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Application of Artificial Intelligence and Computer Vision Techniques to Signatory Recognition

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Abstract: In this paper, some known Artificial Intelligence(AI) and computer vision techniques are applied to the problem of recognizing the writer of an off-line signature(signatory) among many possible signatories. It is shown by practical examples that the way those techniques are used is very effective and may work efficiently even with a very large pictorial signature database.

Key Words: Handwritten Signature, Signatory Recognition, Discrimination Net, Shape Description, Shape Representation, Description Matching, Pictorial Database

Introduction

It is an established fact that, in the general case, a handwritten signature is not readable even by a human. Therefore, when attempting to recogize the signatory (writer), one must deal with the handwritten signature as a shape. In multisignatory bank checks, for instance, it is needed to recognize the signatory of one or two different signatures among several possible signatures (may ecxeed 20) that may appear on a check issued by authorized signatories. In contrast to the classical method used by the author, *et al.* for the recognition of the signatory using a minimum-distance classifier (Ammar *et al.*, 2002), it is shown in this paper that AI and Computer Vision techniques can be used for this purpose *much faster,* and the recognition process can be *more efficient* if it requires using a large signature database.

Computer Vision, as a major application field of the AI received appreciable attention by well known AI book authors (Eugene Charniak *et al.*, 1985; P. H. Winston 1977, 1983 and 1992 and Stuart Russell *et al.*, 1995). In this context, it was shown that computers can be used in interpretation of simple image, stereo vision and shape from shading applications.

Ammar *et al.*, 1990 introduced a symbolic global description of offline handwritten signatures and used it for the analysis of the nature of a signature database and concluded interesting facts about its nature, however, no paper seems to have appeared on using AI and Computer Vision techniques in recognizing handwritten signatures and consequently, on recognizing the writer.

Recognizing the signatories of a two-signatures check of a multisignatory account (25 authorized signatories can be available in some actual accounts) in order to retrieve their reference signature data for verification using minimum-distance classifier, requires computing the distance measure against the 25 signatories for each one of the check signatures. This will take appreciable time, especially when batches of several thousands of checks are to be processed. Therefore, it is desirable to find a faster method. Fig. 1 shows an account opening sheet of a multisignatory account of four authorized signatories and two required signers (signatories).

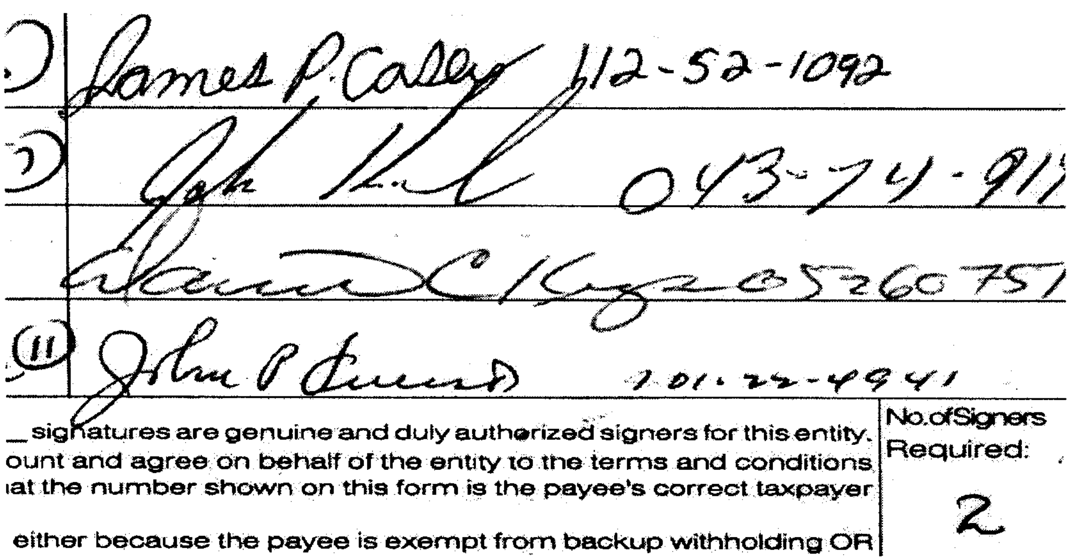

Fig. 1: A part of an Account Opening Sheet of a Multisignatory Account of Four Authorized Signatories and two Required Signers (signatories)

Further, if we are given a specific signature and asked to find if it is available in a large signature database, using only the signature image, the time needed in this case using the classical methods (minimum distance classifier,for example) will be exceptionally large, if functionally possible.. Therefore, in order to be able to realize such application, we have to build a pictorial signature database depending on the pictorial content of the signature with the ability to represent reliably a large number of possible signature classes.

