A Fusion Methodology for Recognition of Off-Line Signatures

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Abstract. In this paper we are presenting a work concerning the classification and recognition of off-line signatures. Signatures form a special class of handwriting in which legible letters or words may be impossible to exhibit but we can extract some features with the help of some parameters. Our proposed fusion methodology for improving the classification and recognition performance of classifiers is based on Dempster-Shafer evidence theory in which our contribution regarding to solve the problems like selection of focal elements and modeling the belief functions is also given. Distance classifiers studied, classify off-line signature images with the help of signature images projection along different axes and by employing some geometrical and fractal parameters which are explained in this article. Dempster-Shafer theory when applied for the fusion of these classifiers has improved the overall recognition rate.

1 Introduction

People have different handwriting styles characterized by more or less distinguishable features. Signatures form a special class of handwriting in which legible letters or words may be impossible to exhibit. Nevertheless they provide secure means for authentication, attestation and authorization in legal, banking or other high security environments and they are recognized as legal evidence. The achievement of an automatic signature recognition and verification system has a lot of problems to solve, which have been reported by many researchers from the very early stages of work in this field. A signature system can be classified as either on-line or off-line based on the hardware front-end. On-line system [1] employs an electronic pen and pad which provides dynamic. In off-line system, signatures written on paper are converted to electronic form with the help of scanner or camera. Here we are concerned with off-line system. The main difficulty can be expressed in form of interpersonal and intrapersonal variations. A lot of useful features have been used to differentiate the signatures of one person from others. Still a work on efficient feature extraction

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system is needed in this area. The features proposed in off-line system can be characterized as global, geometric, structural or statistical. Use of transform-based representations and critical points from off-line drawing of signatures has been reported in [2] and [3] respectively. In [4] combination of global geometric and grid features has been presented. A connectionist scheme of combining classifiers based on moment measures and envelope characteristics has been reported in [5]. Four types of pattern representations via geometric features, moment based representations, envelope characteristics and tree-structured wavelet features have been employed in [6]. In [7] a combination of static image pixel features and pseudo-dynamic structural features have been employed.

In this paper, we are focusing on two points. On the one hand we present easy features and some more relevant in a biometry system. On the other hand we have chosen to split the use of each type of features to highlight the information they are able to bring in the problem solving and then achieve the fusion of different information. This is quite a different methodology from feature selection approaches. We have taken into account very different features. Classification based on these factors and realized with the help of distance classifiers was first achieved. Then recognition by combining these classifiers is proposed. Other methodologies rest on the basis of neural networks or HMM. Here we are proposing Dempster-Shafer evidence theory as a combining tool. This theory has been reported with remarkable performance when applied in different fields in order to achieve fusion. Without being exhaustive, we can mention a certain number of application areas exploiting the advantages of this theory, such as multi-sensors fusion, classifiers combination, pattern recognition, environment monitoring, image processing [8], [9], [10], [11], [12], [13], [14] etc. It proves that use of Dempster-Shafer theory is very productive, but its efficiency depends considerably on the function which is employed as function of allocation of mass of belief. Indeed, this function represents a model for uncertainty and imprecision of information. In the majority of the cases, modeling of the belief function used, is empiricaly fixed by the expert. First, we will precise the features we have chosen and then their performances will be evaluated. After some recalls on Dempster-Shafer evidence theory the merging process we propose will be explained and the results analyzed.

2 Preprocessing and feature extraction

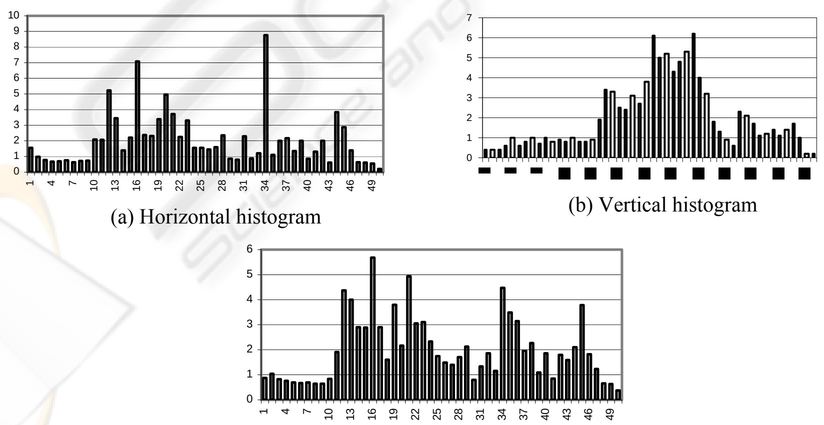
Besides the variability that occurs due to the author of the signature himself, all image-processing applications suffer from noise due to the acquisition process, such as touching line segments, isolated pixels and smeared images. Nevertheless we assume that the signatures have already been extracted from the background. For signature discrimination various aspects can be considered and different features will be extracted from signature images. These different features help to establish several classifiers. We have chosen on the one hand, global simple features as the histograms that omit some spatial information, and on the other hand some geometrical parameters including some fractal parameters either global or local.

