Extraction of Signatures from Check Background Based on a Filiformity Criterion

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Abstract—Extracting a signature from a check with patterned background is a thorny problem in image segmentation. Methods based on threshold techniques often necessitate meticulous postprocessing in order to correctly capture the handwritten information. In this study, we tackle the problem of extracting handwritten information by means of an intuitive approach that is close to human visual perception, defining a topological criterion specific to handwritten lines which we call filiformity. This approach was inspired by the existence in the human eye of cells whose specialized task is the extraction of lines. First, we define two topological measures of filiformity for binary objects. Next, we extend these measures to include gray-level images. One of these measures, which is particularly interesting, differentiates the contour lines of objects from the handwritten lines we are trying to isolate. The local value provided by this measure is then processed by global thresholding, taking into account information about the whole image. This processing step ends with a simple fast algorithm. Evaluation of the extraction algorithm carried out on 540 checks with 16 different background patterns demonstrates the robustness of the algorithm, particularly when the background depicts a scene.

Index Terms—Check processing, filiformity, lines extraction, segmentation.

I. INTRODUCTION

D ESpite electronic payments by credit cards having become so widespread, bank transactions involving checks still are still increasing throughout the world [1]. Many banks have to be endowed with automated check processing systems [2]. One of the aims of automated check processing is to authenticate the signature by comparing it with reference signatures provided by the account holder. This processing technique consists of two modules [3], [4]: a low-level processing, for signature extraction, and a high-level processing, for signature verification. The robustness of such a system depends mostly on the robustness of the extraction module and on its effectiveness in providing the verification module with all the pertinent information that characterizes a signature: the geometry of the lines, line size, brightness along the lines, degree of slant, etc.

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One can find in the scientific literature three approaches to eliminate the check background. Yoshimura et al. [5] and Okada et al. [6] use a subtraction process between a filled specimen and a virgin model of a check. This approach seems to be powerful except that it necessitates the storage of a large number of virgin specimens. The second approach, takes into account the success of the recognition process to supervise the extraction of the useful information such as the amount process [7], [8]. The third approach tries to achieve the extraction directly as a low level process. This approach is still the most followed by researchers and the most widely used technique for extracting handwritten information is a global thresholding. In the ideal case of information written on a uniform background, a simple histogram analysis enables the determination of the global threshold that separates the writing from its background, see Fig. 1. Generally, this threshold is selected just before the peak which corresponds to the background of the image, in an effort to preserve all writing-related information [9], [10].

In practice, these ideal conditions are not always respected; noise can be introduced during image acquisition, and light reflections can cause a decrease in brightness of the image. This makes the global thresholding technique obsolete, because the histogram no longer clearly presents two peaks and a valley. Worse still, the background of the check, which can be colored or textured, frequently depicts a scene.

In a more general context, researchers have, for the past 20 years, continued to propose a wide variety of thresholding techniques (see [11] for a review). Graf et al. [12] use a global threshold to eliminate the background in a noisy check. Liu et al. [13] apply for each rectangular region surrounding an item, a specific global threshold to extract the item information from the background.

Cheriet et al. [14] propose a formal model for processing bank checks in which extraction is based primarily on Otsu’s dynamic thresholding technique. This iterative technique is based on histogram analysis. At each iteration, a class or mode separation factor is calculated and applied to the image. This technique makes it possible to eliminate the background of the check iteratively until there is only one class remaining, i.e. the one that is farthest to the left of the histogram, which represents the writing on the check. The result obtained by this method requires a correction, however, since certain parts belonging to the writing have been eliminated with the background. The authors propose postprocessing in several steps, the most important of which is a topological processing step which takes into account the direction of the gradient in order to correctly connect the parts of the writing together.

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Similar problems related to the background elimination can be found in the field of mail address processing or document analysis. To extract a written address from the image, many approaches are investigated, such as morphological processing [15] or multiresolution approach [16] or by direct detection of “ridges” of characters strokes in grayscale images [17].

For document binarization, Don [18] models the background image by a Gaussian noise of null mean and a standard deviation of $\sigma$. The author separates the written information from the background image by global thresholding, where the threshold is estimated based on attributes which are specific to the noise. Liang et al. [19] extract the characters from a textured background by using the mathematical morphology. The technique is applicable in the case of a background with a periodical texture, and involves a search for the optimal mask for eliminating this periodical texture by analyzing the periodicity of the texture in $x$ and $y$.