The recognition method introduced in this paper, based on Computer Vision concepts and AI techniques consists of extracting a suitable intrinsic image from the gray level one, describing it , representing it using slot-an-dfiller notation, then by using a suitable discrimination net, an input signature is recognized using the discrimination net and the built pictorial signature database. As we will see, the time the new method needs for recognition can be neglected and it makes the recognition more efficient for a large signature database.

Signature Data: The signature data used in this paper consists of 400 signatures collected as follows: (1),200 genuine signatures from 20 writers, 10 samples from each person and (2) 200 skilled forgeries produced by 10 different imitators. Each signature is digitized using 200 dpi and 256 gray levels.

Signature Vision

Human Vision of Signature: If a human is given a specific signature and asked to find whether it is available in some specific files, he will look at the signature, perceive its shape and appearance, then looks at the files one by one to find if a similar signature is available. In fact, this is what is done when finding the reference signature of a claimed one on a check of a multisignatory account for verification. During this process, the human makes use of his ability to perceive, liken and match things.

Computer Vision of a Signature

It has been concluded that high-performance general-purpose vision system is impossible. Therefore the general solution to the vision problem consisting of two-stage process shown in Fig. 2 below, as suggested by (Eugene Charniak *et al.,* 1985), will be adapted to the signature vision problem in order to get the best results. The two stages are:

1. Early processing in which we get useful information from the raw image.
2. Late processing in which we try to find objects from the useful information.

Early processing: Fig. 3 shows some modules of the early-vision system. Each box is labeled with the main phenomenon of interest there. The first step of processing is the production of the primal sketch, a description of edges and their features of interest in the image. Grouping processes organize small features into larger wholes. Finally, physical areas and boundaries are found and the intrinsic image is produced.

Signature Intrinsic Image for Scene Description: The scene description in our case must enable the computer to say: the signature I see (I am given) is the signature of 'Karen', for example, assuming that the computer has at least one reference signature sample of 'Karen' in its signature database.

In order to achieve this goal, we proceed as follows:

1. Find signature intrinsic image suitable for our goal from the 2-D gray level one taking in consideration the findings of (Ammar *et al.*,1990) in this field, where they found the features that can be used for robust and meaninful description of signatures shapes.
2. From the general approach shown in Fig. 3, we note that:

a motion features are not of interest here (not available) because they are related to online signatures while we deal with offline ones;

b texture and photometry features were found to be good essentially for verification (Ammar *et al.*, 1986 and 1990), therefore they will not be considered here for signature shape recognition;

c the primal sketch will give us the edges of the image outline on the background as well as the pseudo dynamic features (High Pressure Regions, Ammar *et al.*. 1986) which are not of interest for recognition here;

d line interpretation, and positional and spatial relations of signature parts (objects) will give us the region oriented intrinsic image of the offline signature used for signature shape description. This kind of image is reached using several preprocessing and processing techniques (Ammar *et al.,* 1986 and 1990) to extract a clean signature image with its bounaries representing the outline of the signature, demarcating the middle zone, segmenting it into its elements, and finally finding the relative size and spatial relations between signature constituents and parts.

Representing and Recognizing the Signature Scene: The next step in visual processing is the late one (high-level). It is scene description. The goal of this description is to produce a meaningful description of the scene from the intrinsic image. The algorithm that perform this task , as suggested by (Eugene Charniak *et al.,* 1985) operates in three stages as shown in Fig. 4:

1. Switching from a region-oriented (intrinsic mage) representation to an object-oriented one.
2. The machine looks in a "catalogue" of known object types to find familiar objects that resemble those it has found in the image.
3. The stored description must match the description of what the machine is looking at.

In order to produce a meaningful scene description, we need a powerful and robust internal representation (shape description represented using some suitable notation). In other words, the internal representation must refluct the appearance of the scene and remain stable for all class members of this kind of scenes (here, the internal representation must be the same for all signature samples of the same person, as long as their variations fall in some acceptable range).

Describing a shape for scene description (recognition) is defined as producing a description of the object or objects (signature and its parts, in our case) from the intrinsic image. The object-description phase should be designed to make the later steps work well... (Eugene Charniak *et al.,* 1985), otherwise, the discrimination net will not find any thing. The projection of this statement on signature problem means that if a new signature sample of the same person is input to the system, the system must give the same description made for genuine sample(s) available in the signature database even if the input sample has some reasonable variations.

