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Skeleton Hinge Distribution for Writer Identification

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In this paper, a feature that is based on statistical directional features is presented. Specifically, an improvement of the statistical feature: edge hinge distribution, is attempted. Furthermore, different matching techniques are applied. For the evaluation, the Firemaker DB was used, which consists of samples from 250 writers, including 4 pages per writer. The suggested feature, the skeleton hinge distribution, achieved accuracy of 90.8% using nearest neighbor with Manhattan distance for matching.

Keywords: Writer Identification; Skeleton hinge distribution; Directional Features; Machine Learning; Clustering

1. Introduction

The handwriting is widely considered as a biometric characteristic. More specifically, it is considered being a behavioral biometric as it is directly related to schooling, personal preferences and other characteristics that make the handwriting of each individual writer, unique. In the past, the accuracy of this biometrics was considered being less important, than other biometric modalities [1]. However, recently, significant improvements on signature verification, writer identification and writer recognition reported an improvement on the accuracy of these systems [1-4].

This paper addresses the problem of offline writer identification, by using scanned handwritten document images. In writer identification, an unknown handwritten sample is matched against a database of samples of known writers. It is considered a promising research topic. Identifying the writer of a handwritten sample, using document image analysis methods, is an interesting pattern recognition problem with direct application to the forensic field [1].

The work presented here, can be considered an improvement of previous works. In more detail, the Skeleton Hinge Distribution is introduced as an improvement of Edge-Hinge Distribution [2] and Edge-Hinge combinations [3], that we first suggested it in [4]. However, while in [4] only simple nearest neighbor technique is used for matching in combination with the use of Euclidian, Manhattan and chi-square distance, in this paper, more experiments are performed, using:

(i) Clustering techniques like kmeans and agglomerative hierarchical cluster trees
(ii) Nearest Neighbor algorithm with a variety of distance metrics,
(iii) SVM on “one-vs-all” and “one-vs-one” schemes

The novelty of the present work consists of:

- The introduction of the novel Skeleton hinge distribution, an improvement of previous edge-directional features. It is the first time that the skeletonization is used in writer identification, considering strokes of one pixel width. The previous techniques were using the edges that include double data. This feature alone succeeds accuracy of 90.8% and computational cost reduction by 35%.
- Experiments with various matching techniques from the area of machine learning.

In section 2, related work on writer identification is presented, while in section 3 the statistical directional features, edge-direction distribution, edge-hinge distribution and edge-hinge combinations are described, along with the proposed feature, the Skeleton Hinge Distribution. In section 4, a writer identification system is proposed, while in section 5 the experimental results are shown, and finally, in section 6 some conclusions are drawn.

2. Related Work

In the literature, various techniques and methodologies have been proposed for writer identification. The work presented here is mostly influenced by statistical directional features like edge-direction distribution [2], edge-hinge distribution [2] and edge-hinge combinations [3]. These features are computed by extracting the directions of two edge fragments attached at a common pixel.

Bulacu et al. [2] suggested the use of edge-hinge distribution feature, an edge-direction feature. In this method, the joint probability distribution of the orientations of the two fragments is computed by traversing the image with a sliding window technique, and considering two edge fragments in the neighborhood, emerging from the central pixel of the sliding window, and stored in a histogram of directions. The nearest neighbor algorithm is used to match histograms of different images. Experimental results reported accuracy of 63% on the Firemaker DB [5] using 250 distinct writers.

Laurens van der Maaten et al. [3] improved edge hinge directional features, by using various window sizes, while combining these features with a codebook of graphemes achieved identification accuracy of 97%. The proposed edge hinge based method, achieved 81% identification accuracy, on the Firemaker DB [5].

Schomaker et al. [6] suggested the use of fragments of connected-component contours, which are classified to identify the writer. A codebook of graphemes is generated, by training a Kohonen SOFM [7] on a large number of grapheme contours. Next, the graphemes are extracted from every document and matched to the graphemes of the codebook. A histogram of graphemes for every document is generated. Experimental results achieved accuracy of 95% on 10 writers, and 83% on 215 writers. Furthermore they combined the codebook of graphemes technique with edge-hinge directional features, achieving 97% accuracy.