Generally speaking, because the images that form the backgrounds of checks vary so widely, the thresholding techniques used to extract signatures are either ineffective, or they entail laborious postprocessing steps to recover the information that has been lost [3]. The problem with these thresholding methods is that they are either global or local. The use of global methods often results in pertinent local information being lost, while local methods fail to take into account global information. A method needs to be developed, therefore, which can adjust these two types of information, local and global. Two studies are particularly interesting in this regard: the research of O’Gorman [20] and that of Kamel and Zhao [21], [22], notwithstanding the objectives of the two studies which are quite different: the objective of the O’Gorman study was to extract characters or lines detected belong to the signature or the writing and which are part of the background of the check.

Considering the difficulty of finding an effective extraction algorithm by standard processing methods, it is interesting to note how extremely easily this task is accomplished by the human eye. This natural ease is due to the fact that our eye does not view an image as a group of pixels, as a CCD camera does, from which information must be extracted. We now know, through physiological data gathered on vision and through psychovisual testing, that the eye contains various types of cells, each of which reacts to particular light stimuli [23]–[25].

In this article, we are interested in one specific type of cell, the most extensively described in retina physiology, the circular receptive field cell, commonly called the X-cell. The current model, which describes the behavior of these cells as a function of the amount of light falling on the receptor field, will enable us to introduce a topological measure linked to the dimensions and to the size of the shape being projected onto the receptive field. This measure, which we call filiformity, represents the topological specificity of the lines we are seeking to extract from the image. In Section II, we present two definitions of the filiformity as local measures for binary objects. In the next section, these definitions are extended to gray-level images. One of these measures takes into account the advantage of the local symmetry of a line, thereby constituting the first processing step. This initial step is completed in Section IV by a global processing step, which consists in thresholding the local filiformity measure obtained for each of the points. The value of this threshold is determined automatically. In Section V, our method is evaluated on different types of checks.

![Fig. 1. Global thresholding. (a) Original image. (b) Histogram. (c) Extracted signature. The histogram (b) of the image of a signature on a uniform background (a), shows the presence of two lobes. The small lobe, which relates to the signature, is more spread out than the lobe to the right of it, which relates to the image background. A threshold selected between the two lobes makes it possible to extract the signature easily, as in (c).](image-url)
II. Filiformity

Intuitively, a stroke or a line is a filiform object, which we perceive as a particular region of the image and which has the characteristic of being longer rather than wider.

Formulating this characteristic mathematically is a delicate operation, because a line in a continuous space is considered as a one-dimensional (1-D) set without thickness. In practice, a line has thickness, and, depending on the resolution of the visualization, this thickness may yield a narrow line or a wide line. Globally, however, the width of the line must be small relative to the maximal length of the object.

There are a number of geometrical measures for an object, notably:

- the length of the skeleton $L$;
- the width of the object at a point $x$ of the skeleton: $\epsilon(x)$.

These measures enhance the definition of the notion “longer rather than wider.” For example, this notion could be defined by $L \gg \epsilon(x) \forall x$. See Fig. 2.

However, the variety of shapes of the objects present in the field of vision is too large to simply classify them in two classes, filiform objects or nonfiliform objects. Indeed, some objects can be composed of parts that are filiform and others that are not. A local definition of filiformity is therefore necessary to take this diversity into account. An object is thus globally filiform if it is locally filiform at each of its points.

One way of defining this local criterion is to consider a quasicircular window in the image of the X-cell receptive field. The idea here is to consider this field as a window through which one area of the image can be seen in order to decide whether or not the object that appears in the “window” is perceived as a line.

The problem, therefore, is to formulate an adequate topological measure for the lines, which is linked to this window. We propose two types of measure for binary images in which the objects present are black and the background is white.

A. Surface Filiformity

The OFF-center ganglionic or geniculate X-cells are composed of a central OFF zone surrounded by a peripheral ON zone. The ON cells have the inverse configuration. The optimal reaction for the OFF cells is obtained when the central OFF zone is obscured and the peripheral zone is illuminated. Thus, the ratio of light $\tau(p)$ expressed as a function of the spatial frequency and phase shift of a lattice composed of a network of alternating black and white bars.