2.1 Histograms

Obviously, a person cannot draw his own signatures twice, 100% identical. In fact, there are always some local alterations in different signatures of a person while the signatures global shape remains the same. We can do an approximate analysis for signatures identification by employing some histograms of the number of projection pixels on various axes. These axes may be linked to the image as horizontal and vertical x-axes and y-axes respectively or may be linked to the signature itself following the direction of the signatures.

Signatures projection on Cartesian axes gives horizontal and vertical histograms, simpler to draw. These histograms allow studying the variations in number of pixels along the horizontal or vertical axe. Projection on horizontal axe of a signature image enables us to see whether the signature points are distributed rather on the left or the right-hand side of the signature. Projection on vertical axe gives an indication on the distribution in height of the signature points. Once the histogram is normalized as frequencies, it makes the study invariant toward either image resolution, or the size of the original signature. The precision of the study depends on the number of classes defined in the histogram. It will be the same for each signature. It is now easy to compare them.

The histogram along the axis of siganture's own slope follows the same principle in general. In this case, first the direction of the signature based on its slope (principal axis of the signature) has to be extracted. This axe can be deduced from the eigen values and vectors of the signature image. With an ellipse similar to the inertial ellipse, covering 90 % of the signature, it would be possible to eliminate certain unnecessary features (for example an underline whose length is not stable on several signatures). The histogram obtained on this new axe is often close to the traditional horizontal and vertical histograms but look more stable. The distance chosen between two histograms is a traditional distance, a quadratic distance. It reflects the variations existing between two signatures.



(a) Horizontal histogram

(b) Vertical histogram

(c) Histogram along principal axis

Figure 1 : Normalised histograms of a same image along different axes.

2.2 Geometric and fractal parameters

A signature being a completely personal graphic has some particular discriminating characteristics. In this part we will present various parameters being able to extract these caracteristics from the signatures images. These are different from those studied with the help of histograms because they represent the complexity and shape of signatures. We will be interested first of all in signature image contours. There are several types of image contours and we will see how they can lead to a signature characteristic. Then we will study the fractal parameters which give an index of signature complexity. Then we will make use of the local fractal dimension to detect the irregular zones in the signature and thus to compare them. Then we will see a mass dimension which gives an index on the shape of image and which appears to be complementary to fractal dimension. The last parameter that we are studying is the direction of the signature which appears rather stable for a person. Finally, we will see how to use these parameters in the framework of signature recognition.

2.2.1 Extraction of image contours

Contours or envelopes of signature have already been used for signature recognition. We will be interested particularly in their proportion compared to whole signature. Thus we will be able to compare the "perimeter" of the signature and its "surface". Indeed two objects having same area may not possess the same perimeter (or vice versa) and it is interesting to see in which measurements they are proportional. In literature there exists several types of contours. For each type of contours used, we will calculate the ratio of “Number of pixels in contour / total number of pixels in the image.”

First we are studying classical contours extracted from a binary image using 4 connexity notion. Second type of contours studied, is the exterior contour. In fact it corresponds to a part of classical contours. We select only the first black pixels on each row and column from the image edge.

2.2.2 Fractal dimension

A fractal dimension is a real number that is used to measure the degree of irregularity and fragmentation of a set [15]. From our point of view, it gives an index qualifying the shape of a signature. Several methods of computing fractal dimension exist approximating the exact formula.

