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OPTIMAL ADAPTIVE BLUR IDENTIFICATION OF NOISY IMAGES

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Abstract. We present a new blur identification procedure based on a hybrid, two-level evolutionary-deterministic scheme which allows dynamic optimization of the size and the pattern of the support of the point spread function. We demonstrate that the proposed techniques can be generalized to the case of multi-band identification.

Numerical simulations demonstrate the overall priority of the proposed identification scheme with regard to the conventional techniques.

Keywords: Hybrid optimization, genetic algorithms, image processing

1. INTRODUCTION

A fundamental problem of signal/image restoration is the identification of the point spread function (PSF) in the presence of noise ([1], [2]). The basic mathematical approach usually involves the minimization of an appropriate least square-type cost function represented by the weighted sum of an identification error and a "regularization" term (see Refs [1]-[7] for various options).

A versatile number of deterministic standard procedures exists to treat the problem numerically, such as: the steepest descent method, the conjugate gradient method (CGM) and the Gauss-Newton method. Alternative approaches are based on stochastic algorithms such as: simulated annealing [8]-[10], the neural network approach [11]-[12] and the genetics/evolutionary algorithms (GA) [13]-[17]. The power of the GA lies in their ability to dodge a local minimum and to range widely over the entire region. Moreover, the GA are well-adapted to discontinuous functions and patterns. Observe that, in spite of their obvious advantages, the GA often display a low-rate convergence performing better results when combined with deterministic strategies [17]. Actually, such a "hybridization" could produce better results than both the GA and the deterministic approach. Recent results have been obtained by a concatenation of evolutionary programming techniques and the direct set method of Hooke-Jeeves [18], the two-level genetic-quasi-Newton method, a hybridization of the GA with the augmented Lagrangian method [20] and hill-climbing type methods [21].

However, the efficiency of the minimization schemes, as applied to *blur identification*, is characterized by the following salient features. First of all, the problem is *ill-conditioned*, i.e. small variations of the initial data could lead to false solutions. Moreover, there could be multiple solutions (in singular cases) as well [22]. Secondly, the performance of the minimization procedures critically depends on the *support* of the PSF due to the large number of consecutive one-dimensional minimizations in which the initial PSF is slightly modified [1]. It should be noted that most (if not all!) blur identification techniques employ the largest rectangular support being (at best!) sequentially reduced at the boundary (although, for the majority of real applications, the rectangular pattern is oversimplistic). Consequently, the pessimistic assumption of the largest support leads to a significant increase of the computational load. Strangely enough, this approach does not improve the quality of the solution. On the contrary, an overestimated support requires additional "dummy" variables which could generate divergence as well as numerical instabilities or even unwanted convergence to a local minimum.

An accurate estimate of the PSF-support is one of the crucial features which characterizes the performance of an identification scheme. An efficient minimization procedure should be "smart" enough to *recognize* the size and the pattern of the support.

2. ADAPTIVE SUPPORT AND GENETIC ALGORITHM

We present a new two-level procedure based on a concatenation of the CGM and the GA which optimizes the size and the pattern of the PSF- support. The deterministic stage involves CGM minimization steps performed for all members of the population combined with the GA producing the next generation.

Each solution is taken as a pair of a real-valued distortion vector $H \equiv (h_1,\dots,h_M)$ and a binary string $S \equiv (S_1,\dots,S_M)$ corresponding to the pattern of the support. M denotes the maximum size of the support. $S_k = 1$ implies that h_k is regarded as an "active" variable. Consequently, the deterministic minimization is only performed with regard to the active variables (while non-active variables are temporarily "frozen"). Our basic idea is that, on the average, a deterministic minimization performs the best steps when the dummy variables are deactivated! Our genetic algorithm (comprising the survival fitness, the tournament, cross-over and mutation) employs a cost function defined by

$$\varphi = E + w_1 C + w_2 V,\ E \equiv \| f_D - f \|_{L_2},$$

where f_D denotes the distorted signal/image and $f \equiv f(H)$ the signal distorted by the PSF produced at the deterministic stage. $C \equiv C(S,H)$, $V \equiv V(H)$ are the penalty functions corresponding to the imposed constraints $S \in S_p$ (S_P is the set of prescribed patterns and w_1, w_2 are the weighting coefficients).