For our purpose, one main result of these authors is that their model responds to specific frequencies of the network. There is a minimal frequency under which the model does not respond. In other terms, there is a maximal spatial period over which the model does not respond. In a two-dimensional (2-D) plane, this means that there is a limit $T_{bh}$ for the surface occupied by a bar, black or white, over which the model does not respond.

Our surface filiformity measure $\tau(p)$ is linked to the rate at which an object $T$, assumed to be dark, covers the surface of the receptive field of the cortical cells, see Fig. 3(a). Let $S$ be the surface of a unit of cortical cell and let $\bar{B}$ be the surface of a black band of the network. Thus, the ratio $\bar{B}/S$ expresses the quantity of “missing” light, or darkness, relative to the quantity of light that would be received by the receptive field if there were no object $T$. If we consider the receptive field of cortical cells as a window through which an observer looks at the object $T$, it is found that the smaller this rate of occupation is, the more the observer sees the object as filiform at this point. Clearly, the observer’s decision is subjective, because it depends on the dimension of the window. The topological criterion of surface filiformity is therefore defined as follows.

An object $T$ is locally filiform at point $p$ relative to a window centered on $p$ if $\tau(p) = (\text{Surface of object contained in the window})/(\text{Total surface of the window}) < T_{bh}$.

In the discrete image space, the information about object $T$ is provided by a set of black pixels. It is more practical, therefore, to define the criterion of filiformity relative to a square window $W$ centered on a pixel $p$ of $T$, see Fig. 3(b). The criterion of local filiformity in $p$ becomes: $\tau(p) = \text{Card}(W \cap T)/\text{Card}(W) < T_{bh}$. In addition, in order not to consider the degenerate cases of small objects or isolated points,
(a) (b) (c)

Fig. 4. Surface filiformity. (a) Original image. (b) $r = 4$. (c) $r = 8$. (d) Original image. (e) $r = 4$. (f) $r = 8$. Images (b), (c), (e), and (f) illustrate the selectivity of the surface criterion in extracting lines of a particular thickness as a function of the size $r$ of the window. The elements extracted appear white. The original image (a) is made up of six curves, representing two different thicknesses and three different curvatures. When $r = 4$, the thinner lines are extracted better if they have little curvature. When $r = 8$, it was possible to extract the thicker lines, except for the linear parts of the thick curve at the bottom of the image, which, because of their proximity to one another, cannot be evaluated using the surface criterion. Images (e) and (f) show the response of the criterion to a series of knots or intersections of curves. These knots have a surface occupation rate that is greater than that of a line. When $r = 4$, these knots are not detected, but for a larger radius, $r = 8$, the only knot that is not detected is the one with five branches, and therefore a larger occupation rate.

the following supplementary condition is added: $\text{Card}(W \cap T) \geq \text{minimal length of a segment which passes through } p$ and which is contained in $F$.

In the case of a circle in the continuous plane, this length equals the diameter of the circle, and, in the case of a square window in the discrete space, it equals the side of the square.

These two conditions are implicitly found united in the criteria for evaluating the local quality of a contour adopted up to now in a number of research studies. They were initially proposed by Kitchen and Rosenfeld [27]. A contour is judged to be of good quality if it is both one pixel thick and regular. The Kitchen and Rosenfeld measure is composed of two criteria: one related to continuity and the other to thickness. The measure is taken over a $3 \times 3$ neighborhood of each contour point. For continuity, the measure requires that there be two points in the neighborhood with the same gradient direction. The thickness measure requires that, apart from the three pixels (the two, plus the central pixel involved in the measure), the six remaining pixels not to be contour points. We obtain the same two conditions of filiformity as above, for a size 3 square window and $T_h = 1/3$, as follows.

1) $\text{Card}(W \cap T)/\text{Card}(W) = \text{number of black pixels/number of window pixels} = 3/9 = 1/3$.

2) $\text{Card}(W \cap T) = \text{number of black pixels} = (\text{length of the minimal segment passing through } p) = 3$.