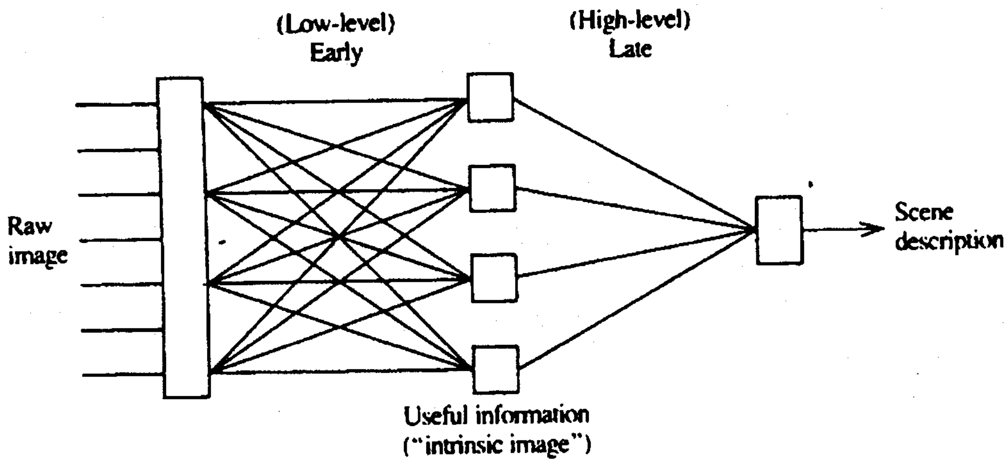

Fig. 2: Stages of Visual Processing

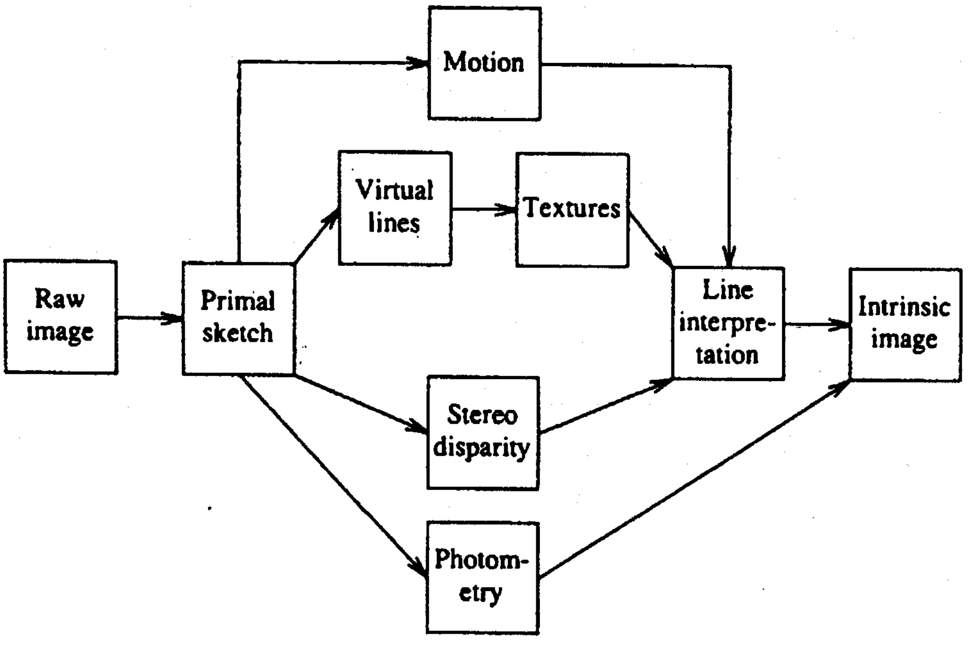

Fig. 3: An Overview of Early Visual Processing

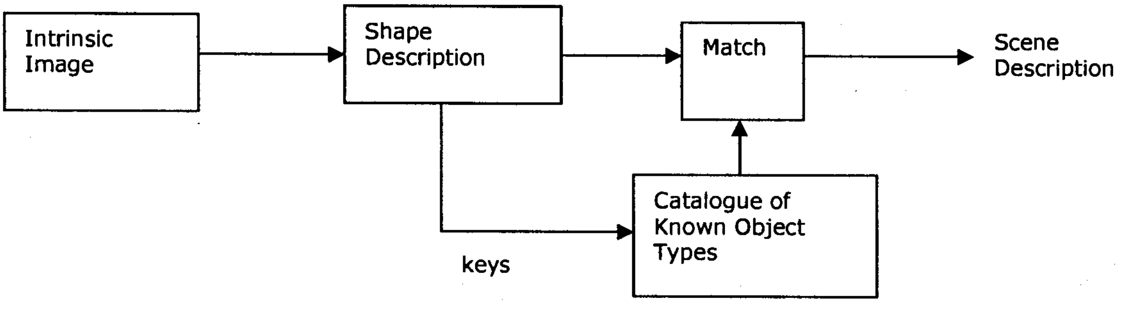

Fig. 4: The Late Visual Processing

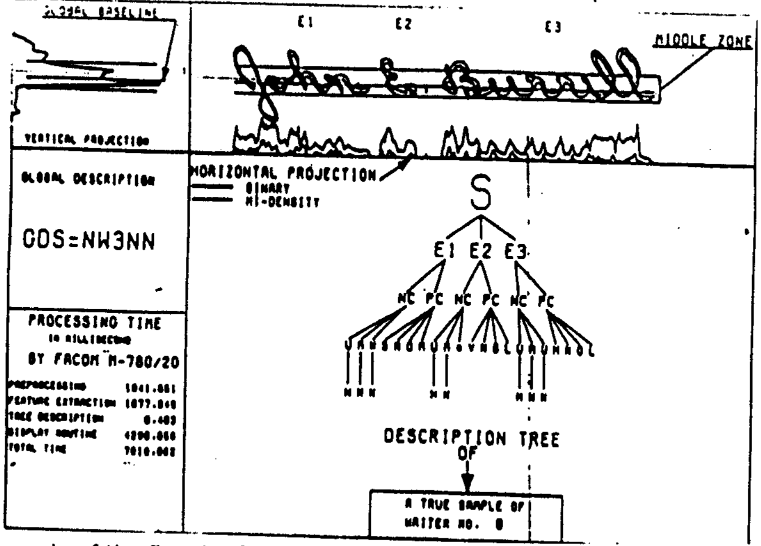

Fig. 5 An Example of the Result of the Description of a Signature of three Segments (elements)

Shape Description: In order that the above algorithm works, we need a shape notation. It will be used in two places:

1. In the catalogue to represent the typical shapes (shape of the different signatures available in the database)
2. As the input to the matcher, to represent the shape of the signature seen now.

In the following, the shape description and representing it in a suitable notation will be described.

Global Description of Signatures (GDS): Ammar *et al.*, 1990, Iintroduced a structural Global and Local description of offline signatures. The global one was represented by a character string and the hierarchical local one was represented by a tree. The GDS involves 5 Global Constituents GCs; (a constituent is a feature or a relation). The 5 GCs are:

GC1: Dominant slant: Negative (N), Indefinite or vertical (I), or Positive (P).

GC2: Contains lower zone (W), or does not (*).

GC3: The number of elements in the signature (n).

GC4: Length/width: much smaller than (V), smaller than (S), equal to (E), larger than (L), or much larger than(H).

GC5: Middle zone width/signature width: Low (L), Normal (N), or High (H).

The same GCs will be used now as an example of switching from region oriented two dimensional signature image to object oriented signature description, then, this description will be represented in a slot-and-filler notation. The notation will be used to build the catalogue and as the description of the input signature to match with the catalogue to find whose signature is the input one.

Fig. 5 shows an example of the result of the description of a signature of three segments (elements). Details of the description and the way of extracting its constituents from the region oriented signature image can be found in the related reference. In this practical exmple, it is obvious that Computer Graphic techniques are widely used to make the result self explanatory to facilitate the evaluation of the results. In this example, the GDS is 'NW3NN'. This means that the dominant slant of the signature is negative, it contains lower zone, consists of three elements, the ratio of its width to its length is normal and the ratio of the width of the middle zone to its width is also normal.

Notation Representation: Now, the same GCs, extracted from the intrinsic (region oriented) image, will be used to build the Internal representation to be used in scene description (recognition). The GCs will be represented using the slot-and-filler notation which is suitable for computer vision applications.

As known in computer vision oriented applications, the general description consists of (1) shape primitive (basic shape) and (2)modifications on the basic shape. The suitable one for our problem is the Constrained-Shape-Description (Eugene Charniak *et al.*, 1985).

The shape primitive of a signature is Handwritten-Signature and the modifications are:

1. Consists of "n" elements (parts).
2. Its dominant slant is N, I, or P .
3. It has a lower zone "W", or does not " * ".
4. The ratio between its length and width is V, S, N, L, or H.
5. The ratio between its middle zone width and its width is L, N, or H.

