Separation of mixed Document Images in Farsi Scanned Documents Using Blind Source Separation

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Abstract

In the field of mixed scanned documents separation, various studies have been carried out to reduce one (or more) unwanted artifacts from the document. Most of the approaches are based on comparison of the front and back sides of the documents. In some cases, it has been proposed to analyze the colored images; however, because of the calculation complexity of the approaches, they are not well applicable in practical applications. Furthermore, none of them are tested on Farsi/Arabic documents. In this paper, an applicable approach to large size images is presented which is based on image block segmentation (mosaicing). The advantages of this approach are less memory usage, combining of the simultaneous and ordinal blind source separation methods in order to increase the algorithm efficiency, reducing calculation complexity of the algorithm into about twenty percents of the basic algorithm, and high stability in noisy images. In noiseless conditions, the average signal to noise ratio of the output images is reached up to 30.26 db. All of these cases have been tested on Farsi official documents. By applying the proposed ideas, considerable accuracy is achieved in the results, at minimum time. In addition, various parameters of the proposed algorithm (e.g. the size of each block, appropriate initial point, and the number of iterations) are optimized.

Keywords: Blind source Separation, Independent component Analysis, show-through, feed-through, background removing, scanned documents processing.

1. INTRODUCTION

In many cases, there is some additional information on scanned or photographed documents in addition to the main document image. Some of this extra information may or may not visually detectable. Depending on the user's goal, it may be interesting to highlight or remove them.

Generally, the noise affected on the documents, could be appeared as two following cases. One of them is pervading the color or no-color-equilibrium in the document, and another is the effects of the existed information behind of the document or another document on the under process document. In the scanning procedure, due to blazing radiation of light, the image of the back side of the document may be mixed with the front side in the resulted image. In this effect, if the back side ink affects the front side image of the document, the effect is named “bleed-through”, and if the document is two-sided or there are consecutive thin documents in the imaging procedure, the effect is called as “show-through” effect. Sometimes, it may be required to separate the various layers of the scanned image in order to focus on each of them. Background removing is a remarkable example in document analysis [1, 2]. Undesired effects on background of a document consists of the various elements such as optical blurring and noise caused by scanning, dots, under writings and over writings [3, 4, 5]. These cases are strictly important in restoring the document images and retrieving data from the ancient documents.

The ideas which are proposed in this paper can be used in decoding of the security documents, in addition to the OCR application, electronic archives and libraries, handwritings and subscript detection, and generally, improvement of image quality.

Various techniques are available to increase the quality of the documents. The earliest methods for the document quality enhancement are binarization and image retrieving approaches which produce acceptable results in the case that one source is accompanied with noise [6]. Some researchers have tried to reduce the show-through effect by using blind source separation (BSS) approach. Although this approach requires registering the documents of both sides of the paper; however, the detection of this one by one correspondence is a hard and time-consuming task [7, 8]. A competing approach is employing Markov model for bleed-through removing, which has caused more readability in the resulted document [9, 10, and 11]. In addition, Markov model has been useful in enhancing the reconstructed image resulted BSS procedure [12].

In [13], a comparison has been performed between independent component analysis (ICA) and diffusion methods, and the advantages of the diffusion method are illustrated. In addition, in [14], various approaches among ICA has been compared, in order to evaluate the quality enhancement of the document based on providing a colored scan of the document, then analyzing it to RGB components, and finally testing on ancient documents containing watermark effect and hidden text. In the mentioned study, by analyzing the RGB components, the need to scan and register the both sides of the document has been removed.

In [15], this procedure has been used by focusing on show-through, ink-bleed, and palimpsests affected documents. In this way, sources have been separated by analyzing the colored image into the three RGB components. In the next step, ICA has been used to solve the equations set containing three equations (colored components) and three unknown elements (background, body text, foreground). In addition, instead of using only RGB components as the three sensors, invisible bands such as infra-red or ultra-violet may be used to gain more independent components [15].

Heretofore, image blocking (mosaicing) idea has been employed in few algorithms. However, the use of this idea has not been dynamic. In fact, they have selected the initial parameters of each block from a constant default values set. Therefore, they calculate each block notwithstanding neighboring blocks again and again. Hence, all respective activities, in this field, are time-consuming. Here, an important point is their less stability against noise. Furthermore none of them has been tested on Farsi documents.

The main proposed idea in this paper is based on mosaicing of the input colored document image, processing of each block separately using BSS algorithm by considering RGB components as the three sensed signals, and finally applying the results of each block as the initial values of the parameters of the next block. The method is inspired from ordinal blind source separation algorithm, while all of these are obtained at the least time and calculation complexity. The algorithm has applied to the two main categories. One of them is the real official documents. In this category, the goal of this paper is separation of the background effect from the body text, and separation of the information on front and backside of the documents from the body text, at least time and higher quality. Another category is the synthesized documents. In this category, the goal of this paper is full separation of the sources which has been synthesized and noise has been added to their combinations. These goals have been satisfied at the least time and high signal to noise ratio comparing with the basic algorithm. Of course, it should be considered that one of the important parts of the text extraction is the binarization procedure which is a complement process in order to gain the final version of the reconstructed document sources.

The structure of the paper is as follows. In the second section, the proposed method for separation of the mixed documents by conjointly use of simultaneous and ordinal BSS is explained and mathematically formulated. In section three, experimental results of applying the proposed method on Farsi official and synthesized documents is presented; and finally, the paper is concluded in the forth section.

2. PROPOSED MODEL FOR SEPARATION OF THE MIXED DOCUMENTS BASED ON BLIND SOURCE SEPARATION

Generally, there are two main methods for blind source separation named simultaneous and ordinal BSS. In simultaneous method, all sources would be separated from each other at the same time, while in ordinal method; the extraction of the sources is performed one by one in a greedy manner and the extraction of each source, improves the system for extracting the other sources.

