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Image Restoration Using M-Flann

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Abstract : In this paper a Modified Functional Link Artificial. Neural Network (M-FLANN) is proposed which is simpler than a Multilayer Perceptron (MLP). It have been implemented for image restoration in this paper. Its computational complexity and speed and generalization ability to cancel Gaussian noise is compared with that of MLP. In contrast to a feed forward ANN structure i.e. a multiplayer perceptron (MLP) the M-FLANN is basically a single layer structure in which non-linearity is introduced by enhancing the input pattern with nonlinear function expansion. With the proper choice of functional expansion in a FLANN problem of denoising of an image. In the single layer functional link ANN (FLANN) the need of hidden layer is eliminated.The novelty of the FLANN structure is that it requires much less computation than that of MLP. In the presence of additive white Gaussian noise, salt and pepper noise, Random variable impulse noise and mixed noise in the image the performance of the proposed network is compared with that of MLP in this thesis. The Performance of the of algorithm is evaluated for six different situations i.e. for single layer neural network, MLP and four different types of expansion in FLANN and comparison in terms of computational complexity also carried out

1. INTRODUCTION

The field of digital image processing refers to processing digital images by means of a digital computer. There are no clear-cut boundaries between image processing and computer vision. An image processing system consists of a source of image data, a processing element and a destination for the processed results. Different noises added in this image are additive white Gaussian noise, Exponential Noise, Uniform Noise, and Periodic Noise salt and pepper noise, Rayleigh Noise, Erlang Noise etc.
In this paper various noise conditions are studied and an efficient nonlinear and adaptive digital image filters are designed to suppress salt and pepper noise. The developed filter may use for offline or for online applications.

The most popular nonlinear filter is the median filter. It is computationally efficient, but one disadvantage is that the edge of image obtained will blurred.

Adaptive neural network filter remove various types of noise such as Gaussian noise and impulsive noise. Single layer neural network accurately detects the impulse noise of fixed amplitude. However it dose not perform well in case of random value impulse noise. An ANN threshold-filtering scheme is an adaptive filter.

Recently artificial neural network (ANN) have emerged as a powerful learning technique to perform complex tasks in highly nonlinear environment . Some of the advantage of ANN model are (i) there ability to learn based on optimization of an appropriate error function (ii) there excellent performance for approximation of nonlinear functions.

As an alternative to the MLP there has been considerable interest in radial basis function (RBF) network in . The RBF networks can learn functions with local variations and discontinuities effectively and also possess universal approximation capability.
This network represents a function of interest by using members of a family of compactly or locally supported basic functions, among which radially symmetric Gaussian functions are found to be quite popular. A RBF network has been proposed for effective identification of non-linear dynamic system. But in these network choosing an appropriate set of RBF centres for effective learning is still remains a problem.

The functional link artificial neural network (FLANN) by Pao can be used for function approximation and pattern classification with faster convergence and lesser computational complexity than a MLP network.

A FLANN using sin and cos functions for functional expansion for the problem of nonlinear dynamic system identification has been reported. Pattern classification using Chebyshev neural networks has been reported in . A Chebyshev polynomial based unified model ANN for static function approximation is reported, which is based on FLANN with Chebyshev polynomial expansion in which recursive least square-learning algorithm is used. It is pointed out that this network has universal approximation capability and has faster convergence than a MLP network.

In this thesis we proposed a FLANN structure similar to i.e. a Chebyshev polynomial-based unified model ANN for denoising in an image corrupted with additive white Gaussian noise. Generally a linear node in its output is used in the FLANN structure reported by other researchers. In our proposed network, we have used a nonlinear node with tanh () non-linearity in the output layer for better performance.

Let $X(m,n), Y(m,n)$ be the original noise free image, noisy image respectively. Image be of size $M \times N$ pixel, i.e. $m = 1,2,3,4..........M$ and $n = 1,2,3,4........N$.

$$MSE = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N}\left(X(m,n) - Y(m,n)\right)^2}{M \times N}$$

(1.1)

$$Noisepower = 10 * \log(MSE)$$

(1.2)

$$PSNR = 10\log_{10}\left(\frac{1}{MSE}\right)$$

(1.3)

When some operation like filtering done on an image we get another image. To study how much noise reduce from the operation NRDB is use. NRDB usually expressed in dB, given by:

$$NRDB = 10.\log_{10}\left(\frac{MSE_{in}}{MSE_{out}}\right)$$

2. Simulation Results

Here results after addition of different type of noises, which is usually added in an image. For which it is it is very important to study what type of noise is present in corrupted image before going to apply the proper filter.

Additive white Gaussian noise (AWGN) of mean zero and different variance is added to an image. The more the noise added to the image it gets more and more invisible i.e. its quality degraded.

Salt & pepper noise of different density is added to 'Lena' face image. If the original image be I and salt and pepper noise of density D is added, then it affects approximately D*PROD (SIZE (I)) pixels. Then both salt and pepper of density 10 and AWGN noise of mean 0 and variance of 0.01 is added to an image. Finally Random value impulse noise (RVIN) is added to an image.

