FIGHTING AGAINST FORGED DOCUMENTS BY USING TEXTURED IMAGE

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ABSTRACT

Verification of a document legitimacy is a current important problem. In this paper we propose to use a textured image containing a visual message, which can be used for identification of differences between printed legitimate document and printed fake document. The suggested textured image consists of specific patterns which should satisfy particular conditions in order to give good recognition results after Print-and-Scan (P&S) process. The identification of a legitimate document is possible by correlating the patterns of the textured image with either the original patterns or representative P&S process patterns. Several experimental results validate the proposed verification method.

***Index Terms*—** pattern recognition, print-and-scan process, document legitimacy, correlation measure

1. INTRODUCTION

These days, an increasing number of documents are distributed in digital format due to their easy transportation, archiving and hard copy reproduction. This fact increases number of Valuable Document Counterfeits (VDC) as electronic versions of bills, bank checks and transport tickets. Therefore, several techniques have been proposed to identify VDC such as flashcodes, watermarks [1] and 2D bar-codes [2].

In [2, 3] authors propose to include an identification number in a 2D bar-code for product authentication. After high quality printing, this 2D bar-code can be authenticated. However, this printed 2D bar-code cannot be used by a counterfeiter, since after scanning the image is so degraded that any reproduction of this scanned image cannot be authenticated.

Most VDC are produced in the interval between the print process and the scan process, since the opponent has only access to the printed protected document. A Print-and-Scan (P&S) process is considered as a physically unclonable function [4], thus the graphical code is hard to be reproduced by the opponent. The P&S process is characterized by several particular properties [5]: 1) printing and scanning devices; 2) image pre- and post-processing (gamma correction, contrast enhancement). Moreover, it has to be noticed that degradation due to printing cannot be distinguished from degradation due to scanning.

The general verification system, illustrated in Fig.1, consists in two steps: the image generation step and the verification step. At the first step, the legitimate source adds the security pattern (i.e. 2D bar-code or watermark) and print the valuable document. The verification step consists on scanning and genuineness verification of the printed document.

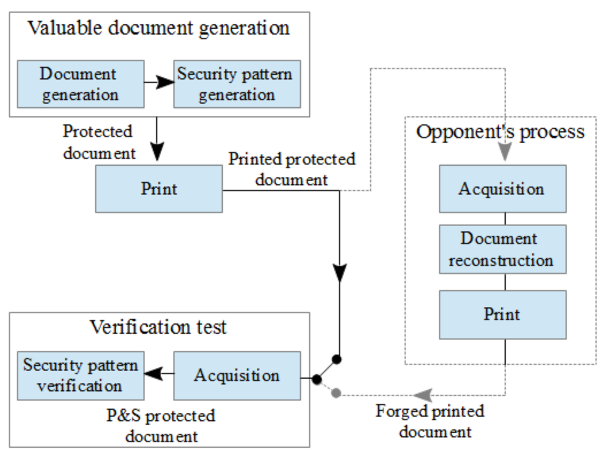


Fig. 1. General verification system for document protection.

In this work we propose to develop a security pattern to identify the genuineness of a printed document. The legitimate source creates a textured image by writing a visual message using n chosen binary patterns belonging to a database of known patterns. During verification, the receiver scans the textured image and applies the detection method in order to verify the genuineness of textured image (i.e. the structure of P&S patterns corresponds to a structure of original patterns) as well as to identify the visual message (i.e. the visual message has to be readable after pattern detection). In this paper, we propose a textured pattern-based method that exploits the fact that a counterfeiter does not have access to the original digital document. This textured image helps the receiver to verify the printed document's legitimacy. The possible ways for an opponent to counterfeit a document, as illustrated in Fig. 1, are not developed in this work.

After the introduction, Section 2 reviews previous work in the domain of P&S process. In Section 3, we describe the generation of textured patterns and how they are combined to make a control textured image. We also study the degradation of the patterns due to P&S process and how it can be used to identify a forged document. Section 4 presents experimental results. Finally, we conclude in Section 5.