In this paper, a combination of two mentioned methods has been proposed which on one hand, optimizes the calculation complexity and the separation accuracy of the mixed images, and on the other hand, reduces the defects of the each method. This approach uses simultaneous BSS method to process the each block of the mixed image, while optimally utilizes the knowledge gained in the previous block for the current block, due to data correlation of the various sections of the image. Equation (1) shows the formulation of the problem.

$$x(k) = H.s(k) + v(k) \tag{1}$$

In this equation, “x” is the vector of observed signals, “H” is the mixing matrix, “s” is the sources which should be reconstructed, and “v” is the noise vector.

In the noiseless system, equation (1) could be written as equation (2).

$$X = H.S \tag{2}$$

$$X = [x(1), x(2), \dots, x(N)]^T \in R^{m \times N} \tag{3}$$

$$S = [s(1), s(2), \dots, s(N)]^T \in R^{n \times N} \tag{4}$$

In order to blind source separation two cases could be defined. One of them is based on exactly extraction of the source signals with high computational complexity, and another is based on iterative operations with less computational complexity. In the first case, by assuming statistical independency of the original sources and linear independency of the columns of matrix H, generally, the ICA technique, could estimate all sources and their quantity, or recognize mixing matrix (H) or the pseudo inverse matrix ($w = H^{\dagger}$). So, by multiplying the pseudo inverse matrix at the sensed signals, the source signals could be estimated as follows.

$$\hat{s}(k) = w.x(k) \tag{5}$$

Here, $\hat{s}(k)$ is the vector of the reconstructed signals. The exact response of the reconstructed sources will illustrate later. If the number of the independent components is great and its distribution is sparse, it is better to use the following form.

$$X^T = S^T.H^T \tag{6}$$

In this case, the rows of the S and the columns of the H should as independent as possible, and both of them should approach to similar statistical attributes (sparse presentation or laplacian distribution). In this way, the vectors of the matrix H^T can be considered as the independent components, the matrix S^T matrix as the mixing matrix and vice versa.

Now, instead of estimating the sources directly, the information should be gathered about the mixing system at first. Since w is the pseudo-inverse of H, the rows of H are corresponded with the columns of w. In most of cases, the sources have been mixed and filtered, linearly and simultaneously. In fact, the mutual vectors h_j of the mixing matrix H or pseudo inverse of it (w_j), should be recognized.

Basically, in blind source separation, it is desired to minimize the average square error between output signals and original sources. In other words, the following cost function should be minimized.

$$J_p(s) = \|x - H.s\|_p = \|e(s)\|_p \quad , \quad (p \geq 1) \tag{7}$$

In this equation, p is the geometric norm and the error vector could be defined as the following equation.

$$e_i(s) = x_i - h_i^T.s = x_i - \sum_{j=1}^{n} h_{ij}.s_j \tag{8}$$

In order to minimize the cost function, by use of least linear squares approach, and considering norm 2, the equation (7) could be transformed as below.

$$J(s) = \frac{1}{2}\|X - H.s\|_2^2 = \frac{1}{2}(X - H.s)^T(X - H.s) = \frac{1}{2}e^T.e = \frac{1}{2}\sum_{i=1}^{m} e_i^2 \tag{9}$$

If the gradient of the cost function be equaled to zero, the exact response for reconstructed sources could be achieved as following.

$$\nabla J(s) = H^T(X - H.s) = 0 \tag{10}$$

$$s_* = H^T(H.H^T)^{-1}X = H^{\dagger}.X \quad , \quad J(s_*) = 0 \tag{11}$$

In this case of BSS, because of unknown quantity of the pseudo inverse matrix, difficulty of finding it, inversion of the large matrixes and as the result more computational complexity, reconstructing the sources is very difficult. So, using an iterative equation could be applicable.
By using gradient based approaches, the problem could be reformulated as below [14].

$$\frac{ds}{dt} = -\mu.\nabla J(s) = \mu.H^T(X - Hs) = \mu.H^T.e \tag{12}$$

In this equation, $\mu = [\mu_{ij}]$ is a positive definite $n \times n$ matrix which usually is diagonal. In order to the source estimation, this differential equation could easily and directly be converted to an iterative equation, as following.

$$\hat{s}(k+1) = \hat{s}(k) + \eta_s . H^T [X - H.\hat{s}(k)] \tag{13}$$

Generally, since the input signals applied to ICA should be independent, regardless of the inherent independency of the observed signals, the operation called whitening should affect on them. So, in order to provide independent signals, the correlation of the observed signals should be removed. The problem could be modeled as equation (14), which therein "$y(k)$" is the whitened vector, and W is a $n \times m$ whitening matrix [14, 15]. Here, in order to prevent be mistaken for the pseudo inverse matrix, the whitening matrix has been indicated with upper case (W).

$$y(k) = W.x(k) \tag{14}$$

After whitening, usually ICA or BSS approaches converge better [14]. This occurs because of describing the secondary separation system (non-mixing system) by the orthogonal matrix for real signals, and an identity matrix for weights of mixed signals.

