A Real-Time Embedded Solution for Skew Correction in Banknote Analysis

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Abstract

Several industrial applications do require embedded solutions both for compacting the hardware occupation and reducing energy consumption, and for achieving high speed performance. This paper presents a computer vision system developed for correcting image skew in applications for banknote analysis and classification. The system must be very efficient and run on a fixed-point DSP with limited computational resources. Consequently, we propose three innovative improvements to basic and general-purpose image processing techniques that can be helpful in other computer vision applications on embedded devices. In particular, we address: a) an efficient labeling with an union-find approach for hole filling, b) a fast Hough transform implementation, and c) a very high-speed estimation of affine transformation for skew correction. The reported results demonstrate both the accuracy and the efficiency of the system, also in presence of severe skew. In terms of efficiency, the computational time is reduced of about two orders of magnitude.

1. Introduction

Image rectification through the removal of the skew introduced during acquisition is an important step in several applications. For instance, in *automatic document processing* (ADP) applications, such as automatic bank check processing, optical character recognition (OCR), mail address recognition for postal office automation, historical document processing and recognition, business card recognition [26, 24, 21], the inappropriate document position due for instance to misplaced documents or feeder failures can make much more difficult the successive processing, such as text extraction, OCR, document segmentation, etc..

Besides ADP, another application where skew correction and image alignment are important is *banknote analysis*, used in cash handling machines, which is the main application study of this paper. Cash handling machines require fast and reliable analysis of banknotes which basically consists of three main steps:

- *Authentication/validation*: the banknote is checked to detect counterfeit or fake notes;
- *Classification*: genuine notes are retained and further classified in a specific currency (i.e., denomination, visible face and insertion side);
- *Fitness test*: once genuine notes are classified, they are further analyzed to detect to which subclass they belong, by detecting fitness problems such as holes, dog-hears, stretches, etc..

It is straightforward to understand that all these steps need that the image is rectified and aligned, allowing pixel-by-pixel or block-by-block comparison with respect to trained models.

Regarding the cash handling machines, on the one hand, the requirements of compactness and costs call for embedded solutions, while, on the other hand, the required responsiveness (in the order of tens of banknotes per second) needs very fast (and accurate) algorithms.

For these reasons, the solution proposed in this paper represents an ensemble of efficient algorithms implemented on a limited-resource embedded device (the Texas Instruments fixed-point TI DM6437 DSP EVM board) which can be of interest for the scientific community on embedded systems since it can be applied in different contexts.

The main improvements are three:

1. A new efficient hole filling algorithm based on fast labeling of connected components is proposed;
2. The system makes use of Hough transform for obtaining an estimate of skew and rectifies the image by an affine transformation: Hough transform is made efficient by reducing accumulator size and decreasing the random accessibility;
3. Affine transformation is made more compact than generally estimated angle of skew rotation in document images, obtaining a very fast estimation procedure.

Although the algorithms are well assessed in computer vision literature, their implementation on limited-resource hardware is not often investigated.

More specifically, the proposed solution has the following important cues:

1. It allows to process one banknote within approx. 70 ms, which is a suitable time given the typical speed of the feeder of cash handling machines, with a gain of two order of magnitude with respect to standard implementation.

2. The proposed technique can handles banknotes in whichever side they are inserted in the machine, and is capable to perform skew correction also in the case of damaged notes (e.g. folded or occluded notes).

3. The proposed skew correction is more general than others presented in the literature and can handle a skew up to ± 90 degrees.

The paper is structured as follows. First, the works related to skew correction in document analysis are reported and commented in Section 2. Our proposed method is detailed in Section 3, where banknote area segmentation (Sect. 3.1), efficient Hough transformation (Sect. 3.2) and affine transformation estimation (Sect. 3.3) are described. Finally, Section 4 shows our accuracy and efficiency tests and Section 5 draws the conclusions.

2. Related Works

In the literature, the general notion of the skew detection is based on the visual cues that reflect the skew in captured images. Skew is estimated from these visual cues which are co-linear or aligned with horizontal or vertical axis of the scanned image. In almost every case, the procedures assume that the input document contains these cues in form of a text line, border of tables, pictures and figures. However, banknotes typically do not have these clear distinctive cues.

