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A Filtering Algorithm for Highly Noisy Images of Brazilian ATM Bank Checks

Carlos A.B.Mello
Polytechnic School of Pernambuco
University of Pernambuco
Recife, Brazil
cabm@ieee.org

Byron L.D.Bezerra, Afonso G.A.Ferreira,
Juliano C.B.Rabelo
AiLeader Technologies
Recife, Brazil
bldb@aileader.com

Abstract— **This paper presents a new algorithm for filtering images of Brazilian bank checks. These images were generated by ATM machines and they present several kind of noise imposed by the digitization process. A new wavelet-based filtering algorithm is proposed for these images allowing a more efficient binarization process using percentage of black thresholding method.**

Keywords-Image processing, filtering, document processing

I. INTRODUCTION

Bank check image processing has gained importance in the last few years. Huge volumes of bank checks move yearly between companies and banks. The manual processing of these checks is a labor intensive task; so a system to automatically analyze and retrieve the information contained in the checks is more and more necessary. However, the complexity and variability of checks make this automatic processing a remarkable challenge but with a high commercial potential.

There are several important research associated to bank check processing world. The main areas involved are document analysis, pattern recognition and image processing itself. The authors in [5] present an algorithm for bank check image binarization applied to the date field of Chinese checks. The method starts with the use of projection profile to locate the characters and uses a signal matching based on minimum mean square error to find the final threshold value.

The segmentation of the characters is one important step for the recognition of the text written in checks. In [14] the authors propose a two-stage segmentation process (one global and another local) for CA (courtesy amount) recognition. The main idea is to find the areas of text and then find the characters themselves. Finally, these possible characters are inserted in a neural network for classification.

Date segmentation is studied in [13] with the proposition of a system for date recognition where the first step is to segment the date field into three sub-images corresponding to the day, month and year. Their system works with an analysis of the writing style derived from four features which are the combined and inserted into three Multi-Layer Perceptrons: histogram, mesh, horizontal and vertical distance.

The paper [7] describes a method for automatically segmenting and recognizing the various information fields present on a bank check by means of connectivity based approach and recognition based on entropy, energy, aspect ratio and average fuzzy membership values.

The focus of this paper is in Brazilian checks. They can be divided into four major areas: the Area 1 with the bank and account information; the Area 2 (the courtesy amount - CA) which has the printed amount of the check; Area 3 has the legal amount (LA) with the written amount; and the Area 4 with the Character Magnetic Code (CMC7) which presents an identification code. In spite of the variety of banks, all of them have to use these areas in specific locations of the checks. Fig. 1 presents a sample check and the distribution of the areas along it. Every bank check image presented in this paper has the client and the bank information scrambled to avoid identification.

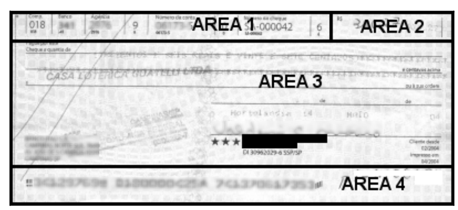

Figure 1. Layout of a Brazilian bank check

Several works are related to analysis of Brazilian checks. Among them, we can report [11] where it is presented an algorithm for identification of textual elements either handwritten or machine printed using a non-contextual approach. The problem of legal amount recognition applied to Brazilian checks is related in [4]. The system is based on Hidden Markov Models and it does a global word analysis. In [6], the authors present a method to locate and extract logos automatically using mathematical morphology. A heuristic algorithm for binarization of images of bank checks is proposed in [2] based on two different thresholds and the combination of the segmented images. This algorithm achieved better results than other well-known binarization algorithms.

The difference between these previous works and ours is that those ones deal with check images in ideal conditions. A first step in a bank check image processing is the binarization or even more the background removal. In our case, we have highly noisy images generated by Automated Teller Machines (ATM) as the one shown in Fig. 2.