In the whitening process, the selection of matrix W follows the following procedure. The covariance matrix of the whitened signals $(E\{y(k)y(k)^T\})$ should become the identity matrix (I_n). In this manner, the whitened vectors $y(k)$ will be mutually independent [14].

$$R_{yy} = E\{yy^T\} = E\{Wxx^TW^T\} = WR_{xx}W^T = I_n \tag{15}$$

In order to achieve an iterative equation, Similar to equation 13, based on gradient approaches, whitening operation could be illustrated as following [16].

$$W(k+1) = W(k) + \eta_w [I - y(k).y^T(k)]W(k) \tag{16}$$

In this equation, $W(k)$ is the quantity of matrix W at kth iteration, $y(k)$ is the whitened vectors at kth iteration, and η_w is the convergence rate of the equation. This equation will converge, if the general matrix as G (in equation 17) could be founded to satisfy either equations (18) or (19).

$$G = W.H \tag{17}$$

$$G.G^T = G^T.G = I_n \tag{18}$$

$$G^{-1} = G^T \tag{19}$$

In this situation, matrix G will be orthogonal. Furthermore, by multiplying equation (16) at the mixing matrix (H) from right side, equation (20) would be obtained [16]:

$$W(k+1)H \stackrel{df}{=} G(k+1) = G(k) + \eta_G [I - G(k) < \hat{s}(k).\hat{s}^T(k) > G^T(k)]G(k) \tag{20}$$

In this equation, $G(k)$ is the quantity of matrix G at kth iteration, $\hat{s}(k)$ is the reconstructed sources at kth iteration, and η_G is the convergence rate of this equation.
Without loss of generality, by assuming that self correlation matrix of the estimated sources (equation 21) is an identity matrix, it is clear that a learning algorithm which uses above equation is stable and converges, if the matrix $G(k)$ is orthogonal ($G^{-1} = G^T$).

$$R_{\hat{s}\hat{s}} = < \hat{s}(k)\hat{s}^T(k) > \tag{21}$$

Finally, by considering the equations 14, 17 and applying them at equation 13, the basic equation for estimation of sources could be achieved as the following equation.

$$\hat{s}(k+1) = \hat{s}(k) + \eta_s . G^T(k+1)[y(k) - (G(k+1). \hat{s}(k))] \tag{22}$$

In this equation, η_s as the learning rate should be a positive constant to guarantee the stability of the algorithm. In addition, the learning rate, η_s should satisfy $0 < \eta_s < 1/\lambda_{max}$ constraint, where λ_{max} is the maximum eigenvalue of $H^T H$. In summary, if η_s is near the upper boundary, the algorithm converges rapidly. In order to effectively apply the algorithm, the largest eigenvalue of $H^T H$ should be estimated to specify the upper boundary.

Fig. 1 shows the overall block diagram which is used for reconstruction of the sources. The goal of this paper is to utilize the BSS approach into blind separation of the image sources resulted from several records on the document such as show-through and background effects in official documents and full separation of the sources in synthesized images, with minimum computational complexity. The first idea is based on partitioning of image or "mosaicing". In most of the cases, because of much length of the signals, a large amount of the memory is needed to apply BSS algorithm. Therefore, it requires the systems with large amount of the memory. On the other hand, in order to keep the correlation of the neighboring pixels, it is better to divide the image into the smaller blocks and process each block separately.

Of course, the choice of the block size is very important. The block size should be as small as possible to keep the correlation between neighboring pixels, and on the other hand, the desired block size should contain textual data. In other words, it should not be so small which its textual data could not be read. For final decision, the output signal to noise ratio and computational complexity of the algorithm should be evaluated.

Fig. 2 shows the block diagram of the proposed algorithm in this paper. It should be mentioned that the algorithms and equations which are expressed in this paper, are quite different from the other available algorithms in blind source separation for document separation [12].
As it is shown in the block diagram, in the first step, the colored scanned image of the document is decomposed into three red, green, and blue components [15]. These components are processed as three independent observed sensed signals (x_1, x_2 x_3).
After mosaicing the images, the corresponding mosaics of each sensor have to be applied to the separation algorithm. Before employing the main separation algorithm, each of the applied blocks should be changed to a one dimensional signal [13]. Then, in order to reduce the correlation between the elements of the obtained three one dimensional signals, whitening operation is unavoidable.

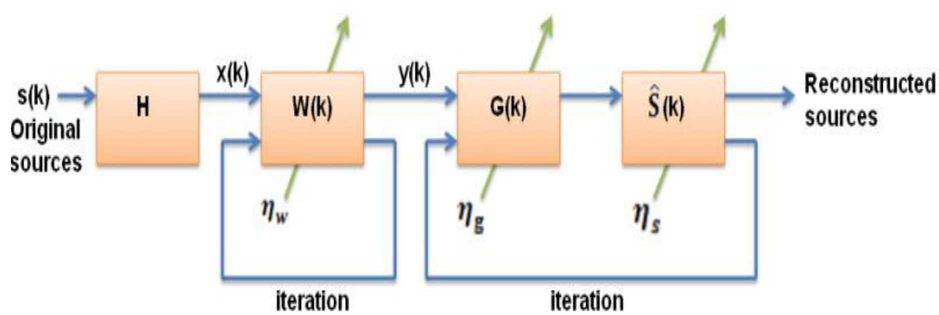


FIGURE 1: BSS Basic Algorithm Block Diagram.

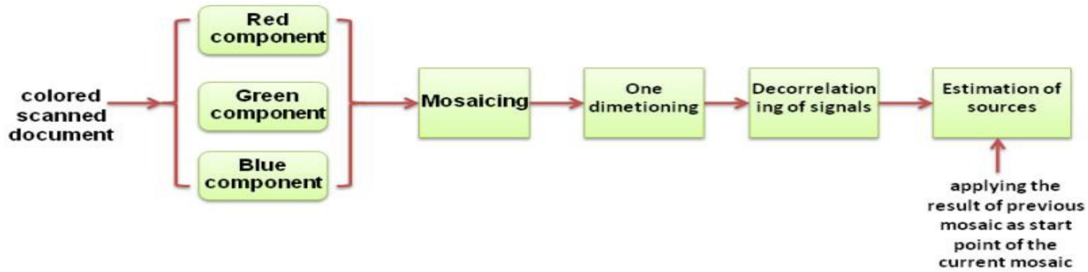


FIGURE 2: Block Diagram of Proposed BSS Approach and Optimization Ideas.

To select the initial values of the whitening and mixing matrixes, they should be assumed in the manner that in each row and column, only one element is dominant. This causes the algorithm converge faster. Then, the source estimation procedure is performed by using the reconstructed sources of each block as the initial values of the next block's estimation (equation 22). This procedure obtains a good initial point for the main algorithm, in order to have less computational complexity.

