Handwriting information extraction from check background based on a multiscale wavelet transform.

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Abstract: We present a new approach to characterize and extract handwriting from textured check backgrounds. This method is based on a multiscale transformation into the wavelet Faber-Schauder basis (FSWT). Such a transformation allows to separate the handwriting from the background. The algorithms of transformation and inverse transformation are very simple and exact with only arithmetic operations. A selection threshold of the multiscale image histogram makes it possible to have a degradation of the background without a ecting the handwriting. We can then apply on the reconstructed image a classical method of binarisation. We obtained good results on di erent bank checks.

1. Introduction

In a global process of authentication or identification including the recognition and the interpretation of all items on the check image as the amount, the date, the owner, etc...[11], the success of the step of extraction, which provides the module of verification with all relevant information, has good repercussions on the success of the global process.

But extracting handwriting information from a check background is not a trivial operation when the background depicts a colored or textured scene. In general, thresholding techniques are used[12] successfully for uniform background. For non uniform backgrounds, researchers have investigated many other types of thresholding: adaptative, dynamical and local thresholding[3][6][7].

In this paper, we present a multiscale approach for the characterization and the extraction of the handwriting from check backgrounds. We choose a multiscale transform because such images contain structures of very di erent resolutions which motivates to detect sharp image variations at di erent scales and wavelet transforms are very adapted to analyze in the same time large objects and fine structures. In fact there is no wavelet transformation that performs better than all the others in image processing [13], We use the Faber-Schauder wavelet transform (FSWT) because it has a very simple formulation and eliminates linear correlation. FSWT makes possible the separation of handwriting information localized essentially at fine scales from the background information which belongs to coarse scales. This makes it very suitable to the information extraction from check backgrounds. In section 2, we describe briefly the Faber-Schauder multiscale transformation. Section 3 presents the algorithms of transformation and reconstruction of images. In section 4, we apply our approach to the handwriting characterization and extraction from the check background presenting scene images. Finally, in section 5, we present the numerical results we obtained.

2. Description of the Faber-Schauder wavelet transformation

An image contains in general many features of di erent sizes and di erent resolutions. Multiscale methods are an important tool to analyze in the same time large objects and fine structures in an image. The pyramid laplacian method, by P.Burt and E.Adelson [1], was one of the first successful multiscale methods with a simple and fast algorithm but it su ers from data redundancy and correlation between di erent scales. S.Mallat uses the wavelet analysis [9] to construct a fast multiscale algorithm with the same philosophy of the Laplacian pyramid but which is more e cient. Multiscale methods are now largely used in image processing as edge detection, image compression and characterization, etc.

We use in this study a method which transforms images into the multiscale Faber-Schauder basis [4]; it has the same construction principle and the same properties of the S.Mallat wavelet transform except the fact that the Faber-Schauder basis is not orthogonal. Our choice of this wavelet transform is motivated by its simple lifting scheme formulation with only arithmetic operations and no boundary treatment [5]; this transformation is also well adapted to contour detection because it eliminates constant and linear correlation of smooth regions and uses only the first neighboring coe cients so it gives more precise edge detection than higher order spline wavelets [5].

3. Transformation and reconstruction Algorithm

We can consider a gray level image as a sequence $(f_{ij})_{i\ j\ \ Z}$ of $l^2(Z^2)$ with finite (2^N) non zero data. The transformed image is constituted of the sequences $((g^k_{ij})$0<k<N+1 and $(f^N_{ij})_{i\ j\ \ Z}$ such that:

$f^0_{ij} = f_{ij}$ for $i\ j\ \ Z$

for 0<k<N+1and $i\ j\ \ Z$:

$$f^k_{ij} = f^{k\ \ 1}_{2i\ 2j}$$
$$g^k_{ij} = (g^{k1}_{ij}\ g^{k2}_{ij}\ \ g^{k3}_{ij})$$
$$g^{k1}_{ij} = f^{k\ \ 1}_{2i+1\ 2j}\ \ \ \tfrac{1}{2}(f^{k\ \ 1}_{2i\ 2j} + f^{k\ \ 1}_{2i+2\ 2j})$$
$$g^{k2}_{ij} = f^{k\ \ 1}_{2i\ 2j+1}\ \ \ \tfrac{1}{2}(f^{k\ \ 1}_{2i\ 2j} + f^{k\ \ 1}_{2i\ 2j+2})$$
$$g^{k3}_{ij} = f^{k\ \ 1}_{2i+1\ 2j+1}\ \ \ \tfrac{1}{4}(f^{k\ \ 1}_{2i\ 2j} + f^{k\ \ 1}_{2i+2\ 2j} + f^{k\ \ 1}_{2i\ 2j+2} + f^{k\ \ 1}_{2i+2\ 2j+2})$$