Then for study the speckle noise was done. Addition of speckle noise to an image. It is also know as multiplicative noise. If I is the image, n be uniformly distributed random number with mean 0 and variance V, then new image will be j. The pixel value of new image will be $J = I + n * I$.

Let $X(m,n), Y(m,n)$ be the original noise free image, noisy image respectively. Image be of size $M \times N$ pixel, i.e. $m = 1,2,3,4..........M$ and $n = 1,2,3,4........N$.

$$MSE = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N}\left(X(m,n) - Y(m,n)\right)^2}{M \times N}$$

(3.7)

Then Noise power will be $10 * \log(MSE)$

$$PSNR = 10\log_{10}\left(\frac{1}{MSE}\right)$$

(3.8)

Then some experiment is done to find out the degradation in quality of an image. In this experiment Gaussian noise of mean 0 and different variance is added to an image and Noise power, Peak signal to noise ratio of the noisy image was calculated. The same process is repeated for salt and pepper noise, presence of both noise and random value impulse noise.

There are different methods of finding how much an image is corrupted by noise. It may be found by using the error image or by finding the noise power of the image. Error image is the difference of the noisy image and the original image. But it will not give any clear idea how much an image is corrupted by the noise. So we will go for noise power in an image. Noise power in an image will be found form the equation. Then Noise power will be $10 * \log(MSE)$

First an image is taken and Gaussian noise of different variance and salt and pepper noise of different density is added. The main objective of this experiment is to find out, when the value of noise power in an image will be same for the two cases. By doing this experiment it can be conclude Gaussian noise of mean zero and variance of 0.0225 will corrupt an image equally, when it corrupted with salt and pepper noise of density 0.0683.

3. Adaptive and Non-adaptive Spatial Filters

Digital image filters may be linear or nonlinear in nature. Linear filters are the simplest filter used for noise suppression in an image. Certain advantage of linear filter is that its computational complexity is very low due to which it is easy to use and easy to implement. But major disadvantage is that it performance is poor for highly nonlinear situations. When this filter is used for noise suppression, the image gets blurred at the edges. To overcome these types of problems in linear filters, various nonlinear filters have been proposed. There are different types of nonlinear filters in terms of their characteristic.

For doing spatial filtering image is divided into number of sub images. This sub images in an image are called as filter mask, kernel, template or window. The values in a filter sub image are referred to as coefficients rather than pixels. The general, linear filtering of an image of size $M \times N$ with a filter mask of size m, n is given by expression.

$$g(x, y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t)\, f(x+s, y+t) \tag{4.1}$$

Where $a = (m-1)/2$ and $b = (n-1)/2$ For $x = 0,1,2,3.....m-1$ and $y = 0,1,2,3,........n-1$.

Different noise reductions spatial filters like moving average filter, median filter, and rank order mean filter are developed to suppress additive white Gaussian noise, impulse noise which also called as salt and pepper noise (S&P), random-valued impulse noise and mixed noise i.e. additive white Gaussian noise and salt and pepper quite effectively. The developed filters are used for offline applications.

4. Modified Functional link Artificial Neural network.

Neural Network (M-FLANN) is proposed in this thesis which is simpler than a Multilayer Perceptron (MLP) works like the universal approximation capability of Functional Link Artificial Neural Network (FLANN). MLP and M-FLANN have been implemented to denoising an image corrupted with Gaussian noise. Their convergence speed and generalization ability have been compared. The results show that M-FLANN which is computationally cheap, performs better and has greater generalization ability than MLP..

Multilayar Perceptrons (MLPs) are the most common type of neural networks employed in process modeling. MLPs have been successfully applied for adaptive identification and control of a variety of nonlinear processes .

Direct Linear Feed-through (DLFANN) neural network combines conventional MLP neural network architecture with a set of linear terms to produce a network for modeling both linear and nonlinear systems simultaneously. Lee and Holt applied direct linear feed-through (DLF) network for modeling of spectroscopic process data. DLF neural network offers many advantages over the conventional multilayer feed-forward networks for process modeling and control.

In Functional Link Artificial Neural Networks (FLANNs), the hidden layer is removed without giving up non-linearity by providing the input layer with expanded inputs that are constructed as the functions of original attributes. Removal of hidden layer makes these networks extremely simple and computationally cheap. Identification of nonlinear processes u sing FLANNs has been reported by researchers . FLANNs have an inherent limitation, of not guarantying universal approximation, which has deterred interest in them. Only a few applications using FLANNs are available in literature. Therefore, this has been a major motivating factor for modifying FLANN and improving upon its approximation ability.

In this work, a Modified Functional Link ANN(M-FLANN) is proposed which is not only simpler than a MLP but also improves upon the universal approximation capability of FLANNs. MLP and its variants (DLFANN, FLANN, M-FLANN) have been implemented to model a simulated Water Bath System and a Continually Stirred Tank Heater (CSTH). The convergence speed, interpolation, and extrapolation ability of the four networks is verified.

In this work, the FLANNs have been modified to improve upon their approximation ability while still maintaining advantages obtained by reduction in computational complexity.