According to tests performed in the next section, most of the calculations occur in the estimator process, although after applying the proposed ideas, in addition to keep high visual quality and quantitative accuracy, the run time of the algorithm is considerably reduced. In this study, all of the proposed ideas, are examined on the synthesized and Farsi official documents, and as the good results, the stability of the proposed algorithm in noisy environments is demonstrated.

3. EXPERIMENTS AND RESULTS

3.1 Experiments Setup

In this section, the results of applying the proposed ideas are presented. All of the templates which are used in this section are selected from Farsi official documents. In this paper, the quantitative evaluation is performed on the synthesized images. The performance criterion is the ratio of the average SNR of the output images to the average SNR of the input images. It is possible to post-process the output image such as binarization and filtering operations. The dimensions of the synthesized images which are used in all of these experiments are 384*384 pixels and the mixing matrix is as following.

$$\mathbf{H} = \begin{bmatrix} 0.4 & 0.3 & 0.3 \\ 0.3 & 0.4 & 0.3 \\ 0.3 & 0.3 & 0.4 \end{bmatrix}$$

In the synthetic experiments, three textual sources have been mixed by above mentioned mixing matrix and three gained mixtures have been applied to the algorithm as the three sensors. The original Images are prepared by scanning Farsi official documents in 300 dpi resolution and 24 bits color depth, while their dimensions is 512*896 pixels. After exploring and selecting the optimum size of the mosaics in the next section, for other experiments, the block size is considered as 64*64. The experiments are conducted on a Personal Computer 2.0 GHz Dual Core Due Intel processor. The simulation environment is Matlab R2008.

3.2 Optimizing the size of mosaics

In order to select the optimum size of the mosaics, various experiments based on the different mosaic sizes such as 4*4, 8*8, 16*16, 32*32, 64*64, 128*128, has been performed. It has been observed that for 64*64 block size, the reconstructed signals would be more acceptable than the other sizes. In this experiment, the base of the block size selecting, is the high separation accuracy with the minimum computational complexity. As it is observable at TABLE 1, for 4*4 block size, the operation time of algorithm is 1109 seconds, and average SNR of the output

images, is 24.82 db, while for 64*64 block size, these values are obtained as 206 seconds and 30.26 db.
The maximum SNR is obtained for 16*16 block sizes by amount of 30.58 db. As it will be presented in the next section, the operation time of the separation algorithm for 16*16 blocks mosaicing is 299 seconds while this time for 64*64 block size is 206 seconds. The average SNR of these two situations differs only about 0.25 decibel. Considering all aspects, 64*64 block size is selected as the best choice. Figure 3 shows the visual comparison between the results of considering 4*4, 16*16, and 64*64 block sizes. As it is observable, the results of 4*4 block size have low quality because of dot effects on them. The results of the 16*16 and 64*64 block sizes do not differ visually, because their SNR is very close together.

SNR / Block size	SNR of first output	SNR of second out put	SNR of third out put	Average SNR of outputs
4*4	27.82	22.99	23.67	24.82
8*8	31.66	29.18	30.12	30.32
16*16	32.46	28.96	30.32	30.58
32*32	31.85	28.68	29.68	30.07
64*64	31.06	30.45	29.28	30.26
128*128	31.57	27.62	27. 87	29.02

TABLE 1: Variations of Average SNR of Reconstructed Sources in Terms of Different Block Sizes in Noiseless System.

FIGURE 3: a, b, c) original sources. d, e, f) three synthetic mixtures in noiseless system. g, h, i) reconstructed sources using BSS by 4*4 mosaic size. J, k, l) reconstructed sources using BSS by 16*16 mosaic size. m, n, o) reconstructed sources using BSS by 64*64 mosaic size.

3.3 Computational Complexity of the proposed algorithm

Figure 4, depicts the operation time of the each block versus the various block sizes. As it can be observed, by increasing in the mosaic sizes, the processing time of the each mosaic increases, while as it is observable in Figure 5, the processing time of the entire image decreases. In Figure 5, the maximum point of curve is assigned to the 4*4 block size which the related operation time is obtained as 1109 seconds. The operation time of 64*64 block size, has been calculated 206 seconds that is the minimum point of the curve. Considering these curves and visual results, presented in section 3.2, the best block size as the trade off point of visual quality, computational complexity, and SNR aspects is 64*64 block size.

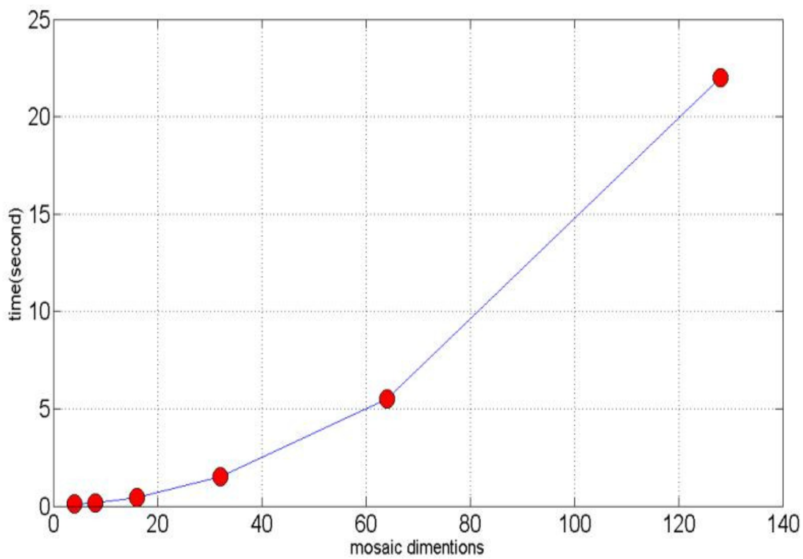


Figure 4: Computational Complexity of the each block versus the various block sizes