The Constrained-Shape-Description represented by a slot-and-filler notation becomes:

```
(constrained (GC1 GC2 GC3 GC4 GC5)
        (handwritten-Signature  ( number-of-elements GC1)
                                ( dominant-slant      GC2 )
                                (  lower zone         GC3 )
                                ( length/width        GC4 )
                                (  middle-zone-width/width GC5 ))

        ( = GC1  n)
        (or ( =  GC2  N)( =  GC2  I)( =  GC2  P))
        (or ( =  GC3  W)( =  GC3  *))
        (or ( =  GC4  V)( =  GC4  S)( =  GC4  N)( =  GC4 L)( =  GC4  H))
        (or ( =  GC5  L)( =  GC5  N)( =  GC5  H)))
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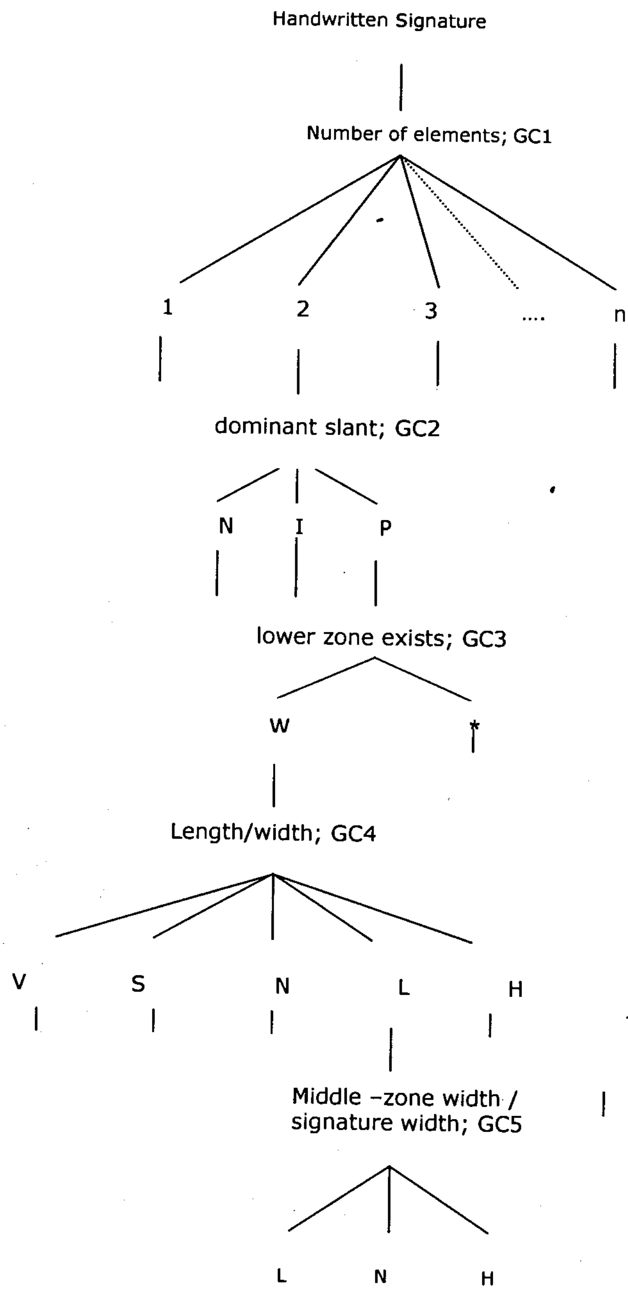

Fig. 6: The Discrimination Net of the Signature Recognizer

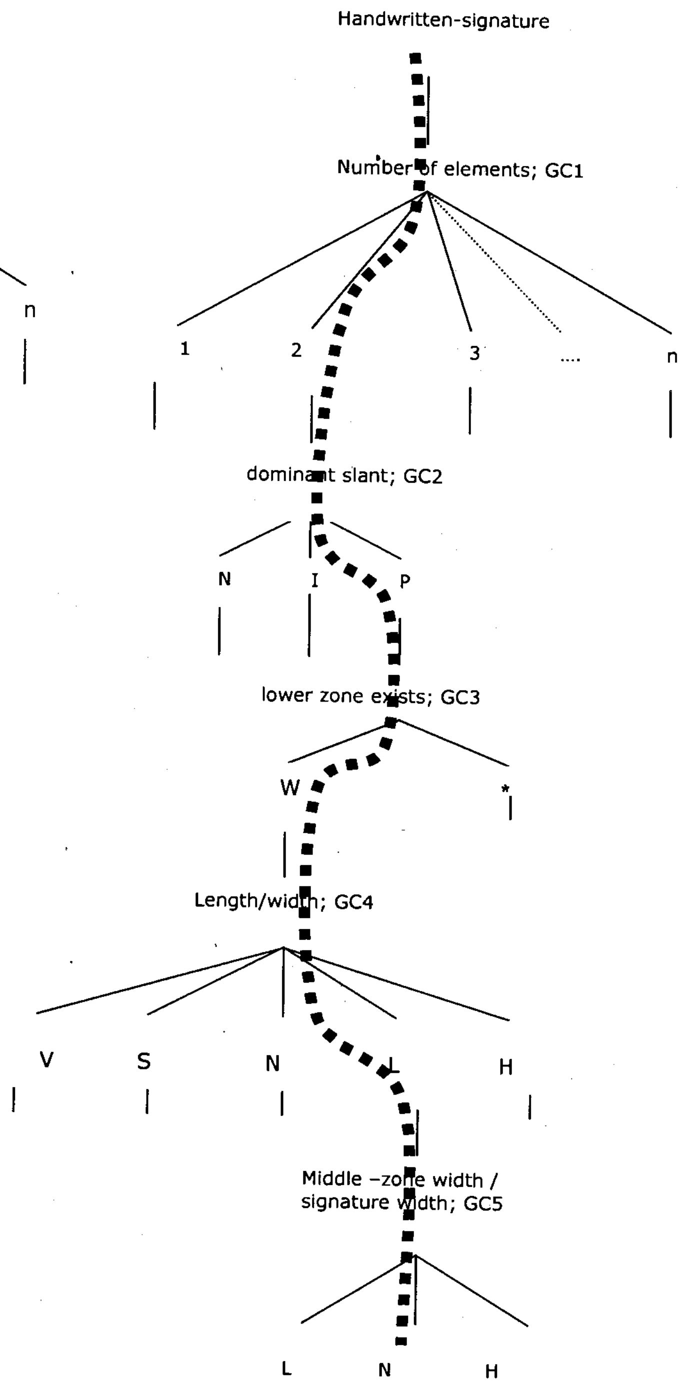

Fig. 7: The path the Recognizer Follows when the Description of the Input Signatur is "PW2LN".The Child Labeled N at the End of the Path, Will Point to the known Signature Type Described as PW2LN, if Available in the Catalogue

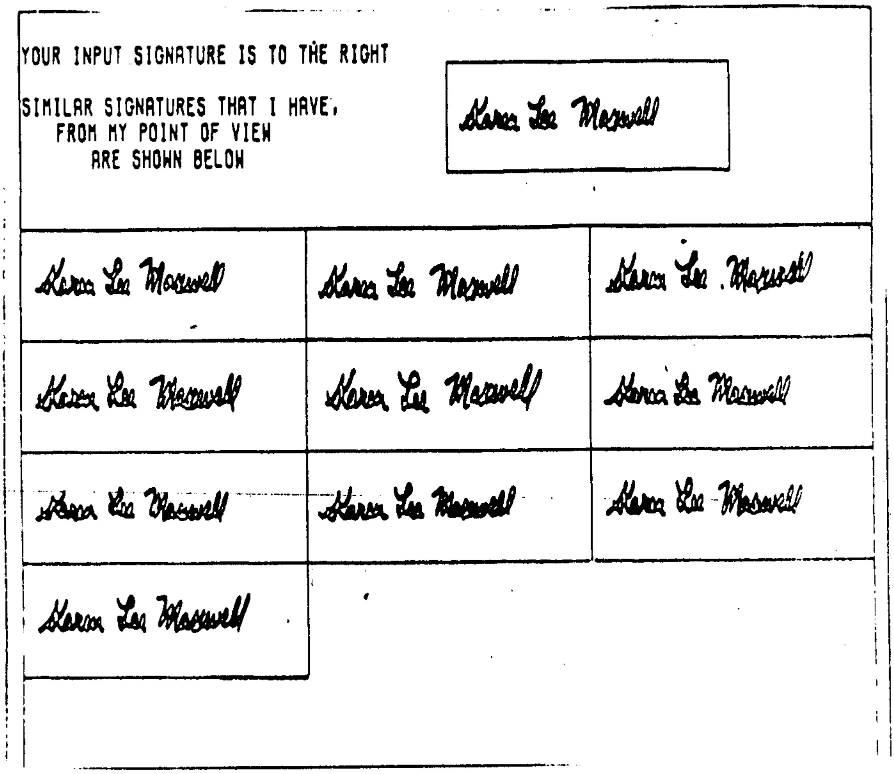

Fig. 8: A Practical Example of Retrieving Samples of the Signatures in the Catalogue Similar to the Input One

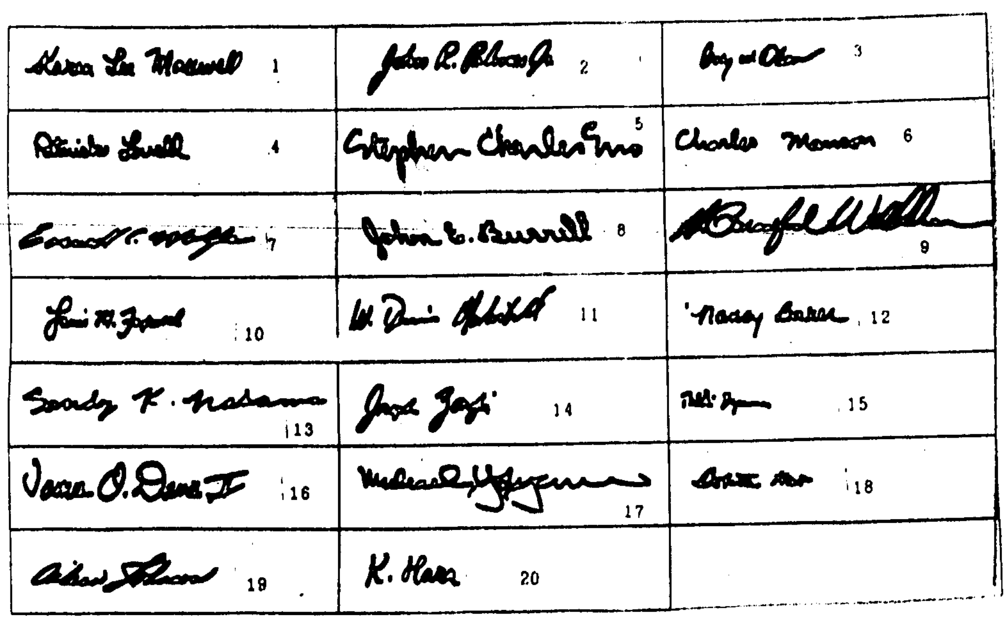

Fig. 9: The 20 different Types of Signatures in the Catalogue

Finding a known Shape to Match Against: According to the algorithm shown in Fig. 4, finding the signature in the database that resembls the one the machine is looking at, requires passing two phases:

(1) producing a description of the signature, which is already explained;

(2) using this description to suggest the object(s) that might match. That is, we use it as a key into the shape-description catalogue. The index is organized as a discrimination net.

The Signature Discrimination Net: Since the vision system to be built is specialized in handwritten signatures, we have one shape primitive (Handwritten-Signature). The recognizer will look at a given handwritten signature in the input and recognize its similar one(s) among many different signature types available in the catalogue, if any similar type is available, otherwise, it will anounce failure (I do not know, or no similar signatures are found). Therefore, the root of the discrimination net will start at the shape primitive (Handwritten-Signature) and goes down the tree according to the shape description.

As the discrimination net in Fig. 6 shows, the children of the root node will lead to all types of elements of the shape primitive (1,2,..,n), then each child will lead to all dominant slant types (N, I, or P), then each child indicating a slant type, will lead to all possible types of the ratio between the signature length to signature width and finally, each child of GC4, will lead to all possible types of the ratio of signature width and its middle zone width. This discrimination net is shown in Fig.6.

The Recognition Process