5. Different Functional expansion used in M-FLANN.

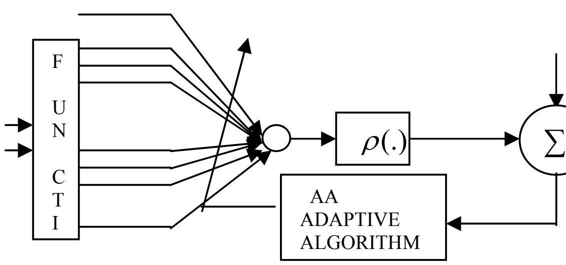
5.1 Trigonometric Functional expansion

Here the functional expansion block make use of a functional model comprising of a subset of orthogonal sin and cos basis functions and the original pattern along with its outer products. For example, considering a two dimensional input pattern $X = [x1x2]^T$, the enhanced pattern is obtained by using a trigonometric functions as

Which is then used by the network for the equalization purpose. The BP algorithm, which is used to train the network, becomes very simple because of absence of any hidden layer.

5.2 Chebyshev expansion

In this study we used Chebyshev polynomial for functional expansion. These polynomials are easier to compute than that of trigonometric polynomials. Here in our study, we found superior performance by using CFLANN. The FLANN structure consider for denoising purpose using Cebyshev functional expansion is depicted here.



The first few Chebyshev polynomials are given by $T_0(x) = 1.0,\ T_1(x) = x$ and $T_2(x) = 2x\char`^2 - 1$. The higher order Chebyshev polynomials may be generated by the recursive formula given by:

$T_{n+1}(x) = 2xT_n(x) - T_{n-1}(x)$.

5. 3 The structure of the FLANN and M-FLANN network:

The structure of FLANN having trigonometric expansion is:

x_0

+1

x_1 x_1

x_2

$\cos(\pi x_1)$

$\sin(\pi x\ )$

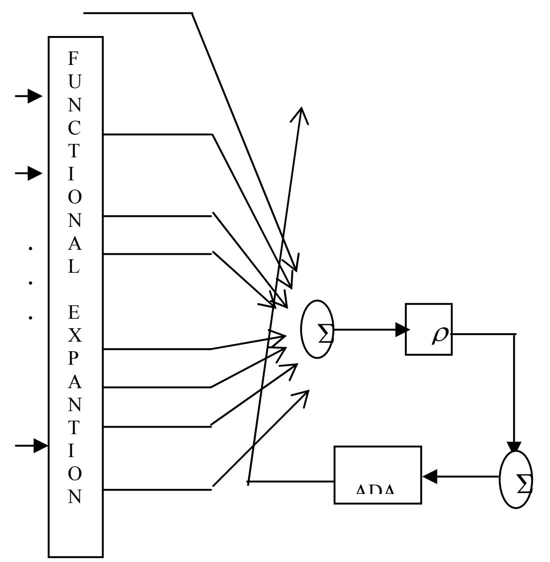
x_2

$\cos(\pi x_2)$

$\sin(\pi x_2)$

x_9

$\sin(\pi x_9\ )$



7. The structure of the M-FLANN network:

It can be seen that the output neurons have self-feedback .It means a dummy output needs to be added for successful implementation of M-FLANN. Further, though the network still has no hidden layer, it is no longer a true feedforward neural network as feedback connections are present.

The output neurons of M-FLANN contain self feedback connections. It means a single hidden layer MLP neural net is equivalent to the M-FLANN network.

M-FLANN whereby it computes the output y' from the original FLANN inputs ψ i (x) , using the equation

$$yk = Gk \sum_{j=1}^{d'} Wik * \Psi i\,(x)$$

The output layer neurons have linear activation function, as their purpose is only to represent the combination of outputs from the self feedback connections in the output layer of M-FLANN, given by equations below.

y = w.y1
where w is the self feedback interconnection weight.
Leaving out inputs at this stage saves significant computational overhead as well as the unnecessary repeated computation step. The equivalent network is akin to a Multilayer Perceptron, and therefore, can make use of any gradient descent based learning algorithm for training.
The inputs of M-FLANN can be expanded using trigonometric or chevsheb polinomials. The proposed neural network is superior to other neural architectures in many respects. M-FLANN has a systematically laid down procedure for selecting its architecture details.

8. Simulation Results

Experiment-1
In this experiment computer simulations are carried out to evaluate the performance of Functional link neural network with exponential functional expansion for denoising of image corrupted with Salt and Pepper noise of mean zero and different variance. Here the 9 inputs of this network were the entries of 3X3 window of the noisy image and the target was the corresponding pixel value of the original image.

TABLE:

Gaussian Noise Mean zero and Variance	Noise Power at Input of FLANN Filter	Noise power at output of FlANN Filter	PSNR at Input of FLANN Filter	PSNR at Output of FLANN Filter	Noise Power Attenuated By the Filter in dB
0.01	0.0429	0.00762	16.5456	26.6325	7.5
0.02	0.0339	0.00724	17.1014	25.6989	6.7
0.04	0.0281	0.00756	16.0198	23.6656	5.7

ORIGINAL IMAGE

NOISY IMAGE