Some of the proposed methodologies treat writer identification as a textural analysis problem. More specifically, Said et al [8] proposed the use of Gabor filters and co-occurrence matrices in order to extract features from handwriting samples. This method achieved 96% accuracy on samples from 40 writers. Shahabinejad and Rahmati [9] proposed also the use of Gabor filters, based on the moments and a nonlinear transform in order to extract features, achieving 82.5% accuracy, on samples from 40 writers. Finally Helli and Moghaddam [10] proposed the use of Gabor filters and extended Gabor filters to extract the features and use the longest common subsequence classification technique in order to classify the features, achieving 95% accuracy, on PD100 dataset.

Some state-of-the-art methodologies, proposed on literature, rely on Hidden Markov Models or Gausian Mixture Models in order to identify the writer. Schlapbacj and Bunke [11][12] trained individual recognizers based on Hidden Markov Models for each writer. In order to classify the writer of an unknown sample, each recognizer gave a score. The recognizer with the higher score determined the writer of the unknown sample. This technique achieved 97.03% accuracy, on a subset of IAM dataset [13], consisting of 100 writers [11]. Schlapbacj and Bunke [14] also suggested the use of Gausian Mixture Models in a similar technique as [11], achieving 98.4% accuracy, on the same subset of IAM dataset [13], consisting of 100 writers [11].

Other methodologies rely on local features such as height, width and the slant of different zones, or a combination of global and local features. Marti et al [15] proposed the use of 12 local features, achieving an accuracy of 90.7% on a subset of IAM dataset [13] consisting of 20 writers. Sadeghi and Moghaddam [16] suggested the use of grapheme based features along with gradient features and a fuzzy clustering method for classification achieving 90% accuracy, on a subset of PD100 dataset consisting of 50 writers. Finally Siddiqi and Vincent [17] proposed the use of Gabor filters and local features, in a technique that combined global and local features and used a Bayesian classifier, achieving 92% accuracy, on a subset of IAM dataset, consisting of 100 writers.

3. Statistical Directional Features

Statistical features have been explored extensively in off-line automatic writer identification [2]. Features like run length distribution, slant distribution, entropy, and edge-hinge distribution can be found in the recent literature [2]. Edge-hinge distribution is considered being a directional feature, as it is related to the directions the writer followed, when writing. Directional features, like the direction distribution of handwriting [18] was first used as a preprocessing step before handwriting recognition, in an attempt to fuzzy cluster handwritings into different groups. In this section, the evolution of edge-direction distribution feature is described. Totally four feature extraction methods, three existed and the proposed one, are presented, namely: the edge-direction distribution [2], the edge-hinge distribution [2], edge-hinge combinations [3] and finally the proposed novel feature, the skeleton-hinge distribution.

3.1. *Edge-direction distribution*

The purpose of this feature is to extract handwriting direction distribution. This feature extraction starts with edge detection. Edge detection is performed using a generic edge detection algorithm (convolution with two orthogonal differential kernels, Sobel was used, followed by thresholding). An important practical detail is that this edge detection algorithm does not produce 1-pixel wide edges, but instead 1-3 pixels width edges. Next, each edge fragment is checked with the help of a sliding widow technique. An edge fragment is considered, being the edge line that starts from the central part of the neighbor window and ends on the periphery of the window, making the edge fragment length in consideration directly related with the window size. Since the direction the writer's pen followed on the paper is unknown, only the upper part of the window is considered and quantized in directions, according to the edge fragment length in consideration. When the central pixel of the sliding window is on, the direction of the edge fragment is checked on the periphery of the window. All the pixels are checked, by the use of logical AND operators, to all directions, emerged from the central pixel and finished on the periphery of the neighborhood, looking for the presence of another edge fragment pixel. In Fig 1, an example with 4-pixel long edge fragment with a window quantized in 12 directions, is presented. All the verified instances are counted into a histogram that is normalized to a probability distribution p(φ). This distribution gives the possibility of finding in the image, an edge based fragment oriented at the angle φ to the horizontal. Moreover, the most dominant direction in p(φ) corresponds to the slant of the handwritten text. Nearest neighbor technique is used for matching, considering Euclidean, Manhattan and chi-square distance.

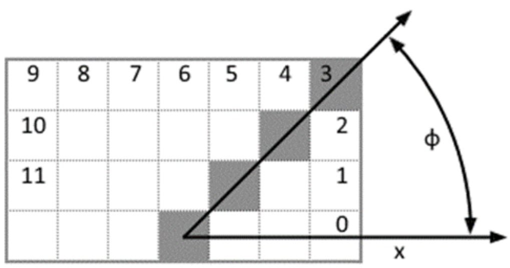

Fig. 1. Extraction of edge-direction distribution from 4 pixels-long edge fragments.