Note that S_P solely relies on a prior knowledge about the structure of the PSF, whereas $C(S,H)$ involves conditions imposed on the pattern *and* the solution. For instance, we assume that any substring $S \equiv (1,\ldots,1)$ satisfies: length $(S) \geq S_{\min}$ or $h_k < h_{\max}, \forall S_k \in S$. Finally, $V(H)$ corresponds to the conditions imposed on the solution [10], for instance, the normalizing and the positivity conditions $\sum h_k = 1, h_k \geq 0$.

3. APPLICATION

We applied our proposed techniques to the so-called identification-restoration scheme. Suppose that a series of distorted images $f_{D,1}, f_{D,2}, \ldots, f_{D,N}$ is supplemented with at least one original image $f_{O,1}$. Consequently, the first stage involves the identification of the PSF given the pair $(f_{D,1}, f_{O,1})$. The performance of the identification procedure is then estimated by the quality of the subsequent restoration applied to the pairs $(H, f_{D,2}), \ldots, (H, f_{D,N})$. Figs 1a and 1b display the pair $(f_{D,1}, f_{O,1})$ where $f_{D,1}$ is characterized by SNR=25. The corresponding Z-shaped PSF (Fig.1c) is identified by means of the proposed adaptive approach and by standard iterative CG-type techniques using the maximum support. The two versions of the PSF, denoted by H and H_D, are then employed by a standard restoration scheme. The next pair represented by an original (unknown) and a distorted image is depicted in Figs 2a and 2b. The corresponding reconstructed images obtained after 100 iterations with H and H_D are shown in Figs 3a and 3b respectively. Contour plots of the corresponding relative error defined by $E_R \equiv E_R(x,y) = 100\,|f_O - f_R|/f_O$ (f_R denotes the partially reconstructed image) are shown in Figs 4a and 4b. Finally Fig. 5 demonstrates the impact of the SNR (signal/noise ratio) on the convergence of the method.

Clearly, the PSF identified by the proposed algorithm generates a reasonable approximation of the original image characterized by max E_R<4%, whereas the maximum support yields max E_R≈10%. Moreover, the maximum support strategy achieves the accuracy E_R<4% only after 210 iterations. In this sense, the hybrid procedure could be interpreted as a restoration combined with a pattern recognition-type procedure whereas the impact of the dummy variables could be regarded as additional "noise". However, the analogy is far from complete. First of all, in our case, the "noise" is involved in convolution whereas the restoration of noisy images implies additive noise. Secondly, since the size of a distorted image typically exceeds the size of a PSF, the application of the hybrid scheme to the inverse (restoration) problem is unlikely to be practicable.

Finally, although the hybrid scheme could lead to an increase of the iteration steps at the identification stage, it provides a considerable decrease of the computational load required for reconstruction. Clearly, this feature is particularly important in the case of large series of distorted images.