2. IMPACT OF P&S PROCESS

Any P&S process, whatever printer and scanner type or brand are used, produces specific image modifications that are visible and invisible by human visual system. These modifications can be produced by ink dispersion in the paper, inhomogeneous lighting conditions during the scan acquisition, resampling inherent to the P&S process or varying speed of the scanning device during the acquisition [2]. As a P&S process is an important part of considered verification system, in this section we aim of discussing more thoroughly these phenomenons and the main modifications added by this process.

As printers use black ink or toner, the visual sensation of a gray level is obtained by creating a binary textured image. This operation, called halftoning, is specific to each printer brand. The resolution of the printer is also a factor of image degradation. It is measured in dots per inch (dpi). The type of paper used, also causes variations of the resulting printed image. There are two types of paper: coated paper and uncoated paper. The most commonly used paper is uncoated paper. With this paper, the ink diffuses into the fibers and causing a loss of resolution of the printed image texture. To obtain a more accurate printing, coated paper is used since it has an additional layer on which the ink is fixed both by absorption and oxidation.

Blurring caused by the impression is aggravated during scanning [6]. The impulse response of the scanner depends on the device definition and the accuracy of the mechanical system that moves the linear camera. It is remarkable that this impulse response is not invariant by translation because the blur caused by the optical system is more important at the ends than in the center of the effective area. The resolution of the scanning system is limited by the number of pixels per inch and by the blurring due to the optical device. The scanned image is tainted by random noise mainly related to the quantification and thermal noise. It is usually modeled by an additive or a multiplicative Gaussian process [5]. Finally, the gamma correction [7] used to correct the physical effect of the scanning process, causes a non-linear modification of the scanned image. For more details on the modeling of P&S process, we refer our readers to [5] for laser printers and [8] for inkjet printers.

The aforementioned phenomenons make the image obtained after P&S very different from the original digital image. It is possible to compensate some changes by using a Look-Up-Table (LUT), dedicated to each printer-scanner pair. Such a LUT can be constructed by measuring the color changes after P&S process.

(a) (b)

Fig. 2. Example of dark colors loss after a P&S process: a) Original image, b) Printed and scanned image (a).

Note that an image loses especially dark colors after the P&S operation. To illustrate this loss, we have printed and then scanned the grayscale image of Lena. Note that the original image, Fig. 2.a, is darker than the scanned image, Fig. 2.b.

3. PROPOSED DETECTION AND VERIFICATION METHOD

In this section we aim of explaining the procedure we use to generate a textured image containing a visual message. We also present a detection method based on correlation measure.

3.1. Textured image generation

The textured image P is an image built by combining n patterns M_l $(l = 1 \cdots n)$. Each pattern M_l corresponds to a small image of size $k \times k$ pixels. The generation of a textured image P consists of the pattern generation, the definition of pattern sets and the generation of resulting textured image.

Pattern generation. In our database we have N patterns $M_l, l = 1 \cdots N$ with $N >> n$. These patterns should satisfy three conditions: 1) being binary; 2) having a constant ratio of black pixels equal to d; 3) having spectrum related among them.

Pattern combination. Due to the specific properties of the patterns M_l, some of them, after P&S process are indistinguishable one from another. We must therefore choose the n patterns among N patterns from database that can be distinguished when they are placed on the same textured image P.

In order to select n necessary patterns for textured image construction, we printed and scanned all patterns from our database. We call S_l $(l = 1 \cdots N)$ the patterns obtained by the P&S of patterns M_l $(l = 1 \cdots N)$. Since the pattern detection is performed by correlation, we use the correlation to characterize the detectability of patterns. The Pearson correlation between a pattern M and a pattern S is defined by:

$$cor(M,S) = \frac{\sum_i \sum_j (M^*(i,j))(S^*(i,j))}{\sqrt{\sum_i \sum_j (M^*(i,j))^2}\sqrt{\sum_i \sum_j (S^*(i,j))^2}}, \quad (1)$$

where $M^*(i,j)$ (rsp. $S^*(i,j)$) are the central values of M (rsp. S) defined by $M^*(i,j) = M(i,j) - \mu_M$ (rsp. $S^*(i,j) = S(i,j) - \mu_S$) with $\mu_M = \frac{1}{k}\sum_i \sum_j M(i,j)$ (rsp. $\mu_S = \frac{1}{k}\sum_i \sum_j S(i,j)$).