In the last decades there have been many attempts to correct skew using these visual cues. The surveys [14, 4] summarize several document skew correction techniques along with a good reference of techniques presented in [23]. These techniques may be categorized into six major classes: techniques based on (1) projection profiles [1, 18, 5], (2) nearest neighbor clustering [12, 19, 32, 22], (3) transition counts [15, 8] (4) Hough transform [27, 13, 17, 31, 2, 3, 16, 25], (5) cross-correlation [30, 10], and (6) morphological transforms [7].

In the absence of strong visual cues within document area, a simplified approach is to find the corners positions [29] of the original document and estimate skew from them. Unfortunately, the banknote in the captured image may not have sharp corners. In such a case skew computation from corners becomes problematic. Conversely, estimating skew from the contour of the banknote is advantageous, as it provides two parallel borders in both dimensions. Even if one of the borders is obscured, occluded and damaged, one can use the second border for correct skew determination.

This paper presents a prototype of a real time embedded banknote skew correction system. The proposed skew correction system is based on the segmentation of banknote area from the background. The complete segmentation of the banknote area is achieved with the help of the morphological operators and an optimized version of labeling-based hole filling. It is followed by the extraction of Hough lines from the contours of segmented image and finally the estimation of the affine transformation for skew correction. The use of Hough transform in embedded devices has been typically limited, due to its computational load, although some proposals in ASIC have been reported in the past [9].

The novelty of this paper is introduced by redesigning of several algorithms for a fixed point TI DM6437 DSP EVM board. The several optimization techniques considered includes instruction parallelism, multiple data packing in a single instruction and floating-point arithmetic optimization or conversion to fixed point arithmetic.

3. Affine Skew Correction

Fig. 1 shows the flowchart of the proposed affine skew correction system for the banknotes. The skew correction procedure has three main steps: banknote area segmentation, Hough line detection and selection of appropriate line, and finally estimation of the affine skew correction matrix. The steps are described in details in the following.

Fig. 2 illustrates one of the example images used in our discussion. Only the grey scale channel of the captured images is considered. The algorithms are designed efficiently with respect to the DSP implementation and optimizations, in order to make the porting of the algorithms as correct as possible in regards to the DSP instructions set and software pipeline. Few of the prominent optimizations are: (a) Segmentation procedure is speed-up by Holefilling operator based on fast labeling.(b) Random accessibility inherent in Hough transform iterations are restricted and floating point arithmetic are reduced by a LookUp Table (LUT) of sinusoidal angle values in fixed point arithmetic. (c) Affine transformation is applied in fixed point arithmetic through up-scaling floating point arithmetic to fixed point arithmetic.

3.1. Banknote Area Segmentation

The skew in the document image is estimated through orientation of visual cues, which are assumed to be collinear or aligned with the vertical or horizontal axis of the image. The banknotes have either insufficient text (the denomination's value number or some other text) or the presence of