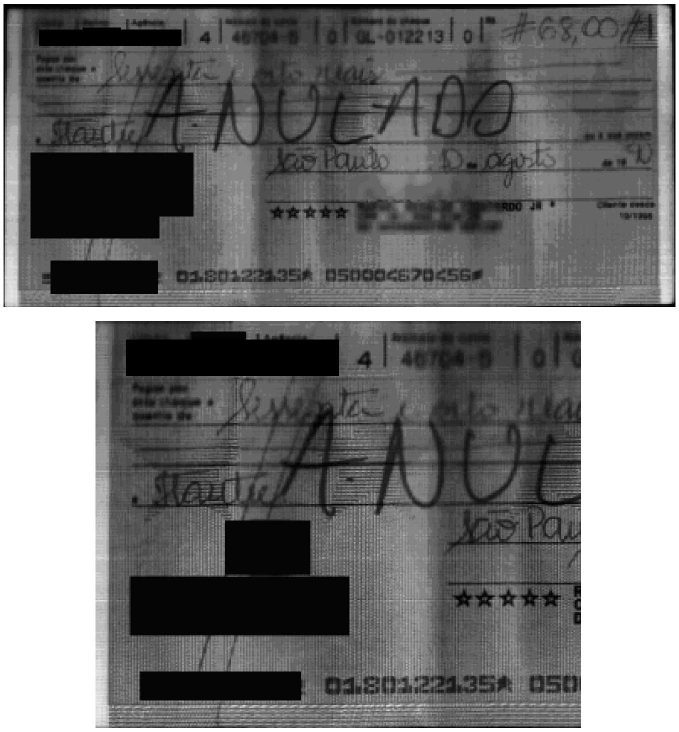

Figure 2. (top) A bank check image generated by an ATM equipment and (bottom) a zooming into part of this check.

One can notice in the image in Fig. 2 that there are several types of noise as difference of illumination along the image. Besides, the image is blurred making very hard to recognize the check information. This can be seen in more details in Fig. 3 where one can see a zooming into part of Area 1 of the image of Fig. 2.

Figure 3. Part of the Area 1 information; high luminance differences and blurring making harder an automatic recognition.

Fig. 4 presents the binarization of the check presented in Fig. 2 by some classical thresholding algorithms [12]: Otsu, C-Means, Pun, Kapur, Renyi and Huang. One can see that the results are very unsatisfactory.

These unique problems make the previous approaches for bank check processing not suitable. Due to the different spatial frequencies, a wavelet approach seems to be effective. A wavelet filtering algorithm is then proposed in this paper and it is evaluated analyzing the influence of its application in the recognition of the CMC7 code.

In the next Section, we make a brief review of the main features of wavelets. Section 3 presents our filtering algorithm and Section 4 analyses the CMC7 recognition. Section 5 concludes the paper.

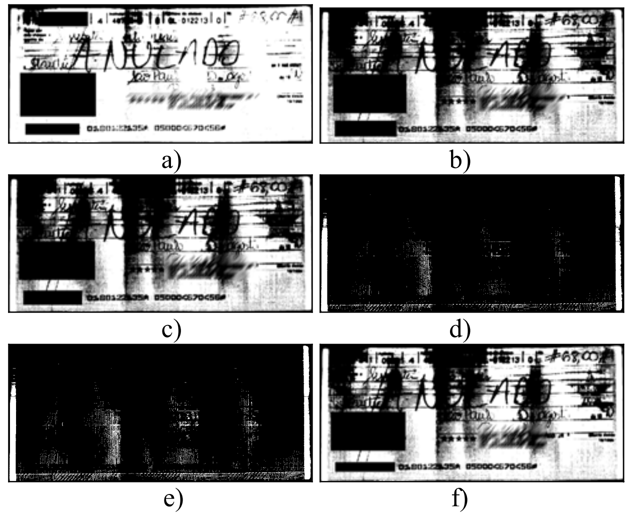

Figure 4. Binarization of the check presented in Fig. 2 using classical algorithms: (a) Otsu, (b) C-Means, (c) Pun, (d) Kapur, (e) Renyi and (f) Huang.

II. WAVELET ANALYSIS

One of the major concepts in signal and image processing is the Fourier transform. The idea is that an image (or a signal) can be decomposed into a sum of a series of sine and cosine components. One can understand the Fourier analysis as a tool which has this sum of sines and cosines as its kernel. With this in mind, many functions can be the kernel of this tool whenever they attend certain properties. This function is the *basis function*. When a Fourier transform is applied to a signal, it loses all its information about time; only the frequency elements remain. In order to solve this problem, the Short Time Fourier transform was created and it analyzes only small sections of the signal at a time. But the problem here is that the size of the window to apply the transform is fixed once it is defined; it can not change over the time. Wavelets analysis [10] came to solve this problem with windows of different sizes (or scaled windows).

The wavelet transform decompose a signal using some basis function which applies dilations (scale) and translations. A wavelet function can be understood as:

$$\psi_{m,n}(x) = |m|^{-1/2}\, \psi\left(\frac{x-n}{m}\right) \qquad m \neq 0$$

where the first component of the function is responsible for the scale and the second for the translation. Ψ is the mother wavelet. This means that windows of different sizes run through the signal analyzing different parts of it. Similar to the Fourier transform, the basic idea of the wavelet transform is to represent an arbitrary signal as a superposition of wavelets.