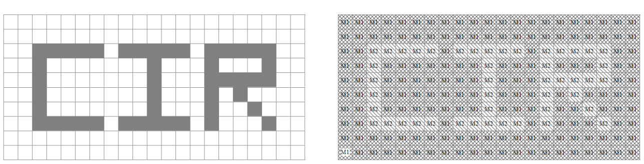
The selection of the n patterns has to satisfy two following criteria:

$$\forall l, l' \in \{1, \ldots, n\}, l \neq l', cor(M_l, S_l) > cor(M_l, S_{l'}). \quad (2)$$

$$\forall l, l' \in \{1, \ldots, n\}, l \neq l', cor(M_l, S_l) > cor(M_{l'}, S_l). \quad (3)$$

Condition (2) ensures that each pattern is better correlated with its degraded (by P&S) version than with all other degraded (by P&S) versions of selected patterns. Condition (3) ensures that the degraded version of each pattern is better correlated with its original pattern than with all other original selected patterns. Thus, the generation of textured image is obtained by combination of patterns satisfying the conditions (2) and (3).

Generation of textured image. In the proposed approach we use 2 patterns, M_1 is used for background and M_2 is used for writing a visual message. These patterns satisfy the conditions (2) and (3). The size of textured image P is $r_a \times r_b$ patterns, where r_a and r_b are integers. An example of a textured image generation is illustrated in Fig. 3. At the beginning we define the visual message (Fig. 3.a). Then we choose the patterns M_1 and M_2 used for textured image generation. The last step consists of composing the patterns as characters are placed at the visual message. For background we use pattern M_1, for characters we use pattern M_2, see Fig. 3.b. Any of chosen patterns can be used for background, the other one will be used for visual message.



(a) (b)

Fig. 3. Generation of textured image containing the visual message: a) Binary visual message, b) Textured image containing the visual message (a).

3.2. Detection of patterns after P&S process

The original image P is made of a combination of n patterns arranged in a $r_a \times r_b$ grid (see Fig. 3.b). Let P_s be the textured image obtained after P&S. Due to the random variations discussed in Section 2, the patterns are modified by the P&S process. We propose to detect each pattern by correlating their representative candidates C_l with selected patches of P_s. Thus, recovering the original arrangement of the patterns can be decomposed in three steps.

1. Selecting a representative candidate C_l $(l = 1, \cdots, n)$ for each pattern M_l $(l = 1, \cdots, n)$.
2. Detecting the pattern positions in the P_s image.
3. Recognizing each pattern.

Representative candidates selection. We experimentally estimate the representative candidates C_l $(l = 1, \cdots, n)$ by repeating t times a P&S process of each of the n patterns, thus obtaining a set of t P&S patterns $\mathcal{S} = \{S_l^1, \cdots, S_l^t\}$. We then propose to use as a representative candidate as illustrated in Fig. 8 :

- the *mean images* obtained by averaging the t P&S patterns: $C_l = \frac{1}{t}\sum_{\tau=1}^{t} S_l^\tau$;
- the *median image*: $C_l = median(S_l^1 \cdots S_l^t)$;
- the *maximal image*: $C_l = max(S_l^1 \cdots S_l^t)$;
- the *minimal image*: $C_l = min(S_l^1 \cdots S_l^t)$.

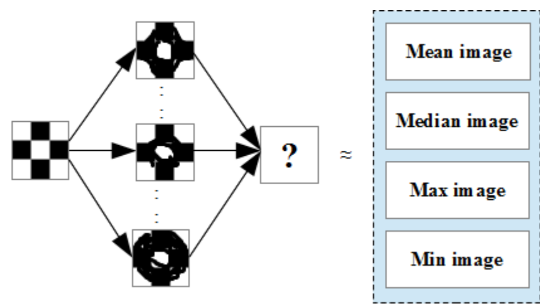


Fig. 4. Random pattern changes during P&S process.

We also consider using the original pattern as a representative candidate ($C_l = M_l$).

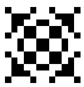
Pattern position detection. We suppose that the size of the textured image after P&S (P_s) is very close to the size of the original textured image P. Thus, the position of each pattern is calculated by using the first pattern position (i.e. top-left corner of P_s) and pattern size k. The detection of the top-left corner is done by using a sliding window moved pixel by pixel. The position of the top-left corner is the first value that maximizes the correlation with C_l $(l = 1, \cdots, n)$.