Henceforth, we fix the value of the threshold to one-third. Fig. 4 illustrates the effect of the criterion on a binary image. The size of the window is a scale factor that must be chosen as a function of the maximal estimated thickness of the lines, but also of the local tolerated curvature of these lines. These local curvatures induce a larger occupation surface than when the line is straight. If we consider a circular window centered on a point in the straight line, it is easy to see that the surface of the line increases linearly as a function of its length. If we call $l$ the width of a line and $L$ the length of the line segment inside the window, then the surface of the segment is $S = lL$. If the size of the circular window changes, then the length of the segment follows this change linearly, and $S$ becomes a linear function of the size of the window. However, when the line is not straight, the variation of $L$ is no longer linear, and increases more than in the case of a straight line. In this case, the surface occupation ratio may no longer be under one-third for larger windows. In fact, the variation in the surface occupation rate as a function of the size of the window reflects the local curvature at this point. This fact is reminiscent of Peano’s classic fractal curves, which are curves in a continuous plane without thickness, but, because they meander, they cover a surface [28].
Fig. 5. Ring filiformity at point $p$. (a) Ring filiformity $R(p)$ is evaluated on the perimeter of a circular ring in a continuous plane. In (b), a square ring is represented whose exterior and interior radii equal five pixels and one pixel, respectively. In this type of figure, the perimeter is made up of two white arcs alternating with two black arcs. The measure $R(p)$ which takes into account the number of black and white arcs on the perimeter, makes it possible to detect all the local configurations of the object $T$.

B. Ring Filiformity

A simple and intuitive experiment can be conducted to determine the topological properties of a line, as follows: if we move the center of a circle along a regular curve in a continuous plane, the circle will only intercept the curve at two points. When the curve is irregular, the circle will intercept the curve at several points. This property can be generalized for lines in the discrete plane by substituting a square ring for the circle; see Fig. 5.

The idea is to sweep the center of this ring over an image and decide whether or not the object which intercepts this ring is filiform, considering only the pixels on the perimeter of the ring.

The use of a circle to measure a characteristic topological size of a line is fairly common in geometry, and is the fundamental principle on which the fractal dimension measures are based, like the Richardson and Minkowski measures [28], for example. Richardson’s measure considers the limit of the area swept to each other, when the radius of these circles tends toward zero. For Minkowski’s dimension, the limit of the number of black and white arcs on the perimeter of the ring; this property can be generalized for lines in the discrete plane by substituting a square ring for the circle; see Fig. 5.

We define a filiformity measurement function $R(p)$ on the ring, the value of which indicates the local configuration of the object. The following parameters are used in the definition.

- $W_i$: length of the white arc, subscripted $i$;
- $B_i$: length of the black arc, subscripted $i$;
- $N_{wb}$: number of white arcs on the perimeter of the ring;
- $N_b$: number of black arcs on the perimeter of the ring;
- $L$: perimeter of the ring or number of pixels on the perimeter.

The following relation is evident:

$$\sum_{i=1}^{N_{wb}} W_i + \sum_{i=1}^{N_b} B_i = L.$$  

We can then interpret the various configurations following the values of $N_{wb}, N_b, W_i,$ and $B_i$:

It is also evident that when one of the parameters $N_b$ or $N_{wb}$ is greater than one, then the quantities $N_b$ and $N_{wb}$ become equal, because there are the same number of white intervals as black intervals. When one of the parameters $N_b$ or $N_{wb}$ equals one, the equality of $N_b$ and $N_{wb}$ is no longer ensured. In this case, the ring is centered on a point in a fairly wide region and all the points of the ring have the same value.

Below are the local configurations linked to the values of $N_b$ and $N_{wb}$:

- $N_b = 0$ and $N_{wb} = 1$: the ring is centered on a white region.
- $N_b = 1$ and $N_{wb} = 0$: the ring is centered on a black region.

These two cases highlight the importance of the size of the ring. They occur for isolated points or small spots included within the ring.

- $N_b = 1$ and $N_{wb} = 1$: we are on the edge of an object; the central point belongs to the contour of the object.
- $N_b = N_{wb} = 2$: The object represents a curve or a line.
- $N_b = N_{wb} > 2$: The central point is a knot with several branches; there are $N_b$ branches.

The filiformity criterion in relation to a ring follows simply by making

$$R(p) = N_b = N_{wb} = 2.$$  

Fig. 6 illustrates the various results obtained by taking as a measurement function: $R(p) = N_b = n$, for $n = 0, 1, 2, 3,$ and 4.