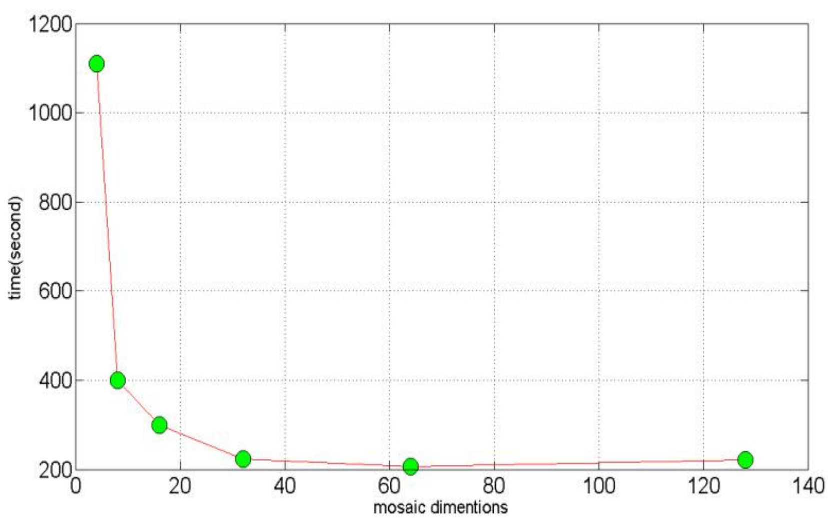


Figure 5: Total Computational Complexity of the typical image versus the various block sizes

3.4 Effect of the Number of the Iterations on the Computational Complexity

In BSS approach, computational complexity increases linearly with the number of iterations (in w, g, s). Thus, by optimizing the number of iterations, the computational complexity and operation time could be reduced. The convergence characteristic of the proposed algorithm is very good. In fact, after specific iterations, the results will not have considerable improvement. Before applying the results of previous block to the under process block, to achieve an acceptable output results, these iterations were as follows: 4000 iteration for whitening algorithm, and 200 iterations for G matrix and source estimator algorithms (Figure 6).

For a typical image, the operation time of the basic BSS is calculated as 750 seconds. After applying the proposed idea, the operation time reduced to 154 seconds, and the required number of iterations for convergence, except first block, decreased to 5 iterations for G matrix, and 100 iterations for whitening and source estimator algorithms (Figure 7). The operation time has decreased to 20 percent of the basic algorithm.

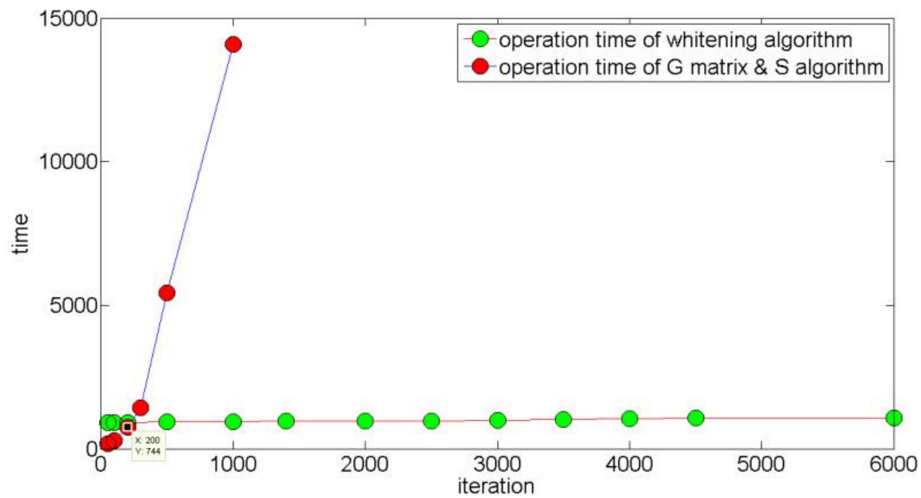


Figure 6: Effect of the Number of the Iterations on Computational Complexity in Basic BSS Algorithm

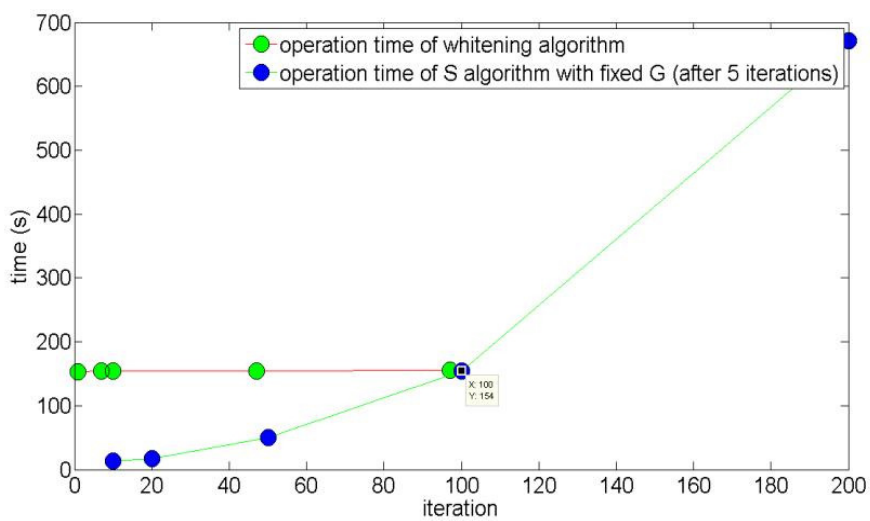


Figure 7: Effect of the Number of the Iterations on Computational Complexity after Applying Optimization Ideas

3.5 Separation of the Background Affected Documents

To investigate the ability of the proposed algorithm in the separation of the background effect of the image, the method is applied to the document that the watermarked logo of the owner corporation was on the background. The results of this experiment are shown in Figure 8. The operation time of the basic BSS, for this document is 825 seconds, with 4000 iterations for whitening and 200 iterations for G matrix and estimator algorithms, while after applying the optimization ideas, the operation time reduced to 136 seconds, with 10 iterations for whitening, 5 iterations for G matrix and 100 iterations for estimator algorithm (except first block). As it is observable in the output images of the algorithm (b, c, d), the algorithm has focused on one component at each output. After BSS operation, the main text could be extracted using binarization (e) and the background effect could be extracted using complementation and binarization of the first output (f). In this manner, the background effect and the main text are fully separated from each other, after post-processing.

