ADAPTIVE IMAGE RESTORATION USING A LOCAL NEURAL APPROACH

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Abstract: This work aims at defining and experimentally evaluating an iterative strategy based on neural learning for blind image restoration in the presence of blur and noise. A salient aspect of our solution is the local estimation of the restored image based on gradient descent strategies able to estimate both the blurring function and the regularized terms adaptively. Instead of explicitly defining the values of local regularization parameters through predefined functions, an adaptive learning approach is proposed. The method was evaluated experimentally using a test pattern generated by a function *checkerboard* in *Matlab*. To investigate whether the strategy can be considered an alternative to conventional restoration procedures the results were compared with those obtained by a well known neural restoration approach.

1 INTRODUCTION

Restoring an original image, when given the degraded image, with or without knowledge of the degrading point spread function (PSF) or degree and type of noise present is an ill posed problem (Andrews and Hunt, 1977) and can be approached in a number of ways (Sezan and Tekalp, 1990).

Iterative image restoration techniques often attempt to restore an image linearly or nonlinearly by minimizing some measure of degradation such as maximum likelihood (Andrews and Hunt, 1977), or constrained least square error (Gonzalez and Woods, 2001), by a wide variety of techniques. Generally the image degradation model suitable for most practical purposes is formed as a linear process with additive noise for which the matrix form is

$$\mathbf{g} = \mathbf{H}\mathbf{f} + \mathbf{n} \tag{1}$$

Where $\mathbf{g}$ and $\mathbf{f}$ are the lexicographically ordered degraded and original vectors respectively, $\mathbf{H}$ is the degradation matrix, and $\mathbf{n}$ represents the noise. The aim of image restoration algorithms is to find an estimate that closely approximates the original image $\mathbf{f}$, given $\mathbf{g}$.

Blind restoration methods which attempt to solve the restoration problem without knowing the blurring function is of great interest in many important application domains, such as biomedical imaging, characterized by a rapid evolution of imaging devices. In blind methods, both the degradation matrix and the original image are unknown, making the problem difficult to solv based on the observed image only. Many methods have been devised to find these two components by incorporating properly specified knowledge (or constraints) (Kundur and Hatzinakos, 1996). However the use of various stringent constraints for insufficient information in the deconvolution process limits the applications of these methods. In the presence of both blur and noise, the restoration process requires the specification of additional smoothness constraints on the solution. This is usually accomplished in the form of a regularization term in the associated cost function (Katsaggelos, 1991)

Regularized image restoration methods aim to minimize the constrained least-squares error measure

$$E = \frac{1}{2}\|\mathbf{g} - \mathbf{H}\hat{\mathbf{f}}\|^2 + \frac{1}{2}\lambda\|\mathbf{D}\hat{\mathbf{f}}\|^2 \tag{2}$$

where $\hat{\mathbf{f}}$ is the restored image estimate, λ represents the regularization parameter and $\mathbf{D}$ is the regularization matrix. A small parameter value, which deemphasizes the regularization term, implies better feature preservation but less noise suppression for the restored image, whereas a large value leads to better noise suppression but blurred features.

The aim of this work is to define and experimentally evaluate an iterative strategy based on neural learning for blind image restoration in the presence of blur and noise. A salient aspect of our solutions is the local estimation of the restored image based on gradient descent strategies able to estimate both the blurring function and the regularized terms adaptively. Instead of explicitly defining the local regularization parameters values through predefined functions, an adaptive learning approach is proposed. The neural learning task can be formulated as the search for the most adequate restoration parameters related to blurring function and regularization term, through the supply of appropriate local/contextual training examples.

Experiments were conducted using synthetic images for which blur functions and original images are completely known.

2 RESTORATION AS A NEURAL-NETWORK LEARNING PROBLEM

This work proposes an iterative method which uses gradient descent algorithm to minimize a *local* cost function derived from traditional *global* constrained least square measure (Eq. 2). We call this method Local Adaptive Neural Network (LANN).

The degradation measure we consider minimizing is a *local* cost function $E_{x,y}$ defined for each pixel (x,y) in a MxN image:

$$E_{x,y} = \frac{1}{2}[g_{x,y} - h * \hat{f}]^2 + \frac{1}{2}\lambda[d * \hat{f}]^2 \quad (3)$$

where $h * \hat{f}$ denotes the convolution computed in a point (x,y).

The blur function $h(x,y)$ is defined as a bivariate Gaussian function:

$$h(x,y) = \frac{1}{2\pi\sigma(w_x)\sigma(w_y)} e^{-\frac{1}{2}((\frac{x}{\sigma(w_x)})^2 + (\frac{y}{\sigma(w_y)})^2)} \quad (4)$$

where the parameters $\sigma(w_x)$ and $\sigma(w_y)$ are functions whose values represent standard deviations in the range $[m,n]$:

$$\sigma(x;m,n) = \frac{n-m}{1+e^{-a(x-c)}} + m \quad (5)$$

and a and c are logistic function's slope and offset respectively. The parameter $\lambda(w_\lambda)$ is a function whose values represent regularization terms in the range $[0,1]$

$$\lambda(x) = \frac{1}{1+e^{-x}} \quad (6)$$

The range $[0,1]$ is suggested by Katsaggelos and Kang (A. K. Katsaggelos, 1995).