The reconstruction of the original image is performed by a similar recursive algorithm:

For - 1 < k < N and $i\ j\ \ Z$:

$$f^k_{2i\ 2j} = f^{k+1}_{ij}$$
$$f^k_{2i+1\ 2j} = g^{k+1\ 1}_{ij} + \tfrac{1}{2}(f^{k+1}_{ij} + f^{k+1}_{i+1\ j})$$
$$f^k_{2i\ 2j+1} = g^{k+1\ 2}_{ij} + \tfrac{1}{2}(f^{k+1}_{ij} + f^{k+1}_{i\ j+1})$$
$$f^k_{2i+1\ 2j+1} = g^{k+1\ 3}_{ij} + \tfrac{1}{4}(f^{k+1}_{ij} + f^{k+1}_{i+1\ j} + f^{k+1}_{i\ j+1} + f^{k+1}_{i+1\ j+1})$$

At each step k the sequence $(f^k_{ij})_{i\ j\ \ Z}$ represents a more coarse description of the initial image (in fact a polygonal interpolation) and $(g^k_{ij})_{i\ j\ \ Z}$ the di erence of information between the two successive resolutions $(f^k_{ij})_{i\ j\ \ Z}$ and $(f^{k+1}_{ij})_{i\ j\ \ Z}$.

The number of operations used in the algorithm is proportional to the number N of non zero data in the signal $(O(N)$) which makes it a very fast algorithm, and there is only arithmetic operations which make the transformation an exact one without any approximation in the numerical implementation.

The multiscale transformation is, in fact, a linear function, from the canonical basis to the Faber-Schauder one, which redistributes di erently the information contained in the original image. So it is more natural to visualize this redistribution in one image as in the original image. So we chose, for the representation of transformed images, the same principle used in the canonical basis which is to put each coe cient at the point where its related basis function reaches its maxima (See figure1).We have then a visually coherent image that looks like a contour representation of the original image, we call this process a mixed multiscale visualization.

4. Handwriting extraction

The extraction of the handwriting is a very important step in pattern recognition and in the problems of authentication and identification such as the one of o -line signature verification. The quality of the extracted data has an important influence on the final results. In a system of authentication or identification, we are interested in the shape of the drawing and therefore we do not need more than two colors: one to represent the background and the other to represent the tracing. This is the reason why a step of binarisation may be necessary. In the case where it would be desirable to extract some pseudo-dynamic features, it would be necessary to work on the gray level images. This operation of binarisation is not trivial because it depends on the color of the drawing, on the ink used, on the background, on the lighting at the time of the acquisition, etc. The technique of global thresholding is the technique most used for binarisation. In the ideal case of handwriting on a uniform background, a simple analysis of the histogram allows to determine the global threshold that separates the handwriting from the background of the image and this, in order to preserve all the relevant information[11]. The global thresholding becomes less e cient in the case where the background is not uniform or presents some scene images. Several other methods of thresholding are used in these cases: local, adaptive and dynamic thresholding [3][6] [7]but do not always give satisfactory results. Some other approaches not based on the thresholding were proposed such as: edge detection methods, mathematical morphology methods [8] and the pretopological approach [10]. In general, the edge detection methods have the problem of selecting the contours that belongs to the handwriting and those of the background. Mathematical morphology methods are made for backgrounds of periodic texture. The pretopological approach based on a pretopological formalism of region growing associated to a measure of filiformity gives good results for the non uniform background but su ers, sometimes, from an exaggerated cost of calculation.

In this paper, we use a multiscale approach for the extraction of handwriting from check backgrounds. It is based on the multiscale transformation of the check image in a Faber-Schauder wavelet basis. Transformation of bank check images has for e ect to concentrate the information of the image in regions of high frequency or contours (see figure1) which correspond in general to the handwriting. This e ect can directly be observed in the mixed scale visualization of the transformed image which looks like a contour description of the original image (figure 1), it is also observed in the histogram of the transformed image the presence of a very characteristic shape. Most of the coe cients are concentrated around a value close to zero (see figure2). This phenomenon can be explained by the fact that the number of coe cients in the multiscale transform increases exponentially when we go from a scale to a higher one. Thus the concentration of coe cients that have significant values becomes important in regions that use a maximum number of scales: i.e. very sharp variation regions. This implies firstly that there are only a few coe cients with significant values that describe the high luminous transition regions in the image and secondly that most of these coe cients are concentrated around image contours which correspond in general to handwriting regions. Most of the others coe cients, close to zero, correspond to low luminous variation regions which correspond in general to the background.