3.2. *Edge-hinge distribution*

As reported by Bulacu et al. [2], the edge hinge distribution is a statistical feature, which outperforms all the other statistical approaches. The procedure followed is very similar with edge-direction distribution. First, by using the same generic edge detection approach as before, the edge pixels are extracted and considered. Next, a sliding window technique is applied, but in this method the entire window is quantized in directions. The main difference in the edge hinge distribution is to consider, not one, but two edge fragments in the neighborhood, emerging from the central pixel, and subsequently compute the joint probability distribution of the orientations of the two fragments. This feature concerns the direction changes of a writing stroke in handwritten text. The edge-hinge distribution is extracted by the use of a window that scans an edge-detected binary handwriting image. Whenever the central pixel of the window is “on”, the two edge fragments (i.e. connected sequences of pixels) emerging from this central pixel are considered only when $\varphi 1 < \varphi 2$. In Fig 2, an example, with 4-pixel long edge fragment quantized in 24 directions, is shown. The directions are measured and stored in pairs. A joint probability distribution $p(\phi 1, \phi 2)$ is obtained over a large sample of pairs. Nearest neighbor technique is also used for matching, considering Euclidean, Manhattan and chi-square distance.

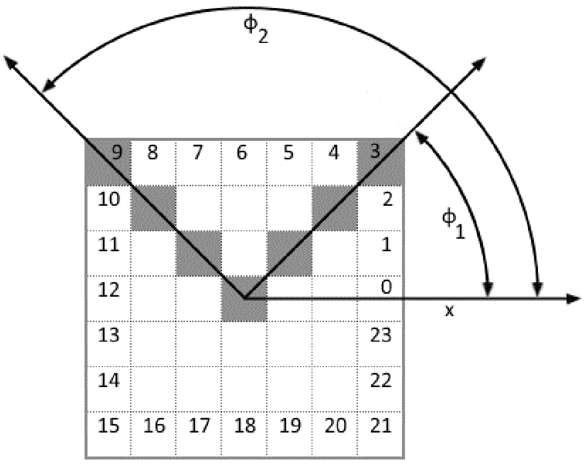

Fig. 2. Edge Hinge Distribution Extraction from 4 pixels-long edge fragments.

3.3. *Edge-hinge combinations*

The edge-hinge combinations technique, proposed by Van der Maaten et al. [3], is considered being an improvement of the edge hinge distribution. Like the previous methods, the procedure followed is similar with Edge-hinge distribution. This method also starts with edge detection, producing an image where only the edge pixels are on. The contribution of this work is that different window sizes are considered for the sliding window procedure that follows the edge extraction, calculating directions of different length edge fragments. In the sliding window technique, as already mentioned, different size windows are used that are quantized in directions, considering two edge fragments emerging from the central pixels. Their directions are measured and stored in pairs. A joint probability distribution p(ϕ1, ϕ2) is obtained over a large sample of pairs. The probability distributions acquired by the various sliding window sizes are combined and considered for matching. Nearest neighbor technique is used for matching considering Euclidean, Manhattan and chi-square distance. Experimenting with combinations of edge hinge distributions and using various fragment lengths, improved the results of writer identification up to 12%, compared with edge-hinge distribution. The algorithm of this implementation is available at [19].

3.4. *Skeleton-hinge distribution*

While the thickness of the stroke is considered as a feature [20] for writer identification in paleography, mostly before the modern pen era, in this work the hypothesis that all stroke widths should be considered of having 1-pixel width is used. In the recent years, writers can choose to write by a variety of different pens, with different ball pen sizes, resulting different stroke widths. Furthermore the dpi on the digitization process can result different stroke widths.

Normally, when something is written on a paper (Fig.3), its thickness is considered being a single line by a human observer. When the image is digitized the same trace of ink is translated into several pixel lines. By considering the edge hinge distribution, on an edge image a lot of unnecessary information, like the bottom or the side curves of the letters, is included in the feature vector. Furthermore on some instances of the extraction, neighboring edge fragments that belong on different characters are considered in the distribution. For an instance of Edge Hinge distribution extraction see Fig. 4.