Building the Catalogue: In this phase, the known types of signatures are described and stored in the catalogue and organized according to the discrimination net.

Recognizing a Signature: In this phase, the input signature the machine looking at, is described and, according the discrimination net, the recognizer search in the catalogue using the GCs symbols as keys until it reaches the bottom level where it must find one or more signature types, or no signature type, if the type of the input signature is not found in the catalogue. Fig. 7 shows the path the recognizer follows when the description of the input signatur is "PW2LN".The child labeled N at the end of the path, will point to the known signature type described as PW2LN, if available in the catalogue.

According to the description analysis (Ammar *et al.*, 1990), 1350 distinct signature types can be produced by the global description mentioned above, therefore, a signature recognition of this kind is expected to work well with hundreds of different types of signatures in the catalogue without any need to read the signature as handwriting.

Fig. 8 shows a practical example of the performance of a Signature Retrieval System using this approach when used with a catalogue containing 20 different types of signatures (shown in Fig. 9) and 10 different signature samples of each type, where the 10 different samples of the same signature type were retrieved when a signature sample of this type was input to the system.

Much More Signature Classes Can be Represented: In fact, much more classes can be represented by this description if we used the local one. In the local description, every element may be descried by thousands of different classes resulting, theoretically, hundreds of thousands of classes, in the general case.

Signature Recognition .May Provide More Applications: Once a class of objects (signature, in our case) is described efficiently, i.e., transfered successfully from the sight World into elements suitable for Internal Representation (known in Computer Vision as transferring the physical phenomenon, optical impression of an image, into internal representation), different useful applications can be built based on it. For example, the signature description used for signature recognition shown above, was used also in an expert system that tells using natural language whether the input signature is genuine of a forgery and explains the reasons of classifying it as genuine or as a forgery (Ammar 1989). This system in turn was also used to simulate different other useful systems in the field of signature applications like practicing signing and training signature analysis expers who are not familiar with computer and computer science.