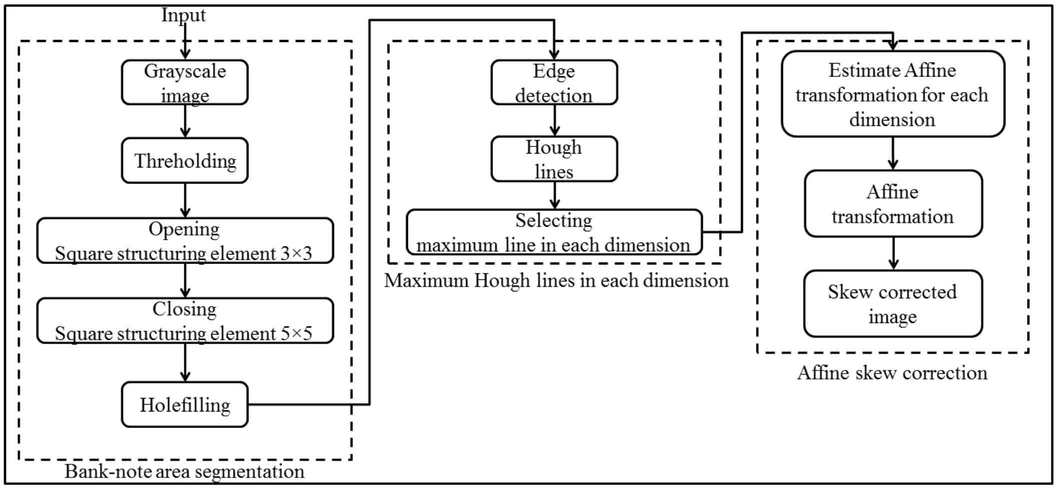
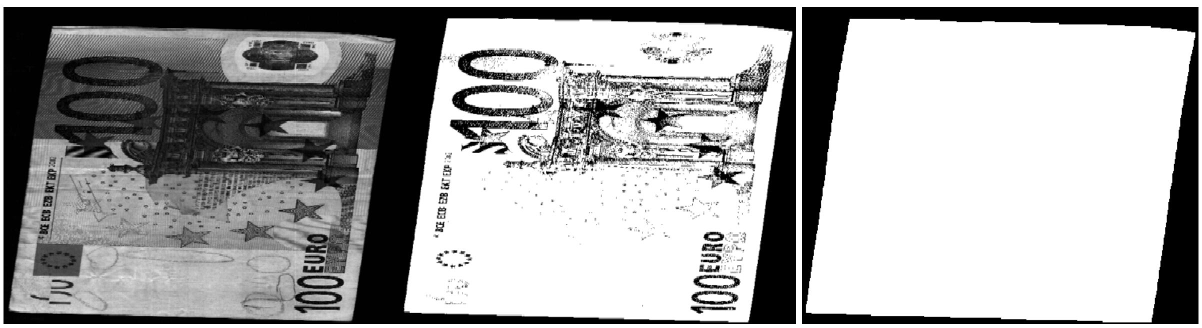


Figure 1. Flowchart of the banknote skew correction.



(a) (b) (c)

Figure 2. (a) An original image. (b) An illustration of a threshold image with holes. (c) A complete banknote area segmentation.

the text is inconsistent for skew detection. The simplest approach is instead to segment the ROI (Region of Interest) and use its contour for skew detection.

The banknote image is acquired with a *Contact Image Sensor* (CIS) (Fig. 2(a)). This image has two main regions: banknote area and background. All the information content is contained in the banknote area while the background has no apparent signal with only few noise speckles. The simplest approach is to apply a threshold to segment the banknote area. As the banknote has many ornaments, figures and text that usually appear similar in grey scale to background, standard thresholding techniques may be ineffective since all of them appear as holes in the segmented result (see Fig. 2(b)).

The proposed segmentation procedure is more complex than a raw threshold applied directly to the banknote image. The segmentation procedure includes following steps:

1. Image is thresholded by an automatically calculated statistical mean of input image acquired through CIS.

2. A morphological opening with a square structuring element of size 3×3 is applied and it is followed by a closing with a square structuring element of size 5×5. The resulting image is free from small noise speckles as well as small holes, and additionally small discontinuities in the border are repaired. The inbuilt binary dilation and erosion operations provided in "TMS320C62x Image and Video Processing Library" are employed. Furthermore, an additional speedup can be achieved by swapping references to the image memory banks in successive erosions and dilations to eliminate overhead of copying image memory.

3. An optimization strategy is proposed to fill holes in segmented banknote by fast labeling. All the holes are labeled as components while the background of the banknote image acts as the first connected component. A fast algorithm for labeling is applied, which is known as two-pass algorithms with tree data structure and union-find implementation [20, 28]. Alternative approaches such as the one proposed in [11], which is based on block analysis optimization and proven to be very fast, can be used as well. The image is

scanned sequentially with 4-connectivity and labels are assigned(see Fig. 3). As soon as equivalent regions are met union of tree is performed. The random access for root determination is reduced by saving root link for each node. In this manner, the analyzing phase is integrated with the scanning phase. The second pass is filling of holes with the help of tree having knowledge of equivalent regions. The tree root refers to the first label for the particular connected component while all child nodes belong to same connected component after one pass. Avoiding the background component and filling all other components will results in a hole-free banknote area. The optimization reduces the highly expensive computational time of the classical morphological hole filling operator (see procedure details in HoleFillwithLabeling).