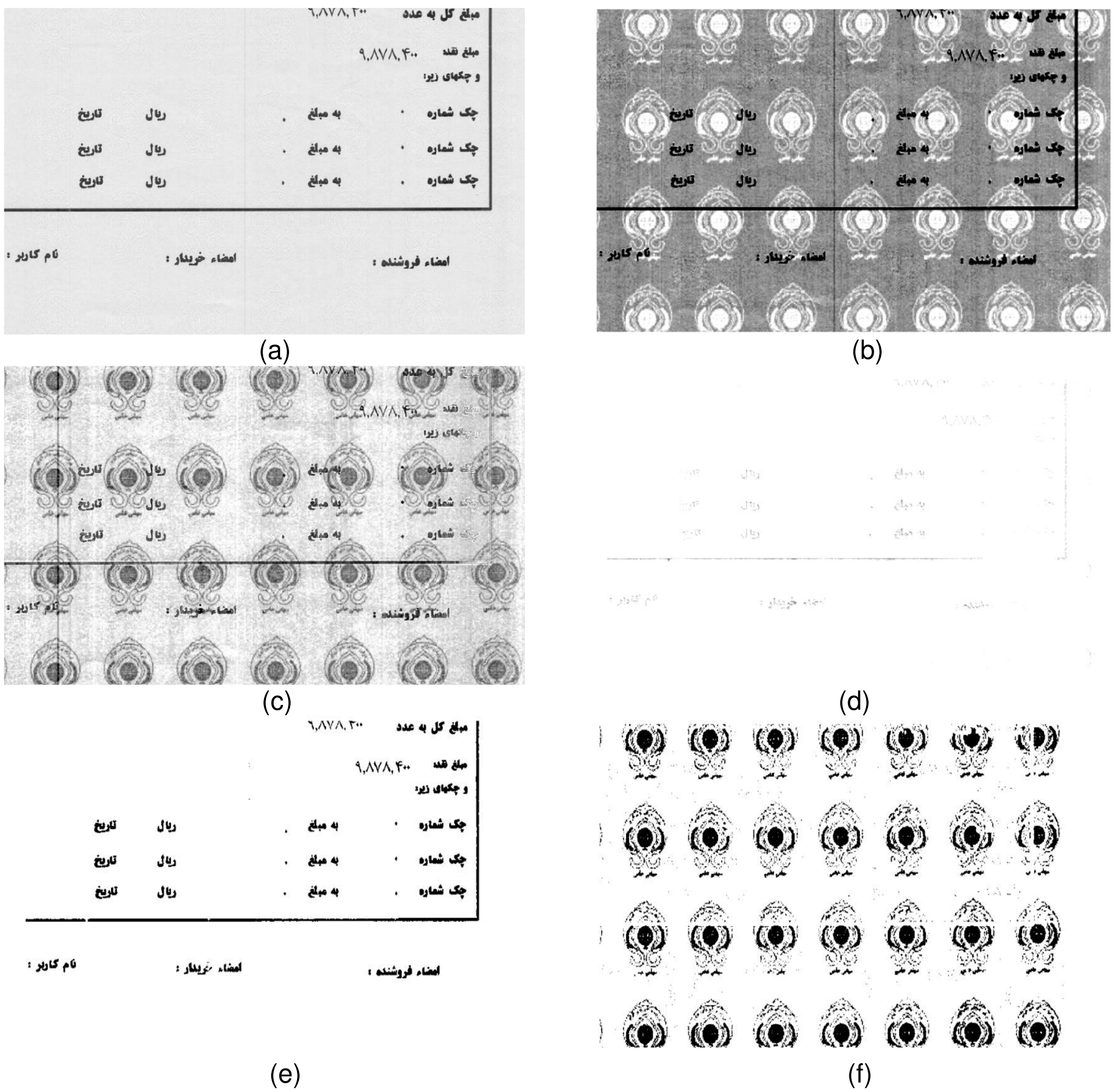


Figure 8: a) Colored scan of a typical official document. b, c, d) results of the extracting RGB components of the original image as three sensed signals. e, f) separated main text and background effect after post-processing operations.

3.6 Robustness of the Proposed Algorithm in Separating the Show-Through Effect

The proposed algorithm was applied to the colored image of the scanned official document with the show through effect. The original image has been demonstrated in Figure 9-a. The front of the document contains signature and main text, while there are some written information and stamp effect in behind. It is cleared that in this test, there are four sources, while only three RGB sensors would be available for applying to the algorithm. As it is observable in Figure 9-g, one of the sources might not been extracted singular. For this document, the operation time of the basic BSS, is 602 seconds, with 3000 iterations for whitening and 200 iterations for G matrix and estimator algorithms, while after applying the optimization ideas, the operation time reduced to 136 seconds, with 20 iterations for whitening, 5 iterations for G matrix and 100 iterations for estimator algorithm (except first block).Figures 9-b,c,d, are the outputs of the algorithm which in each of them, it has been focused on one (or more) component(s). After carrying out the algorithm, the stamp effect has been extracted using binarization, complementation, and median filter (Figure 9-e), the signature effect has been extracted using binarization and median filter (Figure 9-f), and finally, the written information behind of the document, has been extracted using binarization (Figure 9-g). All of these have been occurred at the least computational complexity.