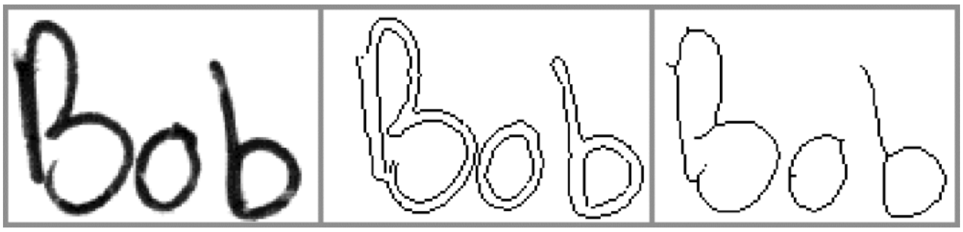

Fig. 3. Left: Hand written digitized word (Part of the Firemaker DB). Center: Edge image of the word. Right: Skeleton image of the word.

Furthermore, differences in line thickness, due to the variety of different pens, may produce significant variations in the extracted features, in both, edge hinge distribution, and edge hinge combinations. The main suggestion in this paper is that all stroke widths, i.e. line thickness, should be considered being the same size. This is achieved by skeletonizing the characters, to a single pixel width line.

This technique starts with the image skeleton extraction using a generic skeletonization approach [21] that removes pixels on boundaries of objects but does not allow them to break apart, and follows a similar approach as Edge-hinge combinations. A sliding window technique that uses several window sizes, quantized in directions, checks for skeleton fragments, emerging from the central window pixel. Their directions are measured and stored in pairs. Only skeleton fragments with φ1<φ2 are counted and stored in pairs in a histogram. A joint probability distribution p(ϕ1, ϕ2) is obtained over a large sample of pairs. The probability distributions, acquired by the various sliding window sizes, are combined and considered for matching. For an instance of Skeleton Hinge distribution extraction see Fig. 5.

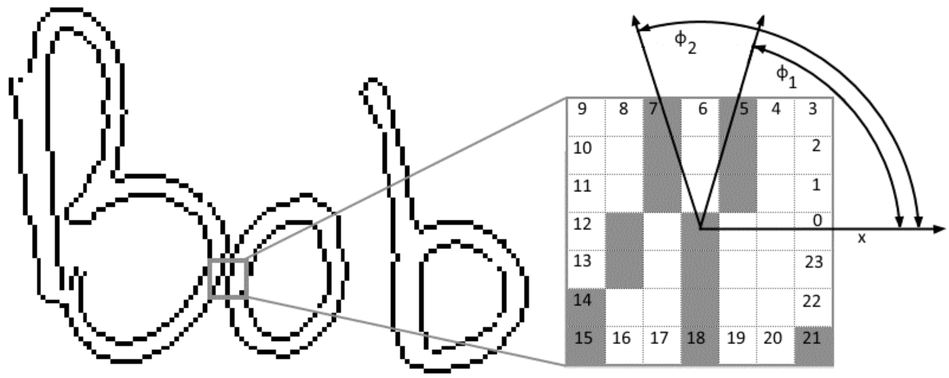

Fig. 4. Instance of Edge Hinge distribution extraction with 4 pixels-long edge fragments on part of the word "Bob".

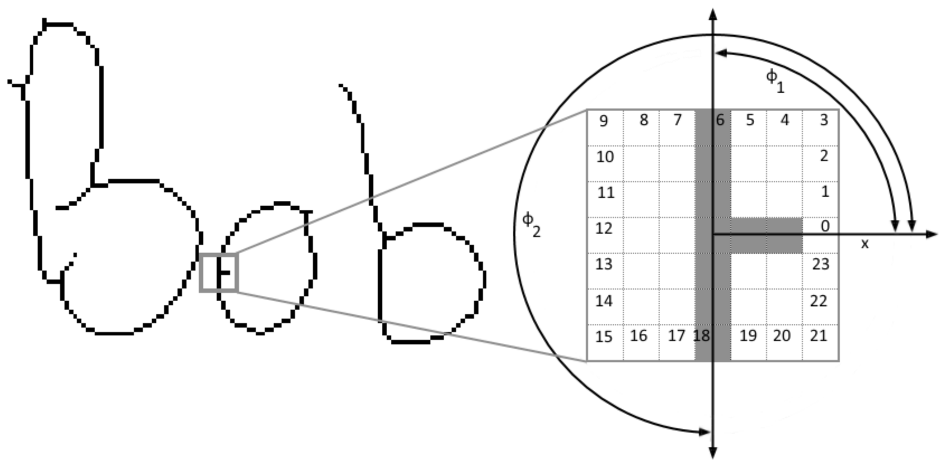

Fig. 5. Instance of Skeleton Hinge distribution extraction with 4 pixels-long edge fragments on part of the word "Bob".