There are several different kernels of wavelets; each one of them forms a wavelet family. Among the most known, there are the Haar family [9], Daubechies [3], Biorthogonal [8], etc.

In a multi-resolution analysis, in fact, we have two functions: the mother wavelet and a scaling function Φ. The dilated and translated version of the scaling function is also introduced as:

$$\phi_{m,n}(x) = 2^{-m/2}\phi(2^{-m}x - n)$$

In this analysis, wavelet transforms are similar to a *filter bank*. Mallat [8] proved that the wavelet transform can be implemented as this filter bank, where one filter (*L*) is a low-pass filter and the other (*H*) is a high pass filter. For an image, this filter bank can be evaluated as two one-dimensional filtering operations: one implemented over the rows and the other over the columns of the image. Thus, there are four main combinations of filters:

a = Lc(Lr(image)) (1)
h = Hc(Lr(image)) (2)
v = Lc(Hr(image)) (3)
d = Hc(Hr(image)) (4)

where the subscripts *r* and *c* mean the application of the filter over the rows or over the columns, respectively. So, for example, Eq. 1 means that a low-pass filter is applied over the rows of the image (*Lr(image)*) and the same low-pass filter is applied over the columns of this result (*Lc(Lr(image))*). In this implementation, Eq. 1 yields a low-pass version of the original image, whereas the other three combinations yield band-pass versions; Eq. 2 yields horizontal high frequencies (coefficient matrix for horizontal details); Eq. 3 yields vertical high frequencies (coefficient matrix for vertical details); and Eq. 4 yields high frequencies in both directions (coefficient matrix for diagonal details).

As said before, there are many wavelets families. One of the most used is the Daubechies [3] because it has the highest number of vanishing moments which allows the scaling function to represent more complex signals accurately. A wavelet of this family is commonly referred as DbN where *N* indicates the number of coefficients. Fig. 5 presents the scaling function and the wavelet mother function for Db12. Fig. 6 presents the Fourier transform of the Db12 wavelet function. As one can see, it has the behavior of a low-pass filter. This information is important for the filtering process proposed herein.

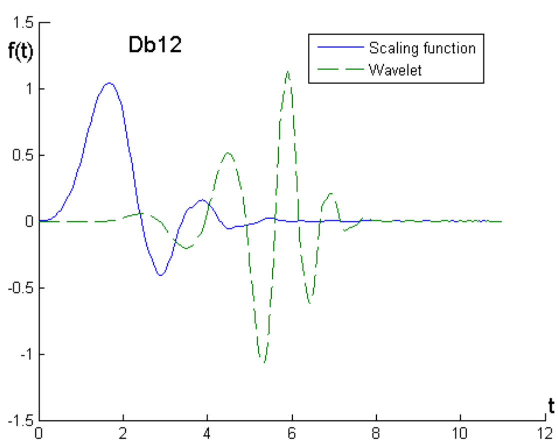

Figure 5. Scaling and wavelet (dashed line) functions for order 12 Daubechies wavelet.

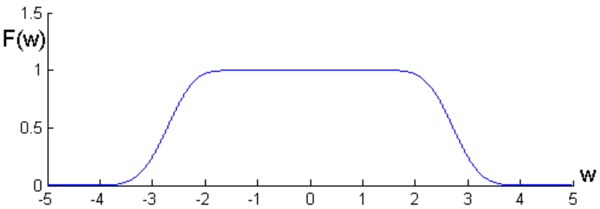

Figure 6. Fourier transform of Daubechies-12 wavelet function.

III. Bank Check Filtering

Section II established wavelet functions and some of their main features. As they are suitable to deal with different spatial frequencies it seems to be reasonable to try them in the bank check images of our file as the one presented in Fig. 2. Due to theirs properties, Daubechies wavelets are going to be tested.

Fig. 7 presents the application of Db12 to the sample check of Fig. 2. Several details of the check are more visible as it is shown a zooming into part of the Area 1 of the check (Fig. 6-bottom). The client's information is scrambled as before. This image corresponds to the visualization of the matrix coefficients of Eq. 1. Other wavelet families were tried but Daubechies achieved the best results.

Although this image is much better than the original one, it still has luminance variation happening in an irregular form along the check. This makes very difficult a binarization process. In order to eliminate more of the noisy different filter coefficients were tested instead of the coefficients of a Daubechies function. This, of course, created new functions which are not specifically wavelets. To be defined as a wavelet a function must satisfy some properties which may not be the case [10]. At this point, the new functions created may not be called wavelets anymore but the filtering process will still be the same as before.