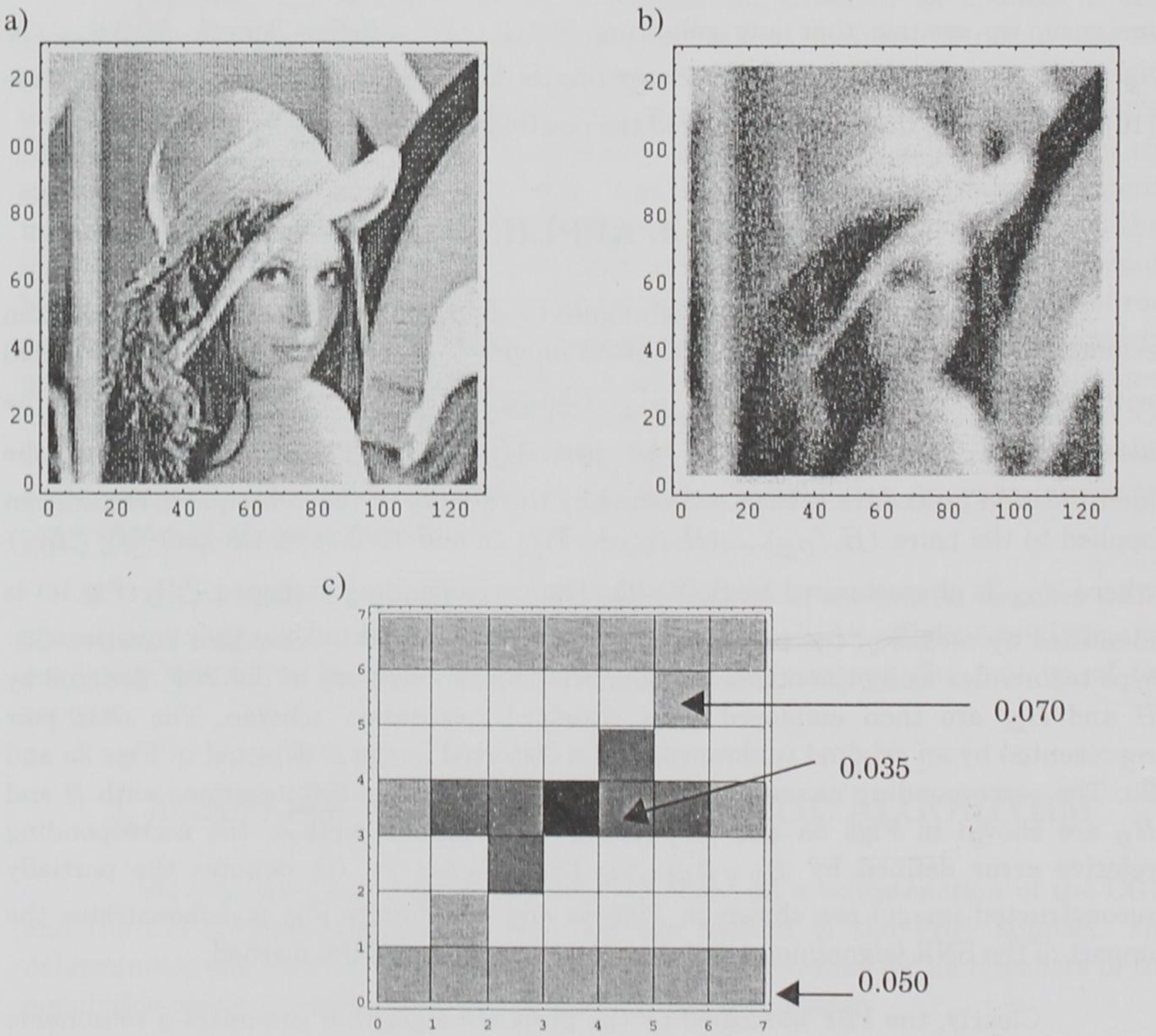

Figure 1. Identification of a PSF: (a) original image, (b) distorted image,(c) Z-shaped PSF- pattern.

a) b)

