Multiscale Image Restoration Approach: Neural Network Based

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In practice, there is not a perfect imaging system, and thus many acquisition systems produce degraded images. Restoration techniques are applied to compensate system degradations such as motion blur, atmospheric turbulence, and optical diffraction (Kulkarni, 2001). The development of techniques for noise removal is very important for image–based measurement systems. The noise present in the images may significantly decrease the accuracy of the operations such as feature extraction and object recognition. Regarding this, Gaussian-like distribution noise is very often found in acquired data (Heijeden, 1994).

Many methods for image restoration have been suggested, including the inverse filter, the Wiener filter, the moving-average filter, the parametric Wiener filter, mean-squared-error filters, the singular-value decomposition technique, and the band-pass filter (Gonzalez and Wood, 1992), and the regularization filter (Bertero & Boccacci, 1998). All of these methods consider the imaging systems are characterized by the standard model $g \ ? \ h * f \ ? \ n$ that is applicable to a large variety of image degradation processes. In this model, h represents a known space-invariant blur kernel (point spread function), f is an ideal version of the observed image, and n represents the noise (usually Gaussian). Restoration techniques deal basically with inversion of the degrading process. Software implementations of conventional restoration methods are often time consuming and not useful for real-time applications. Since the late 1980s, a few artificial neural network (ANN) models for image restoration have been suggested (Zhou et. Al, 1988; Michaelis, 1996; Yuksel, 2005; Wu et. Al., 2006). The model suggested by Zhou et al. uses the Hopfield network, whereas the model suggested by Kulkarni is a six-layer feed-forward network based on the singular value decomposition technique (Kulkarni, 2001).

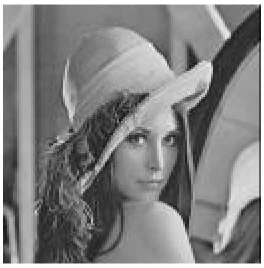
This paper describes an ANN based multiscale image restoration approach. Multilayer perceptrons are trained with artificial images of gray level degraded circles, in an attempt to make the neural network learn inherent space relations of pixels when degraded with the corresponding non-degraded pixels. Different degradation sources may alter the quality of an image. The present approach simulates the degradation by a low pass Gaussian filter blurring operation and adding noise to the pixels at pre-established rates. The training process considers the degraded image as input and the non-degraded image as output for the supervised learning process. The neural network thus performs an inverse operation by recovering a quasi non-degraded image in terms of least squared. The learning process is generalized to different images. The main difference of the approach to existing ones relies on the fact that the space relations are taken from different scales, thus providing relational space data to the neural network. The approach is an attempt to come up with a simple method that leads to an optimum solution to the problem. Considering different window sizes around a pixel simulates the multiscale operation. In the generalization phase the neural network is exposed to indoor, outdoor, and satellite images degraded with the same steps of the artificial circle image. For comparison, the corrupted test images are also filtered by using the conventional and noise removal operator including the Wiener filter (WF). The results show that approach is able to restore the images to a very low error rate (see, Table 1.a., 1.b. and Figure 1).

Table 1.a. Statistics of the images

	Original Image (OI)	Wiener Filter (WF)	Neural Network (ANN) 90% Similarity	Neural Network (ANN) 95% Similarity
Mean	124.0826	124.1155	124.4532	124.2804
Variance	115.1851	114.0722	114.8243	114.4388

Table 1.b. Filtering errors

	WF x OI	NN (90%) x OI	WF x NN (90%)	NN (95%) x OI	WF x NN (95%)
EQM	6.5212	6.1710	3.6852	6.2447	3.7261
Diff. mean	-0.0329	-0.3706	-0.3377	-0.1978	-0.1649
Diff. Var.	1.1129	0.3608	-0.7521	0.7462	-0.3666


(a)

(b)

(c)

(d)

(e)

Figure 1. Image test for net generalization: (a) original image; (b) image corrupted with Gaussian noise and adding noise with 1% noise density; (c) result of restoration by Wiener filter with 3x3 neighborhood; (d) Result obtained by neural network with 3x3 window size and similarity (90%); (e) Result obtained by neural network with 3x3 window size and similarity (95%).

The experiment presented in this work employed the neural network trained with data obtained from a synthetic image with 256 gray levels. The size of the employed sliding window was 3x3 and the image was corrupted with the Gaussian and additive noise with 1% rate. The corrupted image was linearized and a data mining clustering technique was applied to reduce the number of input vectors for the training process. The data was clustered using a fuzzy similarity relation targeting 90% and 95% similarity among vectors. The trained network was than exposed to real images of different scenes. Figure 1 shows the results of applying the network to one of the images (Lena) considered in the experiment. It can be observed that there is a very small increase in brightness and a small reduction in contrast when compared to the original image. Through the error analysis between the original and the ANN images, it can be observed that the ANN results are satisfactory and promising when compared with the Wiener filters results, as can be observed, from the quantitative analysis of the mean, the variance, and the mean square error (MSE) of the ANN restoration and the original image in Table 1.

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