If we keep only coe cients with significant values and set all the others to zero, we are sure to have a degradation of the background with only a small perturbation of the handwriting.

We can refine the handwriting detection by analyzing the density of coe cients with significant values. In low density regions, which are more likely to belong to the background, we set a maximum number of coe cients to zero in order to maximize the degradation of the background, while in high density regions we keep a maximum number of coe cients in order to minimize the degradation of the handwriting in the reconstructed image.

5. Numerical results

The algorithm for extracting the handwriting information from check backgrounds can be presented as follows:

* Firstly we express the check image in the Faber-Schauder multiscale basis.
* The second step consists of identifying the high density regions where it is more likely to find handwriting information. This can be done by counting, at a given point, the number of coe cients with significant values in the neighborhood of each point. The size of the neighborhood is fixed by taking into account the fact that the handwriting information is localized at high frequency scales.
* The third step consists to set non significant coe cients to zero. The threshold value is fixed by calculating the standard deviation ( ) of the histogram. Then we eliminate more coe cients in regions with low density of coefficients. This step produces the degradation of the background and has a little e ect on the handwriting information.
* Finally we reconstruct the original image by using the inverse wavelet transform and we can use a simple global thresholding or a pretopological process on the reconstructed image[10].

We evaluated our approach on di erent bank checks with various background images from uniform to very textured backgrounds with scene images of di erent levels of complication. We obtained 90% of good results with a complete elimination of the background (See figure 3) and 10% of bad results where the background is eliminated but there is a deterioration of the handwriting. This is due to the fact that the background images of these checks present either some rather thick drawings or resembles handwritten stroke. For such di cult cases we can use the spatial orientation information given by wavelet transformation: for each scale j we have the sequences $g^{j+1} = (g^{1\,j+1}\ \ g^{2\,j+1}\ \ g^{3\,j+1})$ where $g^{1\,j+1}$ is computed by a horizontal di erence and $g^{2\,j+1}$ by a vertical di erence while $g^{3\,j+1}$ is computed by diagonal di erences, so we can consider that the vector$(g^{1\,j+1}\ \ g^{2\,j+1})$ gives an approximation of the gradient contour direction and $g^{3\,j+1}$ an approximation of its modulus because we can consider that handwriting contours belong often to plane curves and along these curves the gray levels vary smoothly while the variation is abrupt in the perpendicular direction. Since the gradient of extrema curve points is perpendicular to the tangent; we can, to construct edge curves, chain adjacent local extrema value coe cients in the transformed image if their respective position is perpendicular to the direction indicated by the vector $(g^{1\,j+1}\ \ g^{2\,j+1})$ and if their respective values in $g^{3\,j+1}$ are close.

6. Conclusion

We presented a new approach to characterize and extract handwriting from textured background documents. This method is based on a multiscale transformation which allows to separate the handwriting from the background. An evaluation of the density and a thresholding of the multiscale image histogram allows to have a degradation of the background without affecting the handwriting. This method can be improved by taking into account the contours orientation information in the multiscale transformed image .