Pattern recognition. To detect the patterns, a sliding window is moved k pixels by k pixels. However, to account for the fact that the size of P_s is slightly different from the size of P, the position of the pattern is searched on a $h \times h$ window around this nominal position. The position of the pattern is identified by the fact that it maximizes the correlation with one of representative pattern C_l. These correlation values (with C_l) allow also the identification of the pattern.

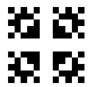
After this last step, the legitimacy of the texture image can be verified since, in a legitimate image, the visual message should be readable.

4. EXPERIMENTAL RESULTS

In this section, we propose an experiment illustrating our method based on a set of $N = 100$ binary patterns of size 12×12 pixels ($k = 12$). During this experiment the representative patter, that gives the best pattern recognition results, should also be defined among candidates presented in Section 3.2. The ratio of black pixels in each pattern is set to $d = 64$ (that corresponds to 45% of black pixels). In this experiment, we generated an image with $n = 2$ patterns non-independent selected from 100 patterns maximizing criteria (2) and (3). These two patterns are presented in Fig. 5.



(a) Pattern M_1

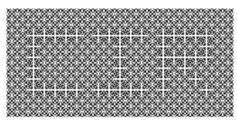


(b) Pattern M_2

Fig. 5. The pattern combination: a) Pattern 1 and b) Pattern 2.

We generated a textured image P of 10×21 patterns. The examples of binary visual message and textured image with this message are presented in Fig. 6.

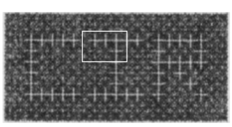
(a)



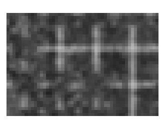
(b)

Fig. 6. Example of textured images containing a visual message: a) Binary visual message, b) Textured image containing the visual message (a).

Then, we create, from the defined textured image, a printable at 600 dpi version, that corresponds to $10.5 \times 5mm^2$. We print and scan this image at 600 dpi using the printer-scanner HP LaserJet Pro CM1415. The resulting image P_s after P&S process is presented in Fig. 7. Note that the image is quite blurred and that the distribution of gray levels has been changed by a P&S process.



(a)



(b)

Fig. 7. a) Example of textured image containing the visual message from Fig. 6.b after P&S process, b) Zoom of its central part.

In order to define representative patterns C_1 and C_2, we print and scan each pattern M_1 and M_2 200 times. From this database, we generate mean, median, maximum and minimum representative patterns as proposed in Section 3.2 (see Fig. 8).

To characterize the process that we propose, we perform pattern recognition of the textured image Fig. 7 obtained after P&S. We present the pattern recognition result in Fig. 9 and Fig. 10. Fig. 9.a shows the true map of pattern places M_1 and M_2. Fig. 9.b and Fig. 10 show the recognition results obtained by using the original patterns (Fig. 9.b), the mean

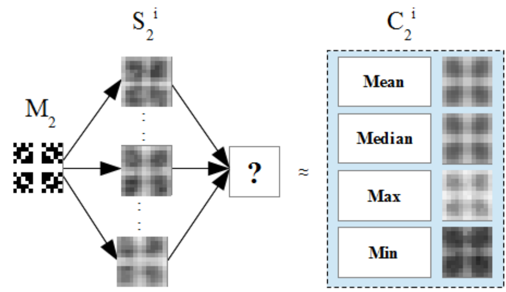
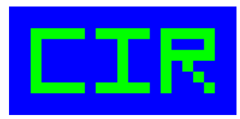
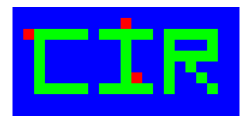


Fig. 8. Examples of Pattern 2 (Fig. 5.b) changes during P&S process.