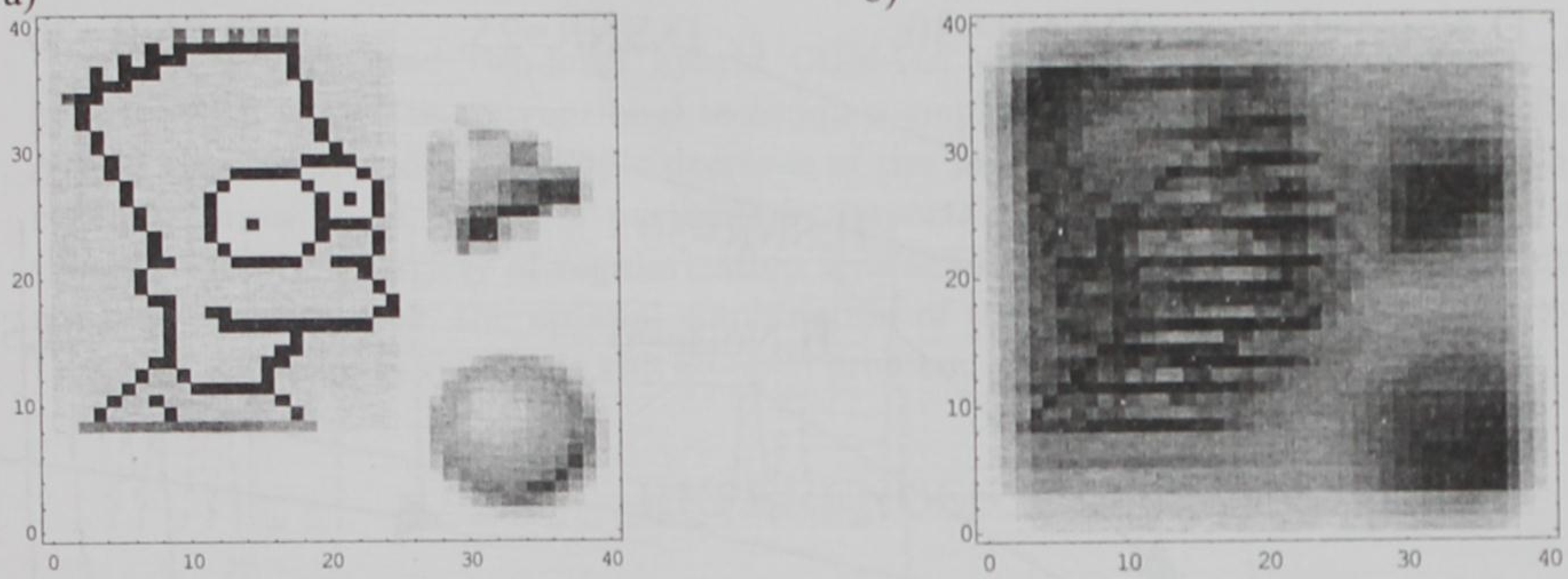

Figure 2. Restoration stage: (a) original image, (b) distorted image.

a) b)

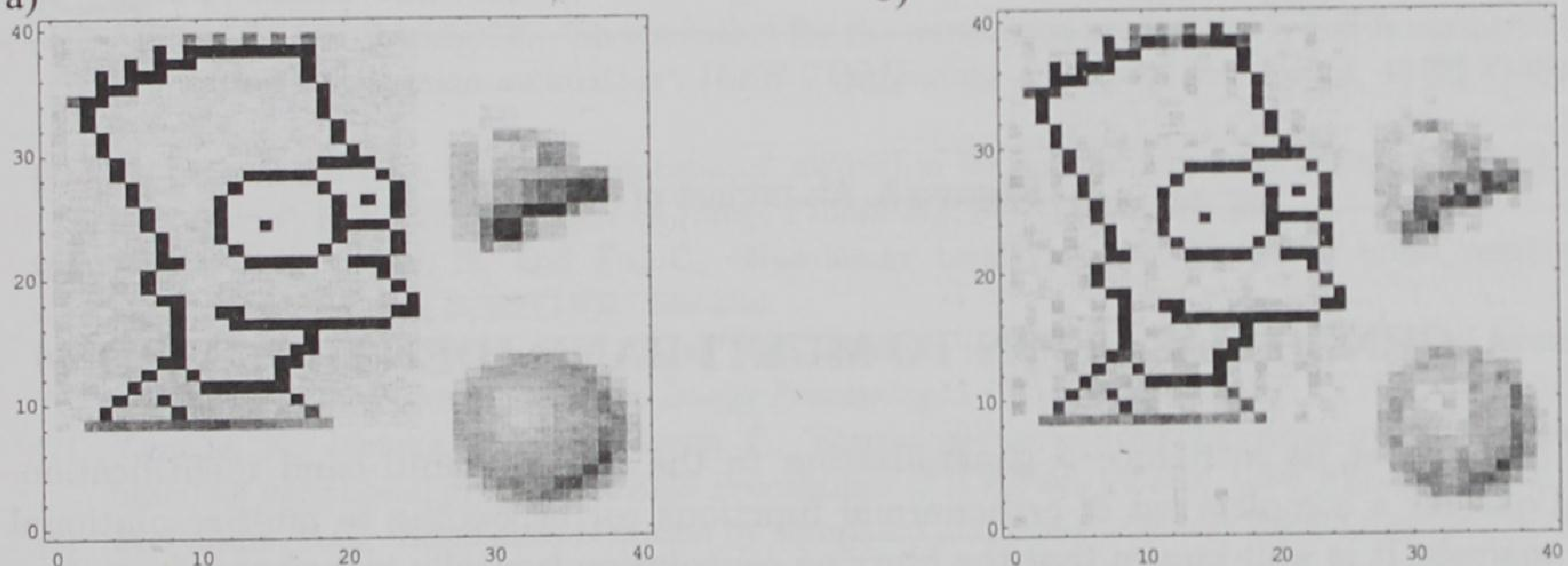

Figure 3. Restoration stage with 100 iterations: (a) hybrid scheme, (b) conventional scheme.