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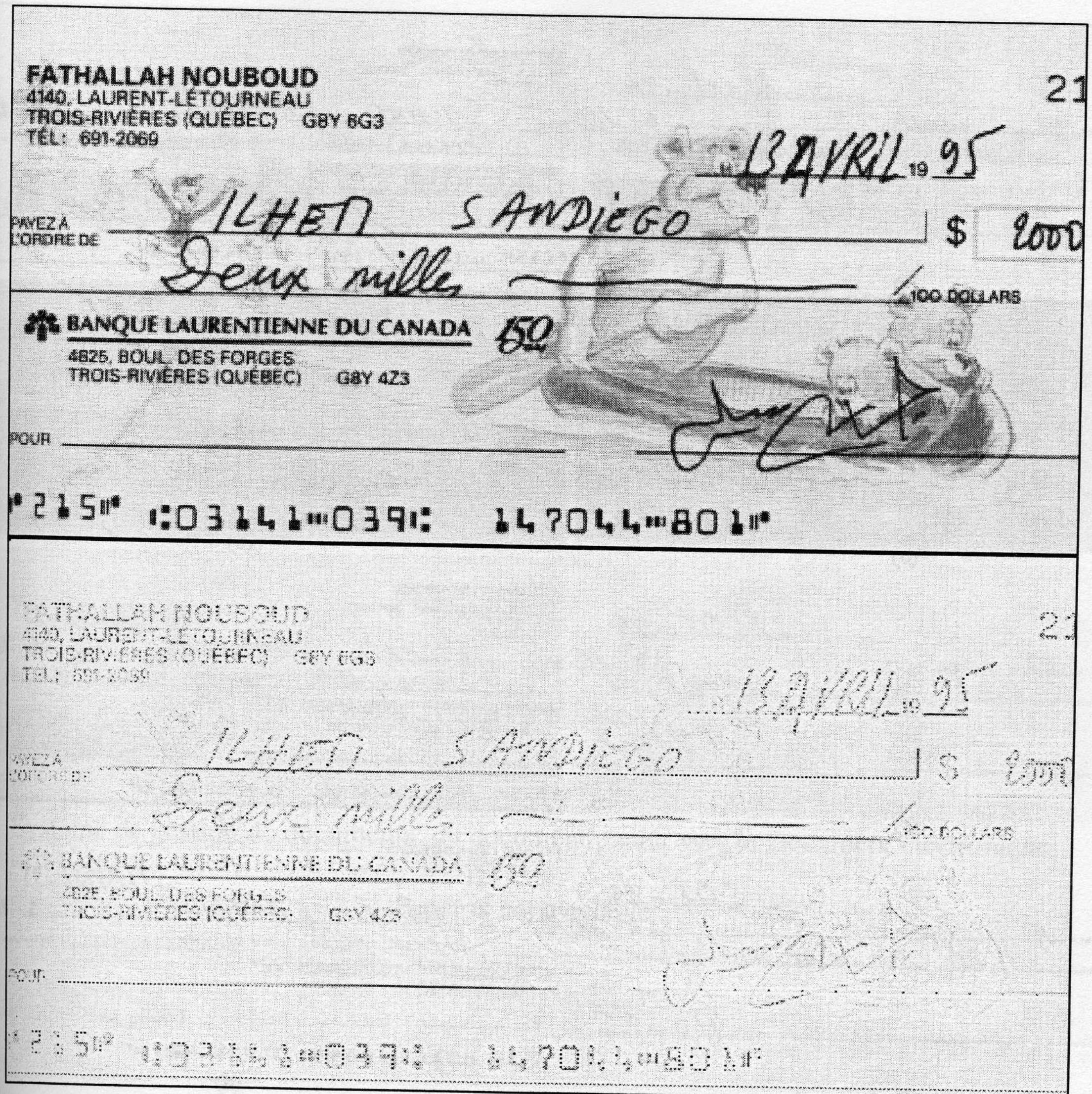

Figure 1: Check2 (Top) Original image, (Bottom) Transformed image presented in the mixed scale visualization

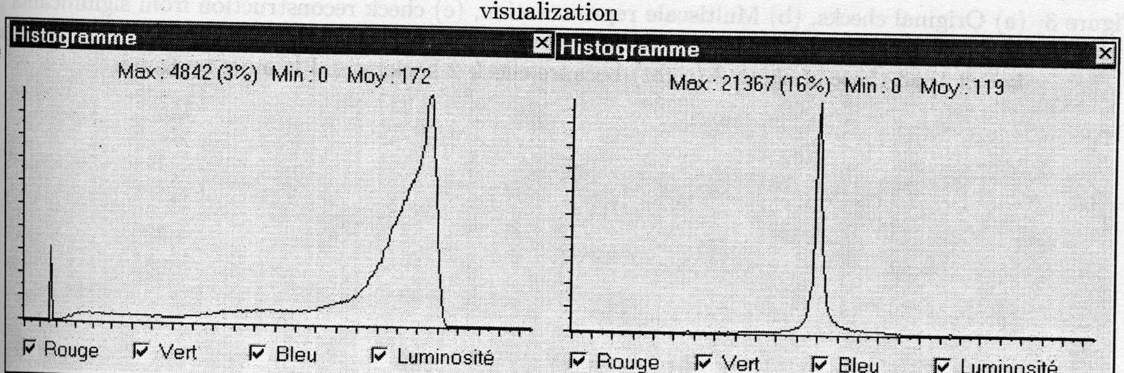

Figure 2: Histograms of check 2 (see below), left: original image, right: FSWT image which have always the same characteristic shape.