Figure 7. (top) Application of Db12 to check image of Fig. 2; (bottom-left) zooming into part of the Area 1 of the sample check of Fig. 2 and (bottom-right) the same part after the processing (more elements are visible).

The only difference from the original process is that Eq. 1 is applied now as Lr(Lr(Image)), *i.e.*, two convolutions over the rows of the image with the low-pass filter. This happens because of the huge amount of horizontal information in the image.

As the original image has a high variation of low and high frequencies, an elliptic filter [1] can be tried as this filter has ripples in both stop and pass-band. Fig. 8 presents the plotting of the tested elliptic filter just as its Fourier transform and the result of its application to the sample check of Fig. 2.

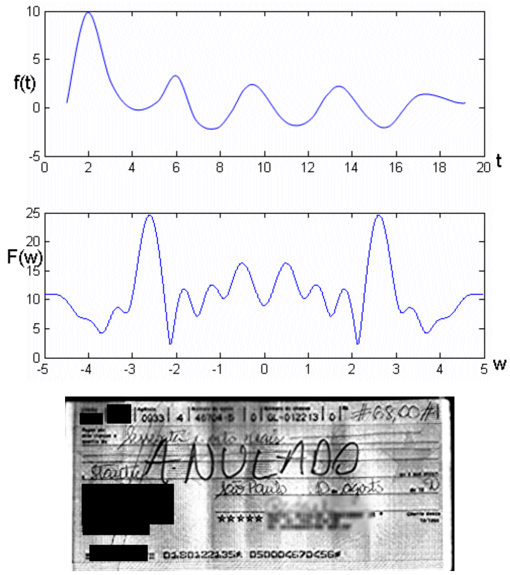

Figure 8. (top) Plotting of the elliptic filter coefficients; (center) its Fourier transform and (bottom) its application to the sample check of Fig. 2.

The image generated by the elliptic filter is not much better than the one created by the Db12 wavelet, but the images generated have fewer high frequencies. The major part of the energy of the filter comes from the coefficients with higher order. The influence of the other coefficients is not so high. Then the filter can be defined with few coefficients (representing now functions with lower order, but this is not relevant for the convolution process). The elliptic filter of Fig. 8 has 19 coefficients. Fig. 9 presents the result of the filtering process using, for example, just the first 6 coefficients. The reduced set of coefficients, of course, has a different Fourier transform. The consequence of this reduction is the loss of more high frequencies. This is a better image for interpretation purposes as we will see next.

Figure 9. Filtering with just few components of the elliptic filter.

The coefficients of the filter were varied in search for a better quality image. The new filters were analyzed using its spectrogram. The best set was achieved with fewer coefficients than the previous tests which improved the efficiency of the algorithm (as the filter is convolved with the complete image). In fact, two configurations were defined: one for the areas 1 and 3 (Filter 1) and another for the areas 2 and 4 (Filter 2) of the bank check (according to the division shown in Fig. 1). The filters have the following values: {-5, -7, 25} for Filter 1 and {-6, -5, 0, 0} for Filter 2. Fig. 10 presents the Fourier Transform of Filter1 and Filter 2 coefficients. It can be seen that they work as a band-pass and a low-pass filter, respectively. Fig. 11 presents the results of the application of the Filter 1 in the Area 1 and Fig. 12 presents the same for Filter 2 in the CA area. The LA area did not achieve satisfactory results.

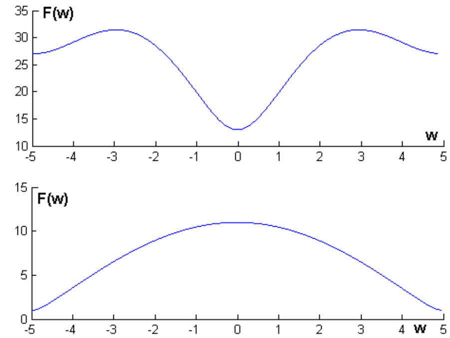

Figure 10. Fourier transforms for (top) Filter 1 and (bottom) Filter 2.

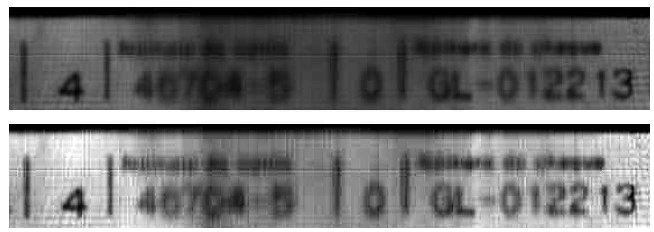

Figure 11. Results of the application of Filter 1 in part of Area 1: (top) original and (bottom) filtered image.