a) b)

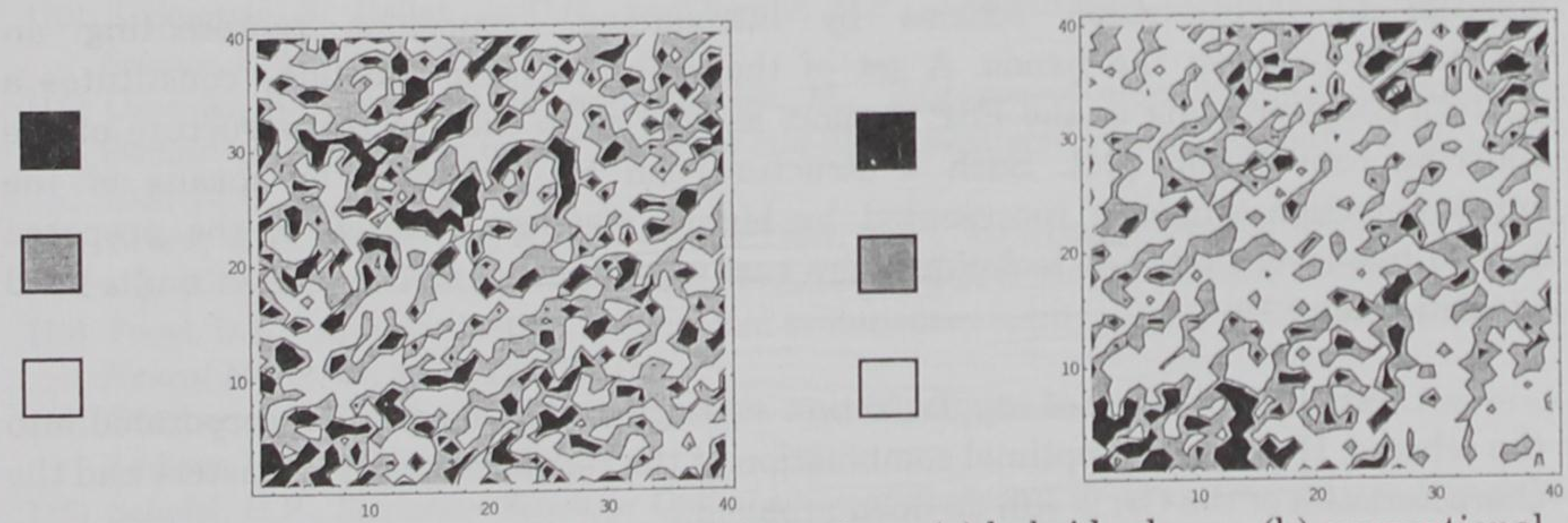

Figure 4. Reconstruction error in %,100 iterations (a) hybrid scheme, (b) conventional scheme.