(a) True map

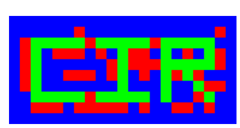


(b) Detection with original patterns

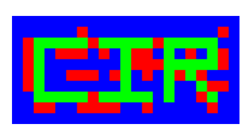
Fig. 9. Detection results by using original patterns : a) With the original textured image, b) With the P&S textured image.

representative patterns (Fig. 10.a), median representative patterns (Fig. 10.b), maximum representative patterns (Fig. 10.c) and minimum representative patterns (Fig. 10.d). Patterns recognized as M_1 are in blue color, patterns recognized as M_2 are in green color. In red are the patterns that have been detected incorrectly. These results are shown in Table 1. As can be seen, the best detection rate is obtained using the original patterns. In this case, only 3 patterns from 210 are not well recognized (with probability of 1.11%). When using representative patterns (that are based on statistical aggregation operation of P&S samples of original patterns), we can see a bias in the recognition, in the sense that the pattern M_2 is often recognized as the pattern M_1. Statistic representatives of pattern M_2 are better correlated with the P&S patterns M_1 that statistic representative pattern M_1.

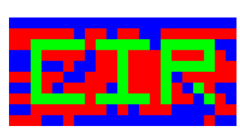
This result may seem surprising. Indeed, as shown in Fig. 11 on one of lines of the textured image, correlations with statistical representatives are generally higher than the correlations with the original patterns. Fig. 11.a indicates the actual positions of patterns (the blue lines correspond to the



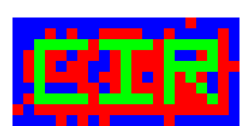
(a) Detection with mean patterns



(b) Detection with median patterns



(c) Detection with max patterns



(d) Detection with min patterns

Fig. 10. Detection results with different representative patterns.

Type of patterns	Error probability
original	1.11%
Modeled patterns	
mean	24.29%
median	22.38%
max	49.05%
min	40.63%

Table 1. Detection results of scanned textured image by using different patterns for proposed method.

pattern M_1, the green lines correspond to the pattern M_2, the red lines to errors in classification). Fig. 11.b (respectively Fig. 11.c) shows the correlation values among the pattern M_1 (respectively M_2) and the original pattern, purple line, and the median pattern, orange line (median pattern from the representative patterns give the best detection rate). In Fig. 11, the detection peaks correspond to pattern locations. While the correlation value is higher with median pattern than with the original pattern, it induces more errors in pattern detection. An explanation that we could give to this phenomenon is that both patterns M_1 and M_2 were selected to optimize the correlation among scanned patterns and original patterns and not to maximize the correlation among scanned patterns and statistic representative patterns.

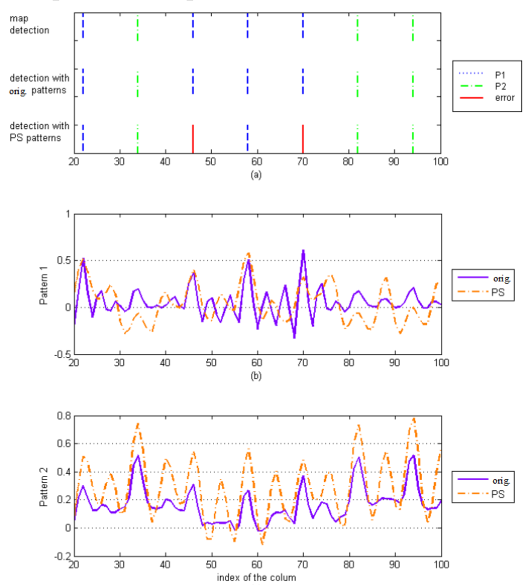


Fig. 11. Correlation values of one line of textured image for pixels in interval $[20 \cdots 100]$.

5. CONCLUSION

In this paper, we have presented a new method for identifying the legitimacy of documents after P&S process. This method is based on constructing a textured image containing a visual message with specific binary patterns which are sensitive to a P&S process.

To detect the patterns, different correlation-based approaches have been tested. We first have modeled the deterioration due to P&S process by using a statistical aggregation process on different P&S realizations (mean, median, maximum and minimum). This approach leads to high correlation values, but low detection results. The second approach consisting of correlating the P&S textured image directly with original patterns leads to lower correlation values, but high detection results.

Our approach has been tested with limited number of printers and scanners, and with uncoated paper. Future work will focus on extending the experiments with wider number of usual printers and scanners, and with coated paper. We will also consider increasing the detection ability of the method by studying more thoroughly the P&S process. The obtained method will then be tested with different attack scenarios.

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