The two measures, surface and ring, are quasi-equal, and constitute a model of our perception of what we call the local filiformity of an object. The ring measure can be richer in terms of information however, because it enables better interpretation of the local shape of a line by an adequate choice of a measurement function, while the surface measure translates an occupation rate without taking into account the local shape of the line. Both measurements assume the following conditions:

- The nonexistence of isolated point or small spots. In the case of a ring of external radii $r$, the maximal diameter in $x$ and in $y$ of these spots must be greater than or equal to half the size of the ring: $r/2$, such that at least one of the points of this spot is on the perimeter of the ring. In the case of the surface criterion, the condition relating to length makes it possible to avoid isolated points or small spots.
- No interception of the ring, or the window $W$ by a branch of another line at the measurement point $p$. Such an interception would falsify the evaluation of the measure. This condition presupposes that one branch of the curve does not come too close to another part of the curve. In this way, the black parts appearing on the ring or present inside the window $W$ are connected to point $p$ by a path which is itself included within the ring or the window.

In practice, these two conditions can be satisfied: the first, by eliminating the isolated points in a preliminary step; the second, by taking the smallest size for the ring or the window when possible.
Fig. 6. Ring filiformity. The above images illustrate the filiformity criterion evaluated on a ring of the original image in Fig. 4(d). The elements extracted, which appear white, are the results of the function \( R(p) = N_b = n \), for different values of \( n \). Each value of \( n \) translates a particular local configuration of the object. For \( N_b = 0 \), only the internal part of the filled region is detected. For \( N_b = 2 \), all of the parts of curves are detected. For \( N_b = n > 2 \), the points detected are located in the neighborhood of knots with \( n \) branches.

III. FILIFORMITY FOR GRAY-LEVEL IMAGES

The definition of a topological criterion for gray-level images is more complicated than for binary images. In the case of binary images, the objects were defined by black pixels at the outset, while in the case of gray-level images, the objects are defined by shades of gray. The difficulty in characterizing each object by the gray level of its pixels is the fundamental issue encountered in image segmentation. In spite of a visual perception of the uniformity of an image region making up an object, it is often difficult to find the model that governs its pixels. As far as our problem is concerned, we are only interested in the lines present on the image of the check. We characterize these lines by means of the following heuristic: A line is generally darker than the background on which it is drawn. Certain parts of lines can cross zones that are darker than they are, but these parts are generally smaller than those which cross lighter zones. We must now develop a measure that takes into account the brightness criterion defined by the above heuristic, based on the filiformity criteria defined earlier for binary images.

A. Surface Measure: \( g_s \)

The surface filiformity criterion takes into account the rate of surface occupation on a square window of size \( r \). Let us denote by \( n_p \) the gray level of the central pixel. If we assume that the brightness of the line we are seeking to extract does not vary too much around \( n_p \), then it is easy to translate the above heuristic by saying that the number of pixels inside the window, whose brightness is equal to or lower than \( n_p \), is at most equal to one-third of the remaining number of pixels. Let us denote by \( N^+ \) the number of pixels whose gray level is higher than \( n_p \), and by \( N^- \) the number of pixels whose gray level is equal to or lower than \( n_p \). The surface occupation rate for gray-level images is then defined by \( g_s = (N^-/N^- + N^+) \) and a point of the image will be designated locally filiform if \( g_s \leq 1/3 \).

Fig. 7 shows the results obtained on a part of a check image as the size \( r \) of the window increases. The lines we are seeking to extract from the check images appear even with small values of \( r \). The result would be nearly perfect, except for the presence of a multitude of isolated points that are not visibly part of the lines and which come from the background pattern of the check. As the size \( r \) increases, the detected points become more concentrated around the contours of objects in the background of the check. A characteristic of this operator is that it detects a handwritten line and a contour line without bias. For our purposes, the extraction of writing, this lack of discrimination constitutes a major default, due to the fact that the operator is insensitive to the local shape appearing in the window \( W \).

B. Ring Measure: \( g_r \)

Electrophysiological studies by Hubel and Wiesel [23] have shown that the receptive fields of simple cells of the cortex of the cat and the monkey always present either an even or an odd symmetry. This observation suggests that the detectors of the human visual system may endowed with even or odd symmetry as well. The experimental study on psychovisual
Fig. 7. Surface filiformity applied to a gray-level image. (a) Original image. (b) \( r = 4 \). (c) \( r = 8 \). (d) \( r = 12 \). \( r \) represents the size of the square window. The lines we are seeking to extract appear with a quantity of other points from the contours of the background pattern. These results show the lack of sensitivity of the surface criterion in differentiating between contour lines and written lines.