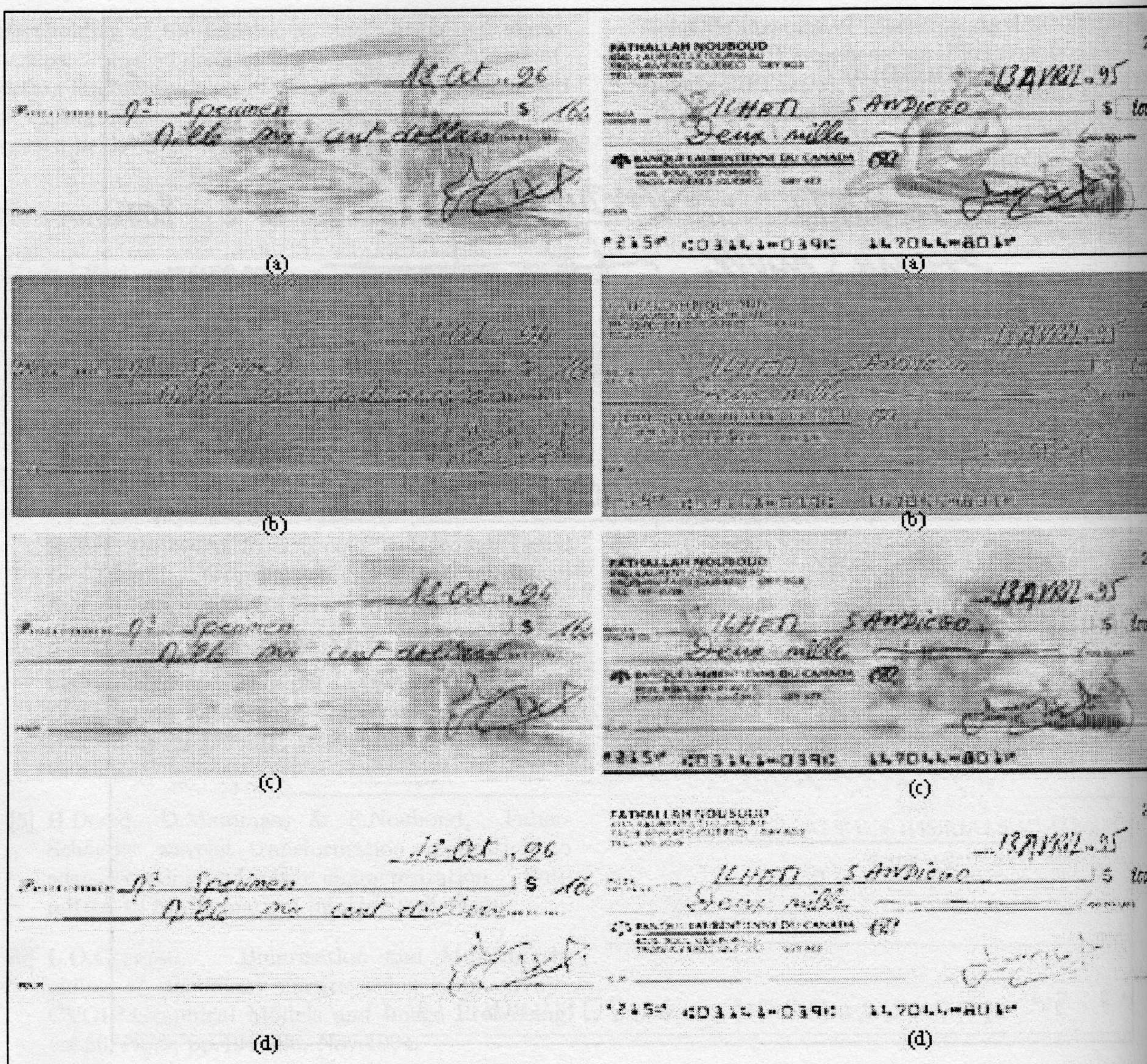

Figure 3: (a) Original checks, (b) Multiscale representation, (c) check reconstruction from siginificants coe cients, (d) Check binarisation with a pretopological process [10]. Results obtained with check1 (left) are better than those of check 2 (right) because check 2 background is more textured.