Another interesting application based on similarity retrieval can be implemented if a big signature database (large catalogue) is available. This applicaton is designing a signature which is not similar to any other one in the database (a unique signature) to be used by some person. By using the signature as an input and adjusting the matching strategy to retrieve similar signatures, similar ones in some aspects in the catalogue can be seen, then altering the input signature design repeatedly untill no similar signature can be retrieved. The result would be a unique signature in the criterion(s) we need.

How Fast the Recognition Can be?

If signatory recognition will be done for verification as in an ASV system, then adding slight modifications to the feature extraction procedures to essentially map desired features into description symbols will require almost no time compared with that required for feature extraction, and since the catalogue is indexed by the discrimination net, the time needed to recognize the signatory can be overlooked. Eventually, the time needed to recognize the signatory by the proposed approach can be omitted.

Results and Discussion

According to the experiments done, the following observations and findings can be fixed here:

1. The approach introduced in this paper can be considered successful for the class of signatures used (American Signatures) where the computer could recogize the signatory of the input signature by recognizing the reference sample of the same person in the catalogue.
2. The conclusion in the previous paragraph is not absolute. We should keep in mind that some people have considerable instability in the shape of their signature due to bad writing habits so that

two main classes or even more may appear in the different samples of their signature. For those cases, we will be facing one of he following situations: (a) the input signature sample fall in the same class of the one in the catalogue and in this case, the computer will be easily able recognize the signature type in the catalogue, determine the signatory and eventually perform the verification or retrieve one or more of the signature type samples available in the catalogue, according to the desire of the user and the abilities available in the system; (b) the input sample is an irregular one or fall in a class other than that of the sample available in the catalogue. In this case, the computer will naturally announce failure, however, this is not a disadvantage since this case must be either a forgery and the result will be a good finding, or an irregular sample. The second case is also a good finding because in this case, we must update the catalogue to contain this class of such person if he insists on considering it as genuine, or ask him to avoid such irregular samples.