The result of the above three processes produces a completely segmented banknote area (see Fig. 2(c)). Sobel edge filter is passed over segmented area to extract the contours.

Procedure HoleFillwithLabeling(*ImIn*,*ImHF*)

Input: A grey scaled image *ImIn*
Output: An output image *ImHF*
begin
    `// Negative of ImIn`
    $ImNeg \longleftarrow (255 - ImIn)$;
    $P_i \longleftarrow$ white pixel of $ImNeg$;
    `// LabelTree with knowledge of equivalent regions`
    `// ImLabel: first scan label image`
    $[LabelTree, ImLabel] \longleftarrow$ **foreach** P_i **do** `FindLabel(`P_i`)`;
    for $L_i \in ImLabel$ **and** $H_i \in ImHF$ **do**
        `// find root label for` L_i
        $Label \longleftarrow$`FindRootLabel(`$LabelTree(L_i)$`)`;

        if $Label \neq 0$ **and** $Label \neq 1$ **then**
            `// 1` $\leftarrow$ `Background`
            $H_i := 0xFF$;
        else
            $H_i := 0x00$;
        end
    end
end
end

3.2. Hough Transform Method

Hough transform [6] is a well-known method for detecting lines and curves in an image. In order to estimate skew in the image from border lines of banknotes, a set of points in Cartesian coordinates (x, y) are mapped to sinusoidal curves in the Hough space parameters ρ and θ.

A multidimensional accumulator is used to count the number of intersections at various ρ and θ values. The maximum valued cells in the accumulator correspond to the lines in input image. A simple approach is to use the boundary of the ROI for the determination of Hough lines. However, the computational cost of estimating the Hough transform makes it unfeasible for the real-time applications.

Here, we proposed a fast implementation of Hough transform by redesigning it and introducing optimizations under consideration of the DSP architecture for a real-time prototypal system:

1. The overhead of the sinusoidal estimation for each plausible point in the image space for the Hough transform are minimized by using pre-calculated LookUp Tables (LUTs) of all possible θ values.

2. Modern computers are well equipped in processing of sequential memory accesses rather than random memory accesses. It is a common fact that read/write operation for random memory accesses will take longer than that of sequential memory accesses. Our optimization strategy for Hough transform is based on this observation. Consequently, a fast implementation of Hough transform is conceived by minimizing the number of random memory accesses. Moreover, the size of the accumulator is down sampled to one half of size of diameter of image dimensions. All white/plausible pixels of the image are processed for a single row of Hough accumulator and the process is repeated for all rows. Eventually, the random accessibility is reduced by eliminating the overhead of buffering other blocks of Hough accumulator in the memory between two successive accumulator iterations.

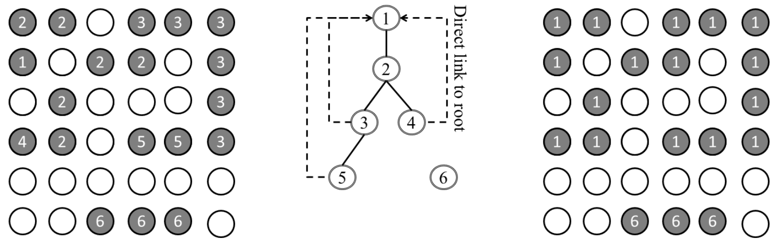
The results of Hough transform is a set of horizontal and vertical lines along the ROI contour (see Fig. 4(a)). The maximum length line in each dimension is selected for the estimation of skew correction.

