested using three test modes, while four variations of the Euclidean distance are used for classification. The accuracy rates ranged from 92.23833% to 100% for 224 signers with a total number of 4845 samples.

The proposal is to use this system for the purpose of identification by individuals, researchers, and organizations due to the ease of implementation and low cost of the system.

Table 3-A comparison between the previous works and the proposed method

Table Keys: (D) Denotes the number of samples that is not stated directly in the literature, but instead it is calculated using the mentioned information in a research paper, (T) Refers to training, (E) Denotes to testing, (√) Presents the method that gives highest accuracy success rates, and (N/A) Means not available, and (%) is the success rate of recognition in a certain system.

Reference #	Pre-processing	Feature and algorithm	Classification	Dataset name	%	# Total samples	# signers	# Samples Per class	# Samples (T/E)
(Proposed)	Grey, binary, crop	5 statistical spatial	Four variations of Euclidian	SigComp2009 SigComp2011 SigWiComp2013 SigWIcomp2015 UTSig	97.62 % 99.16 % 100% 100% 92.23 %	928 239 462 120 3105	78 10 11 10 115	12 or 11 24 or 23 42 12 27	(per class) 8/4 or 3 16/ 7 or 8 30/12 8/4 20/7
[22]	Grey, resize, binary	5 image parameters	ANN	Collected MCYT GPDS	69% 83% 75%	N/A	N/A	N/A	N/A

[3]	Cropping, resizing, grey	Canny edge detector √ average filter	Feed-Forward ANN	Collected	100% T	250	5	50	150/100
[10]	Binary, denoise, crop, morphing, rotate, resize	16 different features and SIFT operator	RBF √ SVM MLP	Collected	98% T 88.97 % E	600 D	30	20	450/150
[16]	Grey, denoise, binary, boundary, crop, resize	DWT, PCA	ANN	N/A	N/A	N/A	N/A	N/A	N/A
[9]	Binary, resize, cropping	WPT √ DWT	Probabilistic NN	GPDS960 Collected	92%	21600 D 300 D	900 20	24 15	15/9 10 or 15/14
[11]	Binary, completion, crop, resize, PSN and AVR	HOG	Feed Forward NN	SigComp2009 SigComp2011 SigComp2012 SigWiComp2013 LAMP PRIP2015	85.05 % to 100%	5739	150	150	50%/ 50%
[14]	Binary, resize	Wrapping Curvelet Transform	OC-PCA FI	CEDAR GPDS	97.99 % 94.96 %	1320 D 7200 D	55 300	24 24	(per class) 2/22 2/22
[17]	Rotate, crop, denoise, resize	HOG	Feed Forward NN	Collected	96.87 %	240	20	12	(per class) 4/8
[19]	Binary, denoise, resize, crop	HOG, PCA	MLP RBF GRNN √	Collected	98.33 %	600	15	40	300/300 D
[4]	Grey, binary, crop, bound box	Moment, min-max, FKCN	Euclidian	Collected	70%	80	8	10	50/30
[7]	Grey, binary, resize	Centroids of local Binary Vectors	Four variations of Euclidian	SigComp2009	94.83 %	928	78	12 or 11	(per class) 8/ 4 or 3
[27]	Gray, resize, gamma, Canny edge	Not stated clearly	Back Propagation NN	N/A	89% to 93%	100 Or 50	3	N/A	(60/ 40) Or (30/50)
[28]	Resize, skew correction	Center of mass and slope of path (i.e., trajectory), waviness of pass, change of path	Recurrent NN with two models	GPDS GPDS-300 MCYT-75 CEDAR BHSig260 Hindi BHSig260 Bengali	83.66 % to 99.94 %	4800 3600 375 660 1920 1200	4000 300 75 55 160 100	24 15 55 160 100	4800/4800 3600/3600 375/375 660/660 1920/1920 1200/1200

12. Future Work

For future work, the proposed algorithm can be developed through performing illumination modification or correction, such as contrast stretching or gamma correction, as a pre-processing step. For binarization, local thresholding may be adopted, and a denoising algorithm can also be applied.

In feature extraction, for each tile, the variance of edges extracted by the edge-detector (canny) can be used as an additional feature, while for classification, different types of ANN may be tested and compared with the results of Euclidean distance measurements.

This method can be applied to recognize other geometrical shapes such as logos, handwritten numerals, or characters.

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