3. Recognizing the signature type in the catalogue that belongs to the input signature will not depend only on the stability of the writing habits of the specific person, but also on the matching strategy used by the recognizer. If it used strict-matching, i.e., the description in the catalogue must completely match the description of the input signature, then a failure may happen if the variation in the input signature exceeded the tolerance the description accepts. This case can be avoided by using loose-matching. For GC4, as an example, where the matching is accepted if the description of this feature in the catalogue is the same or one degree below or above, i.e., PW2LN will match with itself and PW2NN and PW2HN. In this case the signature type will be recognized but another signature type in the catalogue may also match. In order to solve this problem, a classical recognition stage must follow loose match to find the desired type among the few ones recognized, if there are more than one type recogized. Of course, such assumed results will depend upon the signature database size and the writing habits of the different signatories.
4. In fact, most works (if not all) in the field of sigature are restricted to verification and the signatory (or signature) recognition is not a commonly tackled problem. The reason is that all research works dealt with Lab data in which the problem of mltisignatory accounts and multisignature checks is not available, however, in the actual applications, the need for signatory recognition has appeared (Ammar *et al.*, 2002).
5. The number of signatures and signature types used in this study is considered to be quite reasonable because: (a) the majority of accounts in bankes are single signatory ones; (b) most of the multisignatory accounts have less than 10 signatories and in rare cases, 25 signatories may exist. Therefore, a data containing 20 different types of signatures(signatories) and 10 different samples of each type, is a good data to use for evaluation of the reasonability of the recognition approach.
6. As mentioned in the paper, the signatures used are American style, i.e., there is no retrograde strokes that return continously from the end of the signature to its beginning, like what can be found in European style. This problem can be solved by modifying the segmentation algorithm used in the description to overlook such retrograde strokes when segmenting the signature into elements. Much simpler solution can be used without any modification to the description algorithm by modifying the matching procedure to overlook GC1, the number of elements, but of course, this will be at the cost of the number of recognizable signature types by the description. They will theoretically decrease to 20%, i.e., to 270 signature type.

conclusion

As demonstrated in this paper, applying Artificial Intelligence and Computer Vision techniques to the problem of signatory recognition provides fast recognition and efficient search. By building a discrimination net based on a pictorial signature database and using a convenient matching strategy, we will be able to realize several useful applications like simsilarity oriented retrieval, signatory recognition, and designing a unique signature.

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