3.3. Affine Transformation Estimation

Document skew correction usually refers to the estimation of the skew angle . The general model for de-skewing is:

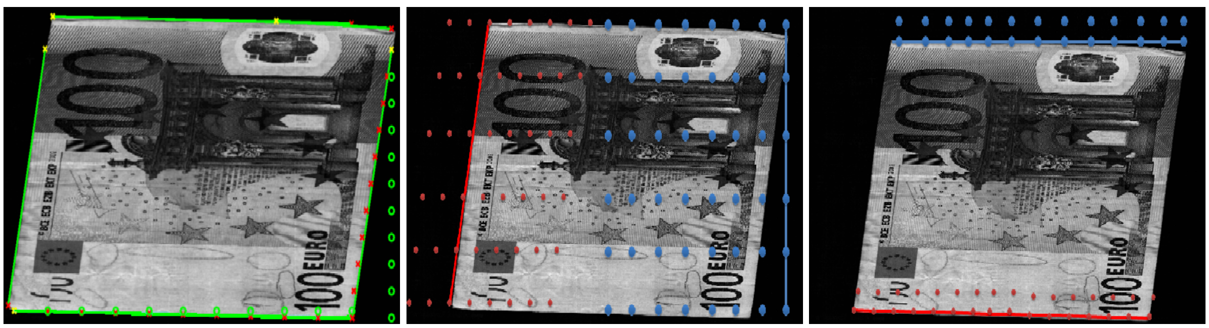
$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} \cos(-\theta) & -\sin(-\theta) \\ \sin(-\theta) & \cos(-\theta) \end{pmatrix} \cdot \begin{pmatrix} x \\ y \end{pmatrix} \quad (1)$$

where $(x, y)^T$ are the input image coordinated of a point p and $(x', y')^T$ are corresponding to the output image point p'. We propose a general and enhanced skew correction model through affine transformation correction, which estimates



(a) (b) (c)

Figure 3. (a) An illustration of labeling after first scan. (b) Corresponding tree of (a) with each node having a direct link to root. (c) Final labels for each connected component.



(a) (b) (c)

Figure 4. (a) Estimated Hough lines in green, and red stars refer to sample points along the contour lines and green circles show projected points on the orthogonal lines). (b) and (c) An illustration of affine transformation component estimated through corresponding points sets with horizontal as major dimension. Red lines and small red dots refer to sample points along the Hough lines, while blue lines and large blue dots show the projected points on the orthogonal lines.

also shear S, scale k and translation t with respect to the origin:

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} S_x \cdot \cos(-\theta) & -k_x \cdot \sin(-\theta) & t_x \\ k_y \cdot \sin(-\theta) & S_y \cdot \cos(-\theta) & t_y \\ 0 & 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \tag{2}$$

where $(x, y, 1)^T$ and $(x', y', 1)^T$ are homogeneous coordinates.

Affine transformation is estimated by projecting the longest line in each direction (horizontal and vertical) onto an orthogonal line in that direction, which gives two sets of points, one in image plane along the banknote contour lines and the other parallel to image axis.

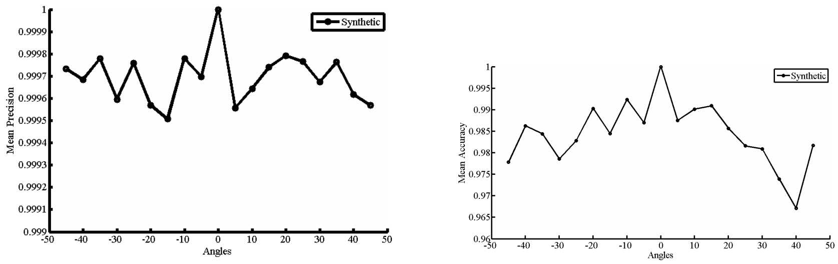
In order to maintain non-collinearity of corresponding points, the procedure of calculating affine skew correction is divided into two steps. In the first step, vertical is taken as major skew correction dimension with horizontal as the minor one (see Fig. 4). A large number of points are sampled in the major dimension (see Fig. 4(b)), while few points in the minor one (see Fig. 4(c)), and this produces non-collinear corresponding point sets in both dimensions. From these corresponding point sets, affine skew correction component in vertical direction is estimated. Similarly, a second affine skew correction component is calculated by taking horizontal as major dimension and vertical as minor one. Since both affine transformations are linear, horizontal and vertical components are concatenated by multiplying to get the affine skew correction transform. The indirect method is applied to get the skew corrected image from the estimated affine skew transform with nearest-neighbor interpolation.