Fig. 8. Difference between a contour line and a stroke line.

tests conducted by Burr et al. [24] clearly confirm the popular idea suggested previously [29], [30], which is that the detectors of the human visual system take advantage of the even symmetry that characterizes a line or a stroke \( f(x) = f(-x) \) and of the odd symmetry that characterizes a contour \( f(x) = -f(-x) \).

Fig. 8 illustrates this difference between the types of lines we are looking for. A contour is generally a fictional line that denotes a strong contrast in brightness and separates two regions of the image with different statistical attributes. In the ideal case of a staircase contour, the contour is designated by the pixels on the edge of the plateau. A written line, by contrast, actually exists in the image, and the zones on both sides of each point of this line belong to the same region of the image, except if the line was drawn on a contour accidentally. But this would be an exceptional case.

The above heuristic can be interpreted in the following way: If we move along a line slightly, we find that the pixels we pass have a lower gray level than those located on either side of the line. This means that there are two orthogonal directions, one along the extension of the line and the other in the orthogonal direction where the pixels are brighter.

This fact is interpreted in the following way (see Fig. 9): Consider the intersection of a straight line \( D \) passing through a point \( p \) with the ring centered on this point. This intersection produces two segments \( s_1 \) and \( s_2 \) as shown in Fig. 9. An orthogonal straight line \( N \) passing through \( p \) is associated with this straight line \( D \). This straight line \( N \) intercepts the ring at a single segment \( u \) centered in \( p \) of a size which is at most equal to the external size of the ring. A point \( p \) of the image is considered as a point of a line, if there is a straight line \( D \) passing through this point, such that the segments \( s_1 \) and \( s_2 \) obtained belong to the same region.

We characterize \( s_1 \) and \( s_2 \) by their respective maximum gray levels: \( M_1 \) and \( M_2 \). The segment \( u \) is also characterized by its maximum gray level: \( M_u \).

We are therefore interested in the deviation \( S_D \) relative to the straight line \( D \), which is defined by

\[
S_D = \min(M_1, M_2) - M_u
\]

The filiformity measure \( g_r \) is defined by \( g_r(p) = \max\{S_D\} = \max\{\min(M_1, M_2) - M_u\} \)

The filiformity condition in \( p \) is \( g_r(p) > 0 \)

In practice, the size of segments \( s_1 \) and \( s_2 \) can be two, three, or four pixels. The ring is defined by an internal and an external radius; the internal radius is fixed to the maximal width of the line that we wish to detect. A fairly large length of the segment \( u \) restricts the detection of points located in nonrectilinear zones. For example, if we take for maximal size of \( u \) the external diameter of the ring, then, in order for a point to have a positive \( g_r \) measure, the line must be locally confused with \( u \) in \( p \), which means that the line must be locally rectilinear in \( p \). This effect is illustrated in Fig. 10, where we can see that the detection of points located on rectilinear parts of the line is less sensitive to the size of segment \( u \). In practice, we have limited the size of the segment \( u \) to the central pixel, in order not to eliminate the points located in zones with pronounced curvature. For any size of ring, the
Fig. 9. Measure $g_r$ taken on a ring. (a) Circular ring to measure $g_r$ on D. Shows the structure of the ring in a continuous space. (b) Three-dimensional representation of segments $s_1$, $s_2$, and $u$. Shows a typical configuration where the stroke is confused with $u$. (c) Ring in discrete space. The external radius is five pixels and the internal radius is one pixel. Here, a discrete representation of the ring, the pixels of $u$, are dark, while those of $s_1$ and $s_2$, which are colored gray, are lighter.