The fractal notion makes it possible to determine the length of a complex curve X. It is realised by the use of fractal dimension. To compute it, we consider the set of X minimum mappings by η radius balls. These mappings are figured by successive dilations of X : X_η, and let $A(X_\eta)$ be its area. The fractal behavior of the X set is expressed by the linearity of the relation that links $\ln A(X_\eta)$ and $\ln \eta$. In [16] a graph called an evolution graph (as shown in the figure) enables to study the relation linking $\ln \eta$ and $\ln A(X_\eta)/ \ln \eta$. The fractal dimension is then computed from the formula: $D(X) = 1\text{-}p$, in which p is the slope of the straight line approximating the plotting.

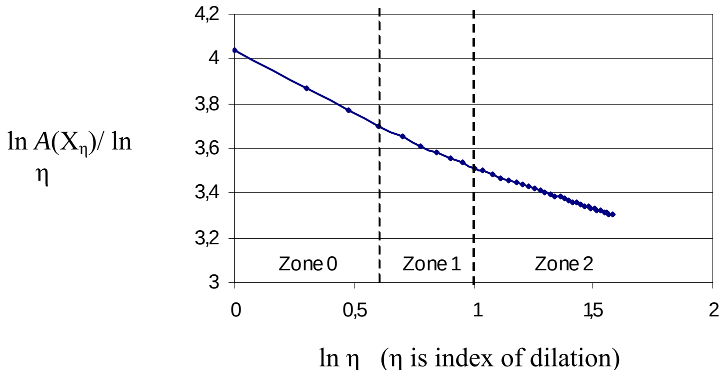


Figure 2 : Evolution graph obtained with 40 dilations from a signature image

In the evolution graph three zones are extracted, each one corresponding to a set of dilations in signature image. First zone (Zone 0) corresponds to first 3 or 4 dilations of the image and thus filling of the signature image contour. The number of dilations necessary for this zone depends on the resolution and width of the signature sketch. Second zone (Zone 1) called as fractal dimension FD1, corresponds to dilations according to the filling of image contours. It is consequently more interesting to study. Indeed it corresponds to a study of the signature image seen at a distance of "normal" reading. It is this zone which will enable us to determine fractal dimension because it gives general feeling from the signature. It thus gives us an index on the "legibility" of the signature. Third zone (Zone 2) called as fractal dimension FD2, has a slope slightly different from that of the zone1. It corresponds to dilations at higher level when the signature image starts "to be filled". Consequently, it figures observation of the signature at an enough large distance from where one cannot any more distinguish the details of the signature but its very general shape. This zone is used to define secondary fractal dimension. It indicates us if the signature is "readable" at a longer distance. To this parameter, we prefer the use of a third parameter called as implication index (Δ = FD1 – FD2), it characterises the evolution of the legibility of the signature when the distance from the viewpoint increases.

2.2.3 Extraction of rigurous zones in signature image

Whereas fractal dimension gives a global indication on the signature, here, we are looking for local zones more complex in the design that others. Then on the grey level image we are caluculating local fractal dimension of each pixel with respect to its neighborhood. It provides us with rigurous zones in signature image. Defining a threshold value for local fractal dimesion allows to reveal a strong local irregularity. A regular zone has a fractal dimension of value 2 whereas a very rough surface can have a fractal dimension approaching to value 3.

2.2.4 Mass dimension

This parameter makes it possible to measure the distribution of the pixels defining the signature image. Its calculation method is relatively simple. It is necessary first of all to select a certain number of points randomly in the signature image, let say 10%. This parameter is then calculated by studying each selected point. For that, the nature of neighboring pixels of the point selected is observed. Thus the number of black pixels (pertaining to the feature of the signature) are counted in the neighboring matrix of 3, 5 and 7 etc. A linear relation between ln(neighboring pixels) vs ln(number of black pixels) is studied. The first coefficient of this relation indicates the mass dimension. Its average value for the 10% points selected in the signature image gives an overall mass dimension value for the signature image under studying and which can be used as a comparison tool with other signature images.

2.2.5 Signature's slope

Generally, people draw their signatures with same angle. One can visually notice it in the majority of the signatures. We thus thought of using this angle as parameter because it appears to be stable. It is calculated from the principal inertia axis.

3 Classifiers and evaluation of their performanace

From these sets of parameters we have studied 4 classifiers based on horizontal histogram, vertical histogram, histogram based on signature's principal axe, and one classifier representing 7 geometrical and fractal parameters as discussed in previous section.