All computations are performed in fixed point arithmetic, which led to highly efficient and optimized affine skew correction.

4. Experiments and Results

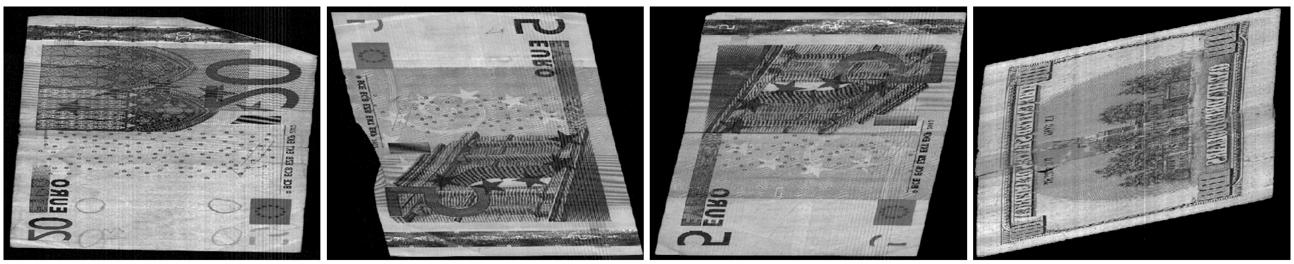
The evaluation of proposed method is carried out in three experiments for the banknote database. The first one is on real images with skew angle of 0° which are synthetically rotated of a given and increasing angle. This experiment makes the setting suitable to test the correctness and accuracy of proposed method with varying skew, by having also an automatic ground truth.

The second experiment is carried out to test the performance of the system on real images. This setting depicts the robustness of the system against noisy and spare database. The database has images with folds, deformed, obscured or

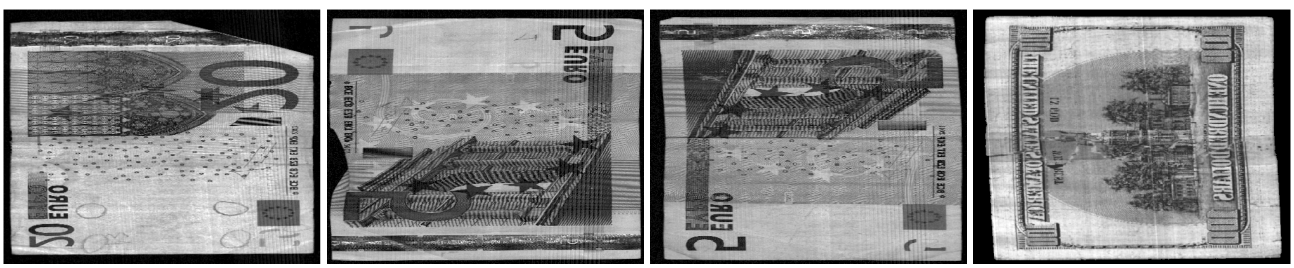


(a) (b)

Figure 5. A pixel-wise (a) average accuracy and, (b) average precision are reported for the angle range of $\pm 45°$ between synthetically rotated and original images.



(a) (b) (c) (d)



(e) (f) (g) (h)

Figure 6. First row illustrates four examples of banknote with defects, (a) and (d) torn boundary and (b) folded boundary of banknote. (c) and (d), Folds in an image caused by malfunctioning of the image capturing process. Second row demonstrates the corresponding skew corrected results.

turned sides.

The third experiment evaluates the execution time for several modules of proposed system with varying banknote image size.