An adaptive neural learning procedure is defined including a non-conventional sub-goal formulated as the search for the most adequate blurring filter size and/or regularization term acting on w_x, w_y and w_λ respectively. Weight updating is performed based on contextual information drawn from a window centered on the current pixel and having dimension $W = \lceil 3\sigma_x \rceil 2 + 1$ and $H = \lceil 3\sigma_y \rceil 2 + 1$.

The restoration algorithm is described in the following (Algorithm 1).

Algorithm 1 Calculate $\hat{f}, \sigma_x = \sigma(w_x), \sigma_y = \sigma(w_y)$ and $\lambda(w_\lambda)$

Require: Scale each pixel of the original gray level blurred image using $(1/2^b - 1)$ as scale factor (b is the number of bits in each pixel of g image)
Require: Initialize w_x, w_y and w_λ to some small random value
Require: Initialize $\hat{f}$ with random values in the range $[0.1, 0.9]$
  repeat
    for $x = 1$ to M; $y = 1$ to N **do**
      select the pixel (x,y);
      compute the new width W and height H of the gaussian kernel;
      compute each partial derivative:

$$\frac{\partial E_{x,y}}{\partial \hat{f}_{s,t}}, \frac{\partial E_{x,y}}{\partial w_x}, \frac{\partial E_{x,y}}{\partial w_y}, \frac{\partial E_{x,y}}{\partial w_\lambda} \quad (7)$$

      update each parameter as follow:

$$\hat{f}^t_{x,y}, w^t_x, w^t_y, w^t_\lambda \quad (8)$$

    end for
  until $(|\hat{f}^t_{x,y} - \hat{f}^{t-1}_{x,y}| < \varepsilon, \forall(x,y))$

To facilitate the algorithm convergence the restored image estimate $\hat{f}$ must be initialized with random values in the range $[0,1]$ obtaining scaling original intensity values.

In principle the algorithm is conceived to estimate simultaneously both the blurring function and the regularization term acting as a complete blind deconvolution method.

The present work investigates experimentally the potentialities and/or limits of the proposed algorithm coping with the restoration task at increasing levels

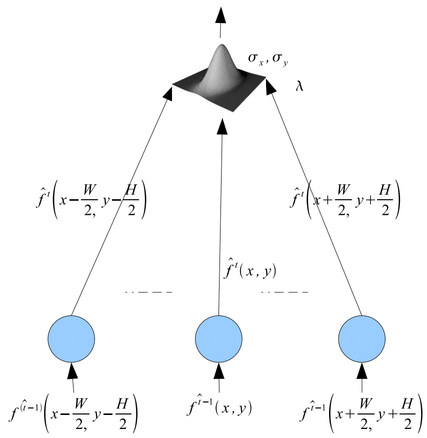
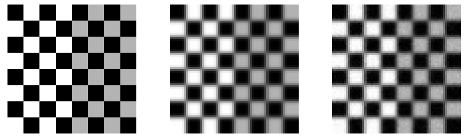


Figure 1: Graphic Representation of the proposed LANN Model



(a) (b) (c)

Figure 2: Original (a), blurred with $\sigma_x = 1$ and $\sigma_y = 1$ (b); blurred image plus Gaussian noise ($\sigma = 5$) (c).

of complexity, i.e. with or without prior knowledge of the blurring function and/or statistics of additive noise.

3 EXPERIMENTS

The method was experimentally evaluated and compared using a test image 64x64 generated by *checkerboard* function in *Matlab* (Gonzalez et al., 2003) (Fig. 2a).

Several experiments were conceived and conducted with the aim of evaluating restoration accuracy under different degradation conditions.

The experiment heuristically assessed the following parameter values: allowing standard deviations min and max values: $n = 3.0$ and $m = 0.2$; ε value for stop condition: 0.0001; w_λ is initialized to a random value in the interval$[-0.1, 0.1]$; w_x and w_y are initialized to a random value in the interval$[-0.6, -0.5]$.

3.1 Restoration in the absence of noise

For these experiments the image was blurred using a Gaussian filter having $\sigma_x = \sigma_y = 1$ (Fig. 2b) while the learning parameters were fixed at $\eta = 0.9$ and $\alpha = 0.5$.

Initially the algorithm was run having fixed all the parameters.

In a second experiment the algorithm was run having fixed the internal parameters related to σ_x and σ_y and varying the parameter related to λ adaptively.