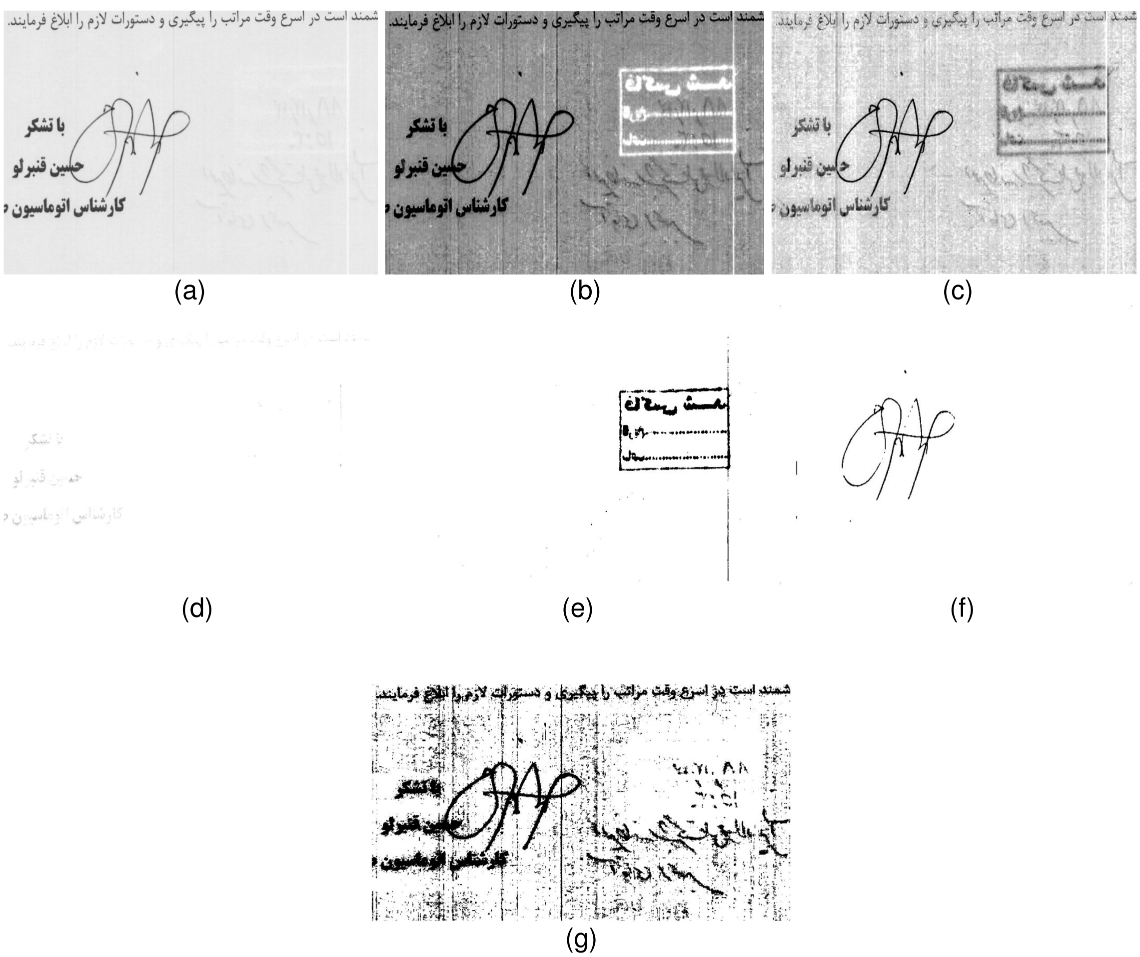


Figure 9: a) The Colored Scan of an Official Document containing show-through effect. b, c, d) The Three Results of Proposed BSS Algorithm. e, f, g) Extraction the Desired Data by Post Processing Operations Such as Binarization and Filtering.

3.7 Robustness of the Proposed Algorithm in Presence of the Additive Noise

This section has focused on the stability of the algorithm in noisy conditions. It should be considered that the noise has been added to the three synthetic mixtures, that is very dangerous kinds of the additive noises. In Figure 10, it is observable that in noiseless system, the SNR of the reconstructed sources has been increased up to 30.26 db that in comparison with the basic BSS, the amount of the improvement is about 2 decibel. In the proposed algorithm, the output signals with the SNR up to 15 decibel have been achieved versus the input signals with the zero decibel SNR. By increasing in the SNR of the input images, the saturation effect will occur. Table II, presents the SNR of the input and output signals, in terms of the different salt and pepper noise energies. While 50% salt and pepper added to the mixtures, the SNR of the output signals has been obtained up to 4 decibel. In Figure 11, a visual example has been given in the presence of 10% salt and pepper noise. It is observable that after binarization of the output signals of the algorithm, the original sources are fully separated.