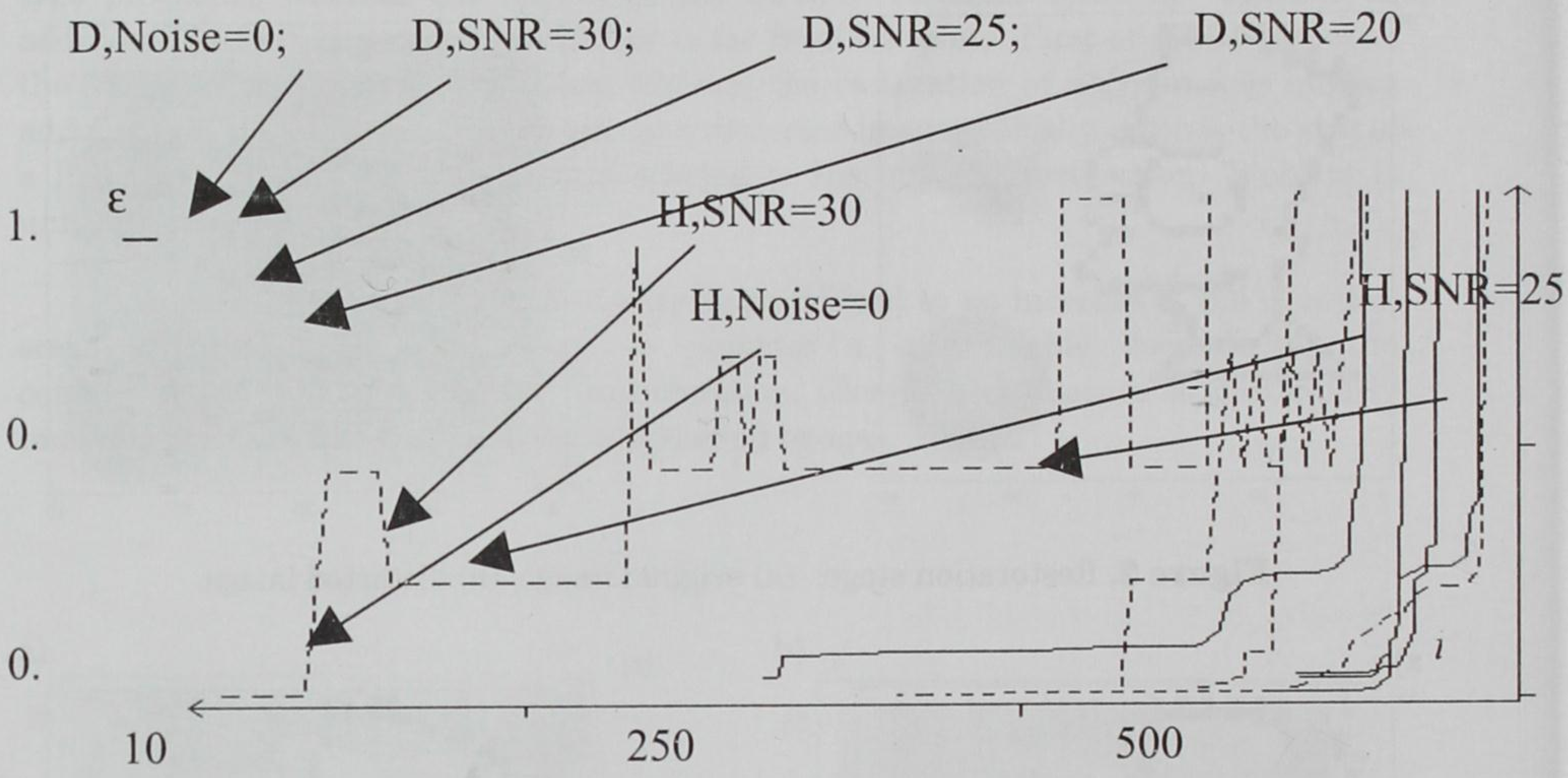

Figure 5. An impact of SNR.

4. GENERALIZATION TO MULTI-BAND IDENTIFICATION

Let us introduce a generalization to the case of multi-band identification. Consider a complete set of orthonormal functions corresponding to multiresolutional analysis. It is well-known that the blurring convolution typically transfers information between the bands [22]. Therefore, the minimization procedure cannot be decomposed into independent minimization with regard to the filtered components of the image. However, the concept of interconnection windowing [23] allows us to construct an appropriate identification scheme by introducing expansions representing an "exchange" between the bands. A set of the required basic functions constitutes a pattern corresponding to the PSF support as well as to the spectral structure of the blurring convolution [24]. Such a structure can be generated by means of the interconnection windows represented by binary matrices. Therefore, the proposed hybrid two-level CGM-GA techniques are easily generalized to the case of multi-band identification.

Finally, a variety of regularization strategies could be easily incorporated into the scheme. However, an optimal combination of the regularization parameters and the characteristics of the GA is still an open problem.

5. CONCLUSIONS

Our proposed two-level hybrid CGM-GA adaptive scheme displays overall priority with regard to conventional techniques employing the maximum support. The hybrid scheme provides a tangible decrease of the computational load required for the reconstruction stage which is particularly important in the case of large series of images. Finally, a variety of regularization strategies could be easily incorporated into the scheme. However, the optimal combination of the regularization parameters and the characteristics of the GA is still an open problem.

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