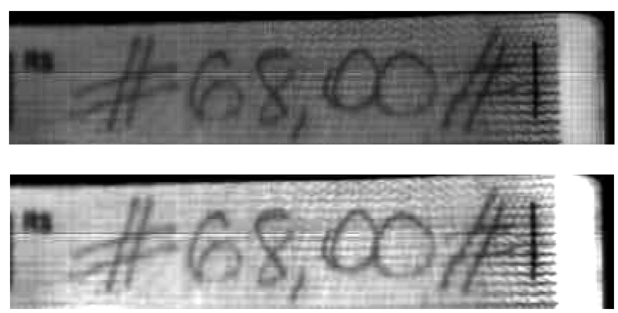

Figure 12. Results of the application of Filter 2 in the CA: (top) original and (bottom) filtered image.

The images filtered by the proposed algorithm are binarized for further recognition. As the four areas are processed with different filters, they must also be binarized in different ways. Global thresholding algorithms are not suitable for these applications. One can see in Fig. 13 the results of the application of Otsu and Renyi algorithms in the sample check of Fig. 2. Otsu algorithm generated CMC7 images with better quality while the images produced by Renyi algorithm brought more information about the CA. This shown that a single and global algorithm is not the best solution. Several algorithms were tested with similar responses. However, the monochromatic images are better than the ones generated without the application of the filtering process.

Another restriction of the complete system is that it must be fast. So, complex thresholding algorithms which deal with maximization or minimization functions are not recommended. At this first step, the CMC7 are the main area to be recognized.

Even though, the best algorithm is searched for the other areas also, but their assessment will come just by visual inspection.

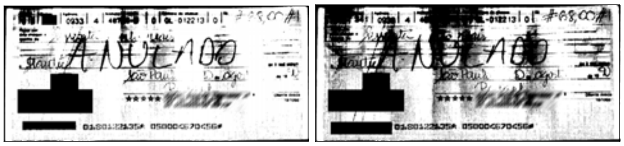

Figure 13. Application of Otsu and Renyi algorithms in the sample check of Fig. 2.

For the definition of the thresholding algorithm, the four areas are going to be analyzed separately.

In some aspects, the filtered images of each area have similar features as their background is brightened and the text is enhanced. This makes easier the definition of a thresholding algorithm.

Several algorithms were tested to achieve the best bi-level image. Considering the imposed restriction of velocity, percentage of black was chosen for thresholding Area 1, CA and LA. The CMC7 area is binarized with a fixed threshold value (140). This value achieved the best visual information and classification rates for every check. As said before, as the filter coefficients are constant, the resultant images have similar features for small areas. This allowed the use of a fixed threshold value. Fig. 14 presents the binarization of part of the CMC7 of the sample check of Fig. 2.

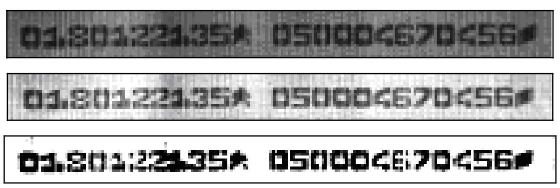

Figure 14. (top) Original CMC7 image, (center) filtered version and (bottom) its binarized version.

IV. CONCLUSIONS

This paper presents a method for filtering bank check images digitized by ATM with high differences of illumination. Due to this specific problem, wavelet transforms are suitable for the processing. The known wavelet families, however, did not achieve satisfactory results. New filtering filters are proposed in order to decrease the noisy aspects of the images. The new filters are applied using a wavelet-based processing to reduce the influence of the illumination in the images. The filtered image is binarized by specific algorithms which are set uniquely for each of the main areas of a bank check.

The analysis of the filtering process proposed herein was made using a recognition system. As the CA contains in general handwritten elements, we are going to test the recognition of the CMC7 information only.

After the filtering and binarization procedure, the images were classified by an engine of automatic bank checks recognition produced by AiLeader Technologies. The recognition rate increased from 50 to 91.66% for the CMC7 area. Other thresholding algorithms were tested but achieved lower recognition rates than our algorithm (Table I).

TABLE I. RECOGNITION RATE FOR CMC7 AFTER BINARIZATION BY CLASSICAL ALGORITHMS AND OUR PROPOSAL

Algorithm	Mode	Recognition Rate
Otsu	Global	83.33%
	Local	25%
Li-Lee	Global	58.33%
	Local	16.66%
New proposal	Local	91.66%

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