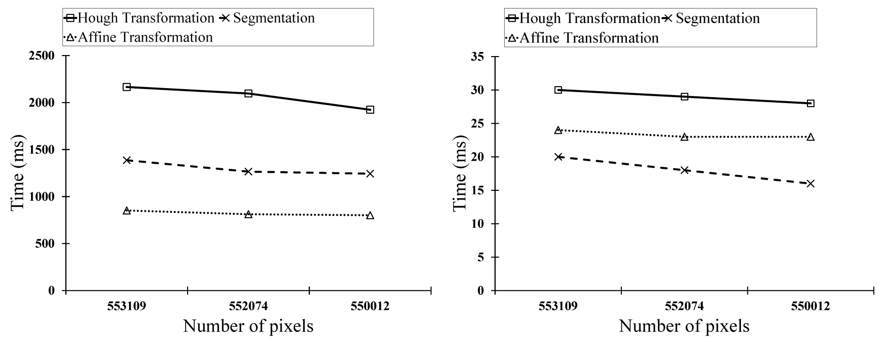
4.1. Synthetic Images

In this experiment, the proposed method is tested on a set of 20 real images with 0° skew. Images are rotated between angles of -45° and 45° with a step of 5°. The dimensions of a banknote are arbitrary, and they depend upon insertion direction in the machine. Therefore, a meaningful skew test is conceived by taking the maximum test angle of 45°. The process generates 360 synthetic images (18 synthetic images for each of the input image). All synthetic images are skew corrected by the proposed method. A pixel-wise comparison is performed between automatically segmented ROI of original and skew corrected images. Two statistical measures (precision and accuracy) are calculated: precision is defined as the proportion of the true positives against all the positive results, while accuracy as the proportion of true results (both true positives and true negatives). The two measures show the robustness of method against miss-alignment caused by malfunctioning of skew correction process.

Fig. 5(a) and Fig. 5(b) show the experimental results on the corrected synthetic images. For the skew corrected images, the mean precision is 0.99 and the mean accuracy is 0.98. The results may not be 100% because of the quantization error introduced during processes of skew correction and generation of synthetically rotated images.

4.2. Real Images

In second experiment, 50 difficult banknote images are skew corrected and a pixel-wise test was performed with



(a) Without optimizations (b) With optimizations

Figure 7. The processing time (a) without and (b) with optimizations (in milliseconds) on DSP is measured against varying banknote area size.

manually drawn skew corrected banknote region. The experiment shows robustness of the proposed method to different border defects as well as to image folds. Fig. 6 shows few examples of several kind of defects such as turned, occluded, folds and torn images.

In this case, the skew correction method gives a mean precision of 0.991 and a mean accuracy of 0.986. The results are quite similar to the test conducted on synthetic images and it enforces the effectiveness of proposed method.

4.3. Tests on Processing Time

In third experiment, the execution time of segmentation, Hough transform and affine transformation of proposed system is evaluated with different sizes of banknotes images. Fig. 7 illustrates time taken on "TI DM6437 DSP board" with clock speed of 600 MHz. The proposed optimizations reduce the processing time for the modules from several hundred of milliseconds to few milliseconds (please consider that Fig. 7(a) and Fig. 7(b) have two different y scale). The number of pixels in ROI of banknote image varies and the execution time in milliseconds is measured as a consequence. The Fig. 7(b) shows that the execution time of the system is stable for each of the modules, which is a requirement of real-time embedded systems. The proposed system gives an average total processing time of 72ms with standard deviation of ± 8 over 100 real images.

5. Conclusions

In this paper, we have proposed several optimizations by the redesign of algorithms for skew correction for banknote analysis in the context of real-time embedded solutions. The proposed methods were implemented and tested for speed and accuracy on Taxes TI DM6437 DSP board. Experiments were conducted on synthetically rotated and real noisy images, and they yield a precision of 0.99 and accuracy of 0.98 with an average processing time of approx. 72 ms.

As a consequence, this fast and accurate skew correction makes banknote images ready for higher level of computer vision processes such as image classification and fitness test. Fast implementations of the computationally expensive Hough transform and hole filling through fast labeling make it an optimum choice for low-cost embedded processing platforms. Furthermore, affine skew correction procedure based on projecting contour lines onto orthogonal lines may be useful for other applications requiring image rectification e.g. building's façade and remote sensing satellite imagery.

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