Fig. 10. Influence of the length of segment $u$ on the detection of points with strong curvature. (a) Original binary image. (b) Segment $u$ reduced at the central pixel. The reduction of segment $u$ at the central pixel of the measurement ring enables the detection of all the points of the lines. The lines present have a thickness of one or two pixels. Because the circle and rectangle are not filiform, they are not detected. (c) Segment $u$ composed of three pixels. A length of segment $u$ measuring three or more pixels only enables detection of points located on the linear parts.

number of straight lines to test is equal to one-half the number of pixels on the exterior edge of the ring. We have established that most of the lines on the checks filled out using ordinary pens and scanned at 100 dpi, have a width that rarely exceeds five pixels on their linear parts. Based on this observation, we have fixed the exterior size of the ring at five pixels, which limits the number of straight lines $D$ to be searched to four, with slopes zero, $\pi/4$, $\pi/2$, and $3\pi/4$, respectively. For larger ring sizes, this minimum of four straight lines constitutes an approximation of all the straight lines that can pass through a point, and the segments $s_1$ and $s_2$ of each straight line are defined by the pixels closest to these straight lines. A negative sign of $g_r$ makes it possible to eliminate at the outset the points which we know do not belong to any line in the image. The points with a positive $g_r$ measure represent a large number of lines that are very difficult to distinguish from the background image. They include all the points that may belong to lines in the image.

From this point on, in this first step of the processing, we use a local number, which translates the degree of filiformity or perceptibility of a line in each pixel of the image.

IV. GLOBAL PROCESSING

The points where the measure $g_r$ is positive present some ambiguity as to whether they belong to true lines or to the background of the image. More global information is required, which takes into account the whole image, before this ambiguity can be removed. The pixels belonging to true lines must present a value of $g_r$ which is greater than that of the other points in the image. The global information must provide a threshold value to which the measure $g_r$ can be compared in order to decide whether or not the point is filiform.

To calculate this threshold, we analyze the distribution of the value of $g_r$ as a function of the number of pixels. This analysis is similar to the histogram analysis which is performed on a gray-level image. We propose an automatic means for
determining the global threshold value \( S_{opt} \) such that the pixels associated to lines verify the relation

\[ g_r(p) > S_{opt}. \]

Given a threshold \( s \), we are interested in the following two quantities.

- \( G(s) \): the number of pixels which verify the relation: \( g_r(p) > s \).
- \( E(s) \): the number of pixels such that \( g_r(p) = s \).

\( G(s) \) and \( E(s) \in [0, N_t] \) where \( N_t \) is the total number of pixels in the image.

\( E(s) \) represents the derivative of \( G(s) \), because \( E(s) = G(s + ds) - G(s) \), and \( G(s) \) is a decreasing function. The evolution of \( G(s) \) and \( E(s) \) depends on the contents of the image, however this evolution may be described in the following way.

When \( s \) is at its smallest value, or zero, a large number of the pixels in the image, including those belonging to the lines we are seeking to extract, respond to this criterion. With a slight increase in \( s \), therefore, \( G(s) \) must necessarily decrease; pixels not registering a high value of \( g_r \) are eliminated. Thus, as \( s \) increases, the pixels having a value of \( g_r \), which is lower than this threshold are eliminated. When \( s \) exceeds the value that characterizes the darkness of the lines, there are no longer enough pixels to be eliminated. The evolution of \( G(s) \) consists of two parts: a rapid decrease followed by a slower one.

Thus, the detection of the optimal threshold \( S_{opt} \) amounts to detecting the point for which there is a change in the evolution of \( G(s) \). This translates into a search for the point which will cancel out the second derivative of \( G(s) \). In practice, we take the value for which the module of the filtered derivative of \( E \) remains lower than a very small threshold of the order of ten, because this value is very small relative to the global dynamics of the second derivative.

The algorithm is composed of three steps, (see the appendix). In the first, we calculate the measure \( g_r \) at each point of the image, and we calculate \( E(s) \). In the second, \( E \) is filtered by a median filter, and the value for which its filtered derivative becomes less than ten is estimated and taken as the value of the global threshold. In the third, a global thresholding is carried out on the value of \( g_r \).

V. EVALUATION OF THE EXTRACTION ALGORITHM

To test the algorithm, we have first synthesized an image from which it is impossible, using simple thresholding techniques, to extract the writing without also extracting other objects that have the same gray levels. The image, illustrated in Fig. 11, is composed of a background, a sentence with the same gray levels as circles, and another sentence with the same gray levels as rectangles. The result shows that almost of expected written lines are extracted and thus we expect for...
Fig. 12. Automatic writing extraction: case judged “very good.” (a) Original check image. (b) Result for a threshold $s = 0$. (c) Optimal result given by the algorithm with $s = S_{opt} = 20$.

real checks to obtain as good results as for the synthesized image.