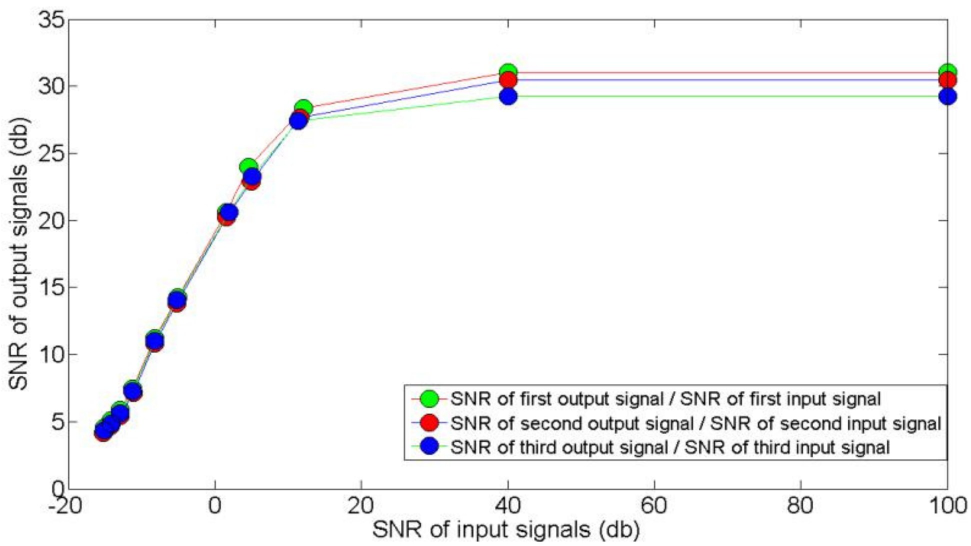
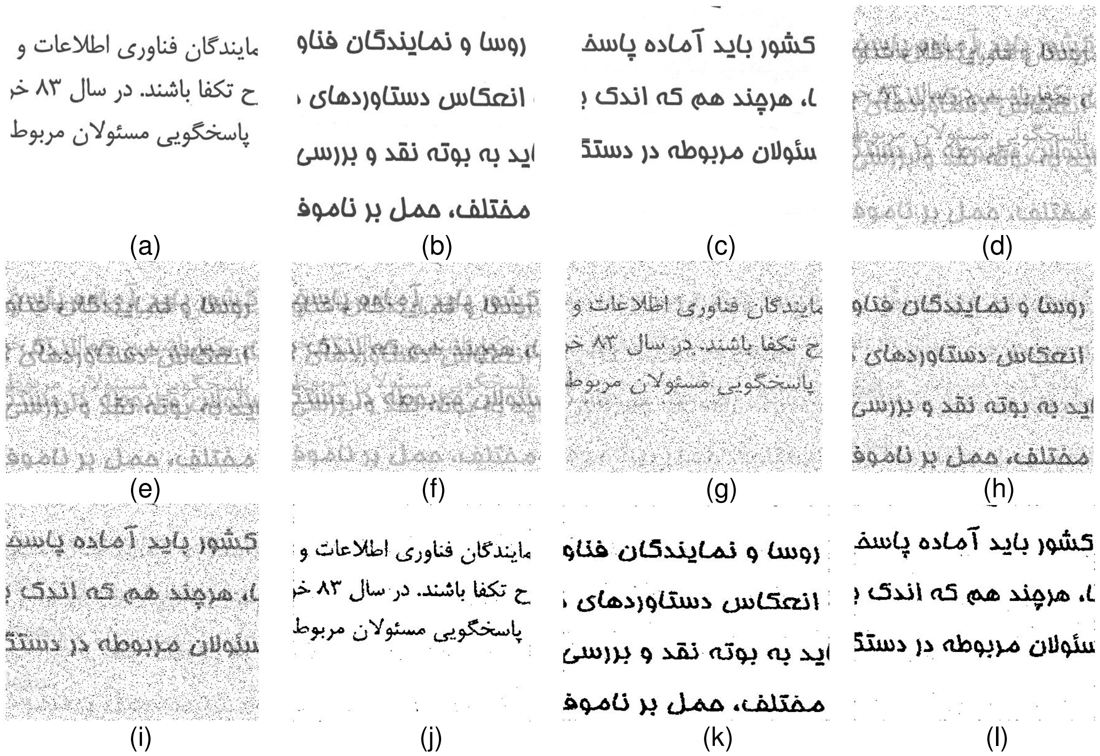


Figure 10: SNR of the Reconstructed Sources versus SNR of the Original Sources with Different Values of the Salt and Pepper Noise applied to the mixture sensed images

Noise (%)	SNR IN_1	SNR IN_2	SNR IN_3	SNR IN_Ave	SNR OUT_1	SNR OUT_2	SNR of OUT_3	SNR of OUT_Ave
0	$+\infty$	$+\infty$	$+\infty$	$+\infty$	31.06	30.45	29.28	30.26
5	-5. 2	-5.15	-5.15	-5.16	14.19	13.87	13.99	14.01
10	-8.22	-8.19	-8.16	-8.19	11.22	10.85	11.05	11.04
20	-11.21	-11.09	-11.17	-11.15	7.44	7.17	7.29	7.3
30	-12.92	-12.9	-12.9	-12.9	5.88	5.45	5.65	5.66
35	-14.17	-14.2	-14.19	-14.18	5.1	4.66	4.88	4.88
50	-15.14	-15.17	-15.13	-15.14	4.55	4.13	4.34	4.34

TABLE II: SNR comparison of the input and output images



(a) (b) (c) (d)
(e) (f) (g) (h)
(i) (j) (k) (l)

Figure 10: a, b, c) original sources. d, e, f) 3 mixtures added 10% salt & pepper noise. g, h, i) reconstructed sources using proposed algorithm. J, k, l) enhancement of the results using binarization method.

4. CONSLUSION & FUTURE WORK

In this paper, an optimization procedure on classic approaches for blind source separation is proposed that could be extended into many similar procedures in the field of the image processing. In this approach, by segmenting the colored image to the equal-sized mosaics and optimizing the algorithm for each mosaic, a considerable reduction in the computational complexity and run time of the algorithm has been achieved. In this approach, the results of the each block are used as the initial point of the separation algorithm in the next block. Therefore, both of the computational performance and accuracy of the algorithm are well increased. This algorithm could successfully separate the background effect from the body text and show-through effect. Of course, in most of the cases, it may be unavoidable to use the post processing operations for gaining desired results. In this approach, no registration operation is required. In addition, the high stability against noise is another considerable property of the proposed algorithm. The study is now continued on proposing better approaches to guarantee the stability of algorithm against other kinds of the image noises. In addition, by deriving a two dimensional BSS algorithm, to consider the spatial correlations of the pixels, more than available one dimensional algorithms, the results may become better.

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