For the evaluation of classifiers performance, we are employing "leave-one-out method". Say that N samples are available for estimating the error rate for a classification system. The leave-one-out method can be applied here by using N-1 samples to train the classifier and the remaining sample to test the classifier. The result is then recorded and this procedure is repeated N times, each time a different test sample is excluded. The error rate is then estimated using the average of these N trials.

4 Dempster-Shafer evidence theory

In order to combine information coming from different sources, Shafer [17] has created the evidence theory on the bases formulated by Dempster. The theory can combine evidence in a consistent manner to come at a more complete assessment of what the entire body of evidence implies. The most important factor is the modeling of belief functions. Once the belief functions are obtained, fusion is carried out by Dempster information combination rule. In this theory, let $\Omega = \{ H_1, H_2, H_3, \ldots, H_M \}$ be the set of possible propositions, called the frame of discernment. Let 2^Ω denotes the set of the 2^M propositions H of Ω : $2^\Omega = \{H / H \subseteq \Omega\} = \{\phi, \{H_1\}, \ldots, \{H_M\},$

$\{H_1, H_2\}$, …., $\Omega\}$. Information bringing an opinion on the state of a system is characterized by a function or a degree of belief *m*. This function m is defined by $m: 2^{\Omega} \to [0,1]$, and has the properties that $m(\phi) = 0$ *and* $\sum_{H \subseteq \Omega} m(H) = 1$. The quantity *m(H)* is called basic probability number of *H*. It measures the belief that is committed exactly to *H*. The subsets of 2^{Ω} whose mass is non null, are called focal elements. A situation of total ignorance is given by $m(\Omega) = 1$ and of total certainty (on a singleton assumption) by $m(H_n) = 1$ where H_n represents a singleton proposition. To obtain the measure of the total belief committed to *H*, one must add to *m(H)* the quantity *m(H')* for all subsets *H'* of *H* such that $Bel(\phi) = 0$, *and* $\forall H \subseteq \Omega \quad Bel(H) = \sum_{H' \subset H} m(H')$. There is one-to-one correspondence between the belief function and the basic probability assignment. The main difficulty consists in modeling knowledge to initialize the basic belief assignment m(.). Many modeling methods have been proposed, which depend usually on the considered application.

Now, if we have several sources of information S_j (j = 1, …., J) providing their functions m_j, then a single belief function can be obtained by combining them ($m = \oplus^{J}_{j=1} m_j$) according to Dempster's orthogonal operator :

$$\forall H \subseteq \Omega,\ H \neq \phi, \quad m(H) = \frac{1}{1-K} \sum_{H1 \cap \ldots \cap Hj = H} \left(\prod_{j=1}^{J} mj(Hj) \right) \tag{1}$$

$$\text{where} \qquad K = \sum_{H1 \cap \ldots \cap Hj = \phi} \left(\prod_{j=1}^{J} mj(Hj) \right) \tag{2}$$

The normalization coefficient *K* represents the conflict between two sources. It has value between 0 and 1. If *K* is equal to 0, the sources are in perfect agreement but if *K* is equal to 1, they are in total conflict. In this last case, fusion cannot be achieved by Dempster-Shafer theory. A conflict mass *K* is generated when the information sources are neither independent nor perfectly reliable and modeling of belief functions is too vague. In order to cope with this problem, other combination operators have been proposed in the literature [18].

Modeling of belief functions lacks of generality. However, two types of approaches can be mentioned : (i) based on distance calculation, (ii) based on similarity measure. According to the nature of our classifiers we are more interested in the first approach but our work differs from other propositions [19]. We now present our contribution to modeling of belief functions in an automatic way [20]. Indeed, we are dealing with pattern recognition. An incoming pattern X has to be classified in class C_i by combining two or several distance classifiers. Distance classifiers give the results by rank level outputs in form of the classes C_i (i = 1 to M) of prototypes X_i (i = 1 to N) according to their distance $d(X, X_i)$. We define a proposition *H* in the frame of discernment Ω as $X \in C_i$ or simply C_i so: $\Omega = \{C_1, ..., C_M\}$ Now focal elements and their belief functions are defined.