4. Matching Procedure

Several different techniques were considered for matching the writers: like a) Nearest neighbor techniques, b) Clustering, and c) Machine learning techniques. More specifically : generic nearest neighbor technique was used like the one mentioned in the previous methods that utilized Manhattan, Euclidean and Chi-square distances in order to find the nearest neighbor in different skeleton fragment combinations. Furthermore other distance metrics, like Chebychev, Minkowski, Cosine, Correlation, Hamming and Seuclidean distance was considered for skeleton fragment combinations of [3,5,7,9]

An attempt was made to cluster the writers in an unsupervised clustering technique. In this approach all the handwritten document images in the train set and in test set was used in order to be clustered in 250 classes. The number of classes is equal with the number of the distinct writers. Each class contained documents from the same writer. Kmeans and agglomerative hierarchical cluster trees were used for clustering.

Finally a machine learning technique was used in order to classify the writers. More specifically, SVM (Support Vector Machines) was used in two schemes, 'one-vs-all' and 'one-vs-one'.

In 'one-vs-all' scheme, each time one writer from the train set was assigned to the known class and all the others in the unknown class. 250 different classifiers were trained to distinguish the known class with the unknown. In order to match the writer, every writer from the test set was classified using the 250 classifiers. The one with the most votes on known class was selected.

In 'one-vs-one' scheme, only 2 writers from the train set were used at a time, in order to train several classifiers. The number of trained classifiers depends on the number of writers on the train set and their distinct combinations of 2. Every writer on the test set was checked against all the classifiers. The class was assigned to the most voted class against all classifiers.

On the skeleton hinge distribution only the skeleton of the letters is considered (Fig.5). It takes into account the basic required information, in order to match the features to already known ones. The main ideas of edge hinge distribution, and edge hinge combinations, are present in the proposed technique. On the other hand, by applying this methodology to a skeleton image, a significant improvement on the results of writer identification task is observed (section 5).

It is important to mention that the resulting feature matrix includes more compact information and it is easier to compare two resulting matrices of test and train samples. Please check a successful application of the proposed system, in Figure 6, where some text samples are provided over their results. On the left side, a train and a test sample from the same writer is presented, and on the right, a train and a test sample from another writer is presented along with, the surface of skeleton hinge distribution and the surface of the edge hinge combinations.

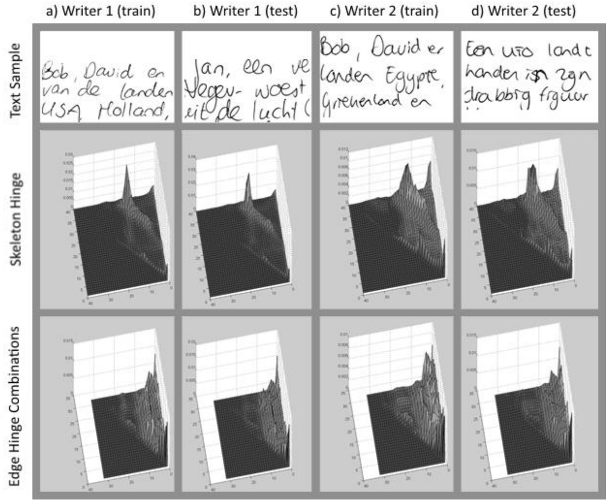

Fig. 6. Text samples from two different writers (train set on left, test set on right) along with skeleton hinge distribution feature surface (middle) and edge hinge combinations feature surface (bottom). The text samples on the top are fragments of the text sample used, and are provided for illustrating the differences of handwriting between those texts.

5. Data And Evaluation

5.1. *Data-Experimental Procedure*

The accuracy of the technique presented on this paper, the skeleton hinge distribution, was evaluated by using the Firemaker DB [5]. This data set was used in order to be able to directly compare the achieved results with the reported ones by other systems.

The Firemaker is a database of handwritten pages from 250 writers, including four pages per writer.

- Page 1 contains a copied text in natural writing style
- Page 2 contains a copied text in Upper-case text
- Page 3 contains copied forged text. The writers here try to impersonate another writer.
- Page 4 contains a self-generated description of a cartoon image in free writing style. In this last page, the text content and the amount of written ink varies considerably per writer.

All pages in Firemaker DB were scanned at 300-dpi gray scale. The text, that was asked to be copied, was specially designed in forensic praxis to cover a sufficient amount of different letters of the alphabet. In our experiments, only pages 1 and 4 were used. Page 1 was used as a train set. While page 4, was used as a test set.

In order to train the system (Extract skeleton hinge train features) only the page 1of the Firemaker DB was used. Each page was binarized and the skeleton was extracted using Matlab. The procedure in use is the one described in the previous section 3 for skeleton hinge distribution.

The train procedure was really fast, about 250 seconds on a laptop i7 2.5Ghz pc, and in comparison to the edge hinge distribution, about 35% faster. On the same machine edge-hinge distribution train took 384 seconds to complete.

In order to test the system (extract skeleton hinge test features) only page 4 was used from the Firemaker DB. The testing process used the same procedure as the training process.

The test procedure was faster than training, due to the variations in the sizes of text, in page 4. Testing took around 200 seconds on a laptop i7 2.5 Ghz. Edge hinge distribution time was about 270 seconds. An improvement of about 35% can be observed here, too.

Different matching techniques were considered for writer identification. Top accuracy achieved with the nearest neighbor classifier with Manhattan distance. Euclidean and chi-square distances were also considered, but they performed worse.

Furthermore clustering techniques like kmeans,agglomerative hierarchical cluster trees and machine learning techniques like SVM were considered.

5.2. *Experimental results*

Various experiments were performed, using combinations of several parameters, e.g., window sizes, matching classifiers, etc. It is hard to compare our results, with results reported on other papers, because of the variation on the data sets. Our results will be only comparable with methods that used the same data set.

Furthermore, even on the same data set, results can have a significant variation. Some methodologies only used a fragment of the entire data set, without mentioning which one, exactly. Also there are differences in train and test sets. Even a slight change in these sets, can change the entire outcome.

Skeleton hinge distribution feature identification results are presented on Table 1. These experiments used the entire data set of 250 writers. Like edge-hinge combinations method, a combination of fragment lengths i.e. window sizes, is used. Furthermore, for the nearest neighbor classifier Manhattan, Euclidian and chi-square distances were used. Our top result is identification accuracy of 90.8 % for a combination of fragment lengths of 5- and 9-pixel length window and Manhattan distance.

Table 1. Skeleton Hinge Distribution Using Nearest Neighbor.

Fragment Length Combinations	**Skeleton Hinge Distribution Accuracy (Percentage)**		
	Manhattan Distance	***Euclidian Distance***	***Chi-square Distance***
3	80%	72%	53.2%
5	89,6%	77,2%	66%

Fragment Length Combinations	**Skeleton Hinge Distribution Accuracy (Percentage)**		
	Manhattan Distance	***Euclidian Distance***	***Chi-square Distance***
7	90%	81,6%	69,6%
9	88%	85,2%	76%
3 , 5	85,2%	75,2%	58,4%
3 , 7	85,6%	75,6%	55,2%
3 , 9	86%	74,8%	53,2%
5 , 7	90%	78,8%	64,4%
5 , 9	**90.8%**	78,8%	67,2%
7 , 9	90%	83,2%	73,6%
3 , 5 , 7	86,8%	76,8%	60%
3 , 7 , 9	89,6%	76,8%	55,6%
5 , 7 , 9	90%	79,2%	68,8%
3 , 5 , 7 , 9	89,6%	76,8%	60,4%

Comparative results for the proposed technique, and previous statistical directional features, presented in section 3, are presented on Table 2. All the experiments have been performed on the same database, Firemaker DB. The results for Edge Direction Distribution, Edge-Hinge distribution and Edge-hinge combninations are presented as reported in [2][3]. While in [2] there is no separation between test and training set, all handwritten document images are tested against all the other document images. In [3] and in the proposed technique all experiments are conducted by considering a segmentation on training and test data sets.

Table 2. Comparative Results of the Statistical Directional Features.

Method	**Accuracy**
Edge Direction Distribution [2]	35%
Edge-Hinge Distribution [2]	63%
Edge-Hinge Distribution [3]	70%
Edge-Hinge Combinations [3]	81%
Skeleton-Hinge Distribution	**90.8%**

An attempt was made to identify writers using the k-means algorithm, and partitioning the collection in clusters. The entire collection, which consisted of 250 writers, with 2 pages per writer, one page in training data and one page in test data were combined. Skeleton hinge distribution features were extracted from 500 pages, and partitioned in 250 clusters. Standard kmeans technique was used, as well as kmeans with different distance parameters were explored. Only clusters which included both pages of each writer were considered as correctly identified.

Furthermore, experiments of clustering the 500 pages with the use of agglomerative hierarchical cluster tree were also performed. Agglomerative clusters from linkages, as well as agglomerative clusters directly from data were constructed. Only clusters containing both pages of the same writer were considered as correctly identified. Accuracy in both methods reached 63.6%, using [3 5 7 9] skeleton hinge distribution combinations. Identification results for kmeans and Agglomerative clusters are presented in Table 3.

Table 3. Skeleton Hinge Distribution Using Clustering and Fragment Length Combinations of [3,5,7,9].

Clustering Method	**Parameter**	**Accuracy**
kmeans	normal	66.8%
kmeans	manhattan	46.4%
kmeans	cosine	66.8%
kmeans	correlation	66.8%
hierarchical cluster tree	linkages	63.6%
hierarchical cluster tree	data	63.6%

Furthermore several other distance metrics were considered for nearest neighbor classification, using a combination of fragments [3 5 7 9]. Results are presented on Table 4.

Table 4. Skeleton Hinge Distribution Using nearest neighbor classification and Fragment Length Combinations of [3,5,7,9].

Fragment Length Combination	**Distance**	**Accuracy**
3 5 7 9	Chebychev	51.6%
3 5 7 9	Minkowski	76.8%
3 5 7 9	Cosine	76.8%

3 5 7 9	Correlation	76.8%
3 5 7 9	Hamming	1.2%
3 5 7 9	Seuclidean	0.4%
3 5 7 9	Manhattan	89.6%

Support vector machines (SVM) were used as well, in order to identify the writer. A simple scheme of "one-vs-all" was used in an iterative process. In each iteration a single document from the training set, which consists of 250 documents from 250 writers, was assigned to the class known, and the rest to the class unknown. An SVM was trained using the [3 5 7 9] skeleton hinge distribution combinations that were extracted from the training set, and the class information assigned to them. Next a new iteration was used to classify the documents in the test data set, after extracting the [3 5 7 9] skeleton hinge distribution combinations, according to the model trained.

SVM with 'one-vs-one' scheme was also considered but trained only in the first 100 writers. In each iteration a classifier was trained to distinguish between documents of 2 distinct writers. All the possible non overlapping combinations were considered. A total of 4950 classifiers were trained. The SVM classifiers was trained by using the [3 5 7 9] skeleton hinge distribution combinations from the train set. Next a new iteration was used to classify the documents in the test set. Every handwritten document was classified using the trained classifiers. Matching is achieved with a voting procedure. The most voted class is assigned to the document. Experimental Results are presented in Table 5.

Table 4. Skeleton Hinge Distribution Using Support Vector Machines and Fragment Length Combinations of [3,5,7,9].

Scheme	**Number of writers**	**Accuracy**
One-vs-all	250	53.6%
One-vs-one	100	63%

6. Conclusion

In this paper a writer identification system was presented. Our experiments indicate that the use of a novel feature, the Skeleton Hinge Distribution, yields promising results.

While the nearest neighbor technique achieved top accuracy, the performance of machine learning methods was also beyond our expectations. The machine learning algorithms that use few train samples usually present low performance. In the presented work, for a train set of only one sample per writer, on unknown test text, for 100 writers, reached an accuracy of 63%.

The idea of skeleton hinge distribution came from the assumption that in writer identification, all stroke widths, i.e. line thickness, should be considered the same size. By applying skeletonization, this criterion is met. All stroke widths are transformed to a line of single pixel width. The experimental results proved that our assumption is correct. It is our belief, that this assumption should be considered in other statistical methods as well, methods like run lengths, entropy etc., which may be our future work.

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