Next the restoration algorithm was run having fixed the internal parameter related to λ and varying parameters related to σ_x and σ_y adaptively.

Finally the algorithm was run varying all the parameters adaptively, while in the last experiment all the parameters were fixed.

To evaluate the restoration performance of our approach quantitatively ISNR and RMSE measures were adopted. These can be estimated as follows:

$$ISNR = 10\log_{10}\{\frac{\sum_{i=1}^{MN}(f_i - g_i)}{\sum_{i=1}^{MN}(\hat{f}_i - f_i)}\} \quad (9)$$

$$RMSE = (\frac{1}{MN}\sum_{i=1}^{MN}(\hat{f}_i - f_i)^2)^{1/2} \quad (10)$$

Results obtained are summarized in Table 1. When applied under favorable conditions of absence of noise, the restoration algorithm shows a good behavior confirming the feasibility of the approach. Increasing the number of free parameters during learning the algorithm shows a stable behavior with less difference among performances.

3.2 Restoration in the presence of noise

For these experiments the image, blurred using a Gaussian filter having $\sigma_x = \sigma_y = 1$, was corrupted by Gaussian noise having standard deviation $\sigma = 5$(Fig. 2c). The learning parameters were fixed at $\eta = 0.01$ and $\alpha = 0.5$.

Initially the algorithm was run having fixed all the parameters.

In a second experiment the algorithm was run having fixed the internal parameters related to σ_x and σ_y and varying the parameter related to λ adaptively.

In a third experiment the restoration algorithm was run having fixed the internal parameter related to λ

Table 1: Results obtained restoring the image shown in Fig. 2b using the proposed LANN model. The grey cells contain fixed parameters.

ISNR	RMSE	time	σ_x	σ_y	λ
11.61	11.91	272s	1.0	1.0	0.0
12.68	11.0	261s	1.0	1.0	0.001
9.68	14.88	316s	0.97	0.95	0.0
8.31	17.42	300s	0.96	0.92	0.002

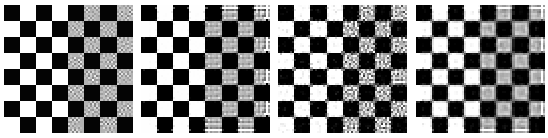


Figure 3: Restoration results in the absence of noise: (a) result by LANN with all parameters fixed; (b) result by Hopfield. Restoration results in the presence of noise: (c) result by LANN with all parameters fixed; (d) result by Hopfield.

and varying parameters related to σ_x and σ_y adaptively.

In the last experiment the algorithm was run laying to vary adaptively all the parameters.

Results obtained are summarized in Table 2.

Under noisy conditions the algorithm registered a decrease in performances evaluated both using ISNR and RMSE indexes for all four cases examined. The behavior is again quite stable, even if a slight decrease in performance was recorded in cases in which blur filter size was free to vary.

3.3 Comparison analysis

The proposed method was compared with the neural restoration method proposed by Zhou *et al.* (Y.T. Zhou, 1988) based on the Hopfield model. Results obtained in non-noisy and noisy conditions are reported in Table 3. Consistently with the LANN method performances are superior in the case of non noisy conditions. Comparing results in Table 3 with those present in the first rows of Tables 1 and 2, our method prevails under non noisy conditions, whereas the Hopfield-based method yielded better performances under noisy conditions.

Visual inspection of images restored by the two methods in Fig. 3 highlights perceptual differences. The image restored by the LANN method lacks the ringing effect that is evident in the other image near the boundary; the image produced by the Hopfield based method appears more smoothed. Focusing on the right half image produced by the LANN method, some artifacts in the gray squares, probably related to initialization conditions, are evident.

Table 2: Results obtained restoring the image shown in Fig. 2c using the proposed LANN model. The grey cells contain fixed parameters.

ISNR	RMSE	time	σ_x	σ_y	λ
3.38	30.92	592s	1.0	1.0	0.0004
3.61	30.09	586s	1.0	1.0	0.06
1.46	38.56	418s	0.82	0.81	0.0004
1.51	38.34	393s	0.81	0.80	0.14

4 CONCLUSION

The objective of this work was a preliminary experimental investigation into the potentialities of a new restoration method based on neural adaptive learning.

Results obtained demonstrate the feasibility of the approach. Limitations of the method in terms of restoration quality and computational complexity are evident dealing with noisy images.

Further investigations and improvements of the method are planned focusing on faster neural learning, initialization conditions and robustness in handling different levels of noise.

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Table 3: Results obtained restoring the images shown in Fig. 2b-c using the Hopfield model proposed by Zhou. The grey cells contain fixed parameters.

ISNR	RMSE	time	σ_x	σ_y	λ
7.827	18.417	323 s	1.0	1.0	0.0
4.97	25.73	264s	1.0	1.0	0.0004