Focal elements are the sets of n classes that are concerned by the first neighbors (n varying from 1 to k). Before combining results each classifier is considered on its own. For the purpose of modeling belief function associated with each incoming element, we are introducing a fuzzy membership function to X_i prototype classes. The prototypes are those in the neighborhood of incoming X, it is noted by $F_{Xi}(X)$. A fuzzy membership function for a class noted by $F_C(X)$ is calculated by taking an average value of its prototypes membership values. The function has values between 0 and 1, and has to give a maximum value towards 1 when X belongs to the class. The main variables we have taken into account for a given classifier are (1) Choice of k nearest neighbors of incoming pattern X and the distances associated with. (2) Rank $R_X(X_i)$ of the output classes of prototypes, ordered according to the distance $d(X, X_i)$. (3) $N_X(C)$ which is a class repetition number among the k nearest neighbors considered. (4) $V_{Xi}(X)$, the ratio between the distances $d(X, X_i)$ and $d(X, Xz)$ where Xz represents the preceding prototype in the rank level output of the classifier. Here is our prototype based formalism:

$$F_{Xi}(X) = f_{Xi}(X) \Big/ \sum_{X_z} f_{X_z}(X) \qquad (3)$$

where

$$f_{Xi}(X) = \Bigg[\frac{1/d(X,\ X_i)}{1 + 4 / \sum_{X_z} d(X,\ X_z)} + \frac{1/\sqrt{R_X(X_i)}}{1 + 4 / (\sum_{X_z} \sqrt{R_X(X_z)})} + \frac{(N_X(C))^2}{1 + 4.(\sum_{X_z} N_X(C))} + \frac{1/V_{Xi}(X)}{1 + 4 / (\sum_{X_z} V_{Xz}(X))} \Bigg] \qquad (4)$$

Each term has to be maximum when X and prototypes considered belong to the same class. The weights are chosen in order to balance the different influences. This function is then employed for modeling the belief function.

$$m_i(\{A_1\}) = F_{X\sigma(1)}(X), \ \ldots, \ m_i(\{A_1, A_2, \ldots, A_g\}) = F_{X\sigma(g)}(X) \qquad (5)$$

where $X_{\sigma(j)}$ (j = 1, .., g) represents the prototypes appearing in k nearest neighboring prototypes. m(Ω) complements the evidence to 1. the results using this modeling approach and its performance are shown in the following section.

5. Experimental results

Our database consists of 540 scanned images of handwritten off-line signatures obtained from 36 persons who were asked to sign for 15 times each. Four trained distance classifiers (e_1, e_2, e_3, e_4) with Euclidean distance classified these signature images after their feature extraction. First three classifiers are those constructed from horizontal, vertical and signature's own direction based histograms and the 4th classifier is based on a set of primitives as fractal dimension, mass dimension, signature's slope and signature's image contour fraction etc. Performance of these classifiers was calculated with *leave-one-out method*. The recognition rates obtained for four classifiers employed, are shown in the table 1 with 5-NN and 10-NN. Here, the decision that incoming prototype $X \in C_i$ was taken by the classifier with k-nearest neighbor rule taking into account the classes of first 5 or 10 nearest neighboring prototypes of X.

The recognition rates of classifiers were improved by combining them with the help of Dempster-Shafer evidence theory based on our fuzzy modeling approach of belief functions. The results obtained are shown in the Table 1. Fusion by employing DS theory with our belief function modeling was achieved by taking first 5 or 10 rank level outputs of classifiers. The decision rule was the proposition with the maximum belief value. We can note from the table 1 that Dempster-Shafer evidence theory can deal with several classifiers even if some are of poor quality. This is not the case with a general vote majority method whose result is also shown in the table 1.

Classifier / method		e_1	e_2	e_3	e_4	A vote majority method	Evidence theory
Recognition rate (%)	5-NN	68,69	53,98	71,81	69,33	82,30	94,10
	10-NN	61,97	50,08	67,79	65,75		

Table 1 : Performance of different classifiers and our fusion methodilogy.

6. Conclusions and perspectives

A work concerning the recognition of off line signature has been presented. Some easy features based on histograms and some particular biometric features based on geometric and fractal behaviour were used for classification of different signatures. The classification information of these rather poor classifiers were then combined by use of Dempster-Shafer evidence theory with our belief function modeling approach. The results obtained with real signatures images has shown very tremendous improvement of the individual classifier's performance.

In our next works, we intend to compare our results with those obtained by feature selection among 157 features that are involved in the four classifiers employed. We also will quantify the improvement brought by each classifier and introduce new features.

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