The evaluation involved samples of bank checks filled out with four different pens by ten writers. We first isolated the simple checks from checks with more complex designs. By “simple,” we mean checks that had either a uniform background or a background image characterized by very little contrast. Out of 29 different check backgrounds, 13 were simple, while 16 had more complex designs. The evaluation of our algorithm involved only the checks with the more complex designs, for a total of 540 checks representing 16 different backgrounds. The checks were scanned with a resolution of 100 dpi and 256 levels of gray.

A significant way to evaluate our algorithm is to provide its output to a handwriting recognition process. This kind of evaluation takes into account the robustness of the two processes: extraction and recognition. To avoid evaluation of the complete process and to evaluate only the extraction, our criterion is that the resulting image, by this algorithm, should be well suited to any verification or recognition system.

We classified the results in four categories. 1) Very bad (VB) was for results where there was either absence of a part of the
written information or the signature, or the presence of false lines belonging to the background image which interfered with the writing. This type of result was judged to be unusable for any high level process. 2) Bad (B) was for results where all the written lines were present, but also some residual lines of the background image that did not interfere with the writing. This type of result was classified as usable as long as it would be possible to eliminate the additional lines by means of
Fig. 14. Automatic writing extraction: case judged “very bad.” (a) Original image. (b) Extracted lines (ou: result). (c) Q": second derivative of histogram of $E$.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>EXPERIMENTAL RESULTS</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>blue ink pen</td>
</tr>
<tr>
<td>VB</td>
<td>10</td>
</tr>
<tr>
<td>B</td>
<td>7</td>
</tr>
<tr>
<td>G</td>
<td>65</td>
</tr>
<tr>
<td>VG</td>
<td>8</td>
</tr>
<tr>
<td>Number of checks</td>
<td>90</td>
</tr>
</tbody>
</table>
additional ad hoc processing. 3) Good (G) was for results that included at most one segment of the background image, but which did not interfere with the writing. 4) Very good (VG) was for results where isolated points of the background image appeared that are easy to eliminate. Figs. 12–14 illustrate cases of results judged to be very good, good, and very bad, respectively.

Table I represents the evaluation of quality as a function of the type and color of the pen used.

What we gather from this evaluation is that the principal limitation of our method has to do with the nature of the background image and not with the nature or color of the pen. When the background of the check represents an image of a scene, the method gives very good results. However, when the background image is a drawing created with handwritten lines, these lines are extremely difficult to eliminate, and indeed cannot be completely eliminated except by a process that could differentiate between the lines that make up the drawings and those that make up the writing.

The image of Fig. 14 constitutes a typical case of the limitation of our algorithm. The presence of lines belonging to the background image, in this case the water-skier, cannot be eliminated. A higher-level process giving a significance to every line would be needed.

The algorithm was implemented on a Sun SparcStation 2. The time needed to process a check depends mainly on its size. The checks used in the evaluation have the same image size. The checks used in the evaluation have the same size (158 mm × 69 mm) and the time taken by the algorithm to process each check was approximately the same: 0.95 ± 0.06 s.

VI. CONCLUSION

The complexity of the task of extracting a signature or handwritten information from the background of a check by standard threshold methods led us to define a specific line detector. In doing so, we have created a new concept, which we call the filiformity of an object, by means of an intuitive approach inspired by human perception of strokes and lines. This approach was motivated by the existence within the eye of cells with concentric receptive fields which specialize in the detection of lines. We first defined filiformity for binary objects, and then extended the definition to gray-level images by proposing two local measures: one relative to a surface and the other relative to a ring. The ring measure is more effective because it is capable of differentiating between contour lines and the written lines that we are seeking to extract. The local information provided by this measure is then processed by global thresholding, the value of the threshold being determined automatically. The evaluation carried out on various types of checks, in spite of their restricted number, reveal that the algorithm is robust when the background of the check is an image of a scene rather than a drawing created by hand. The algorithm is easily implemented and fast, because just a double-scan of the image is required. The proposed algorithm constitutes an important preliminary step for an automated signature verification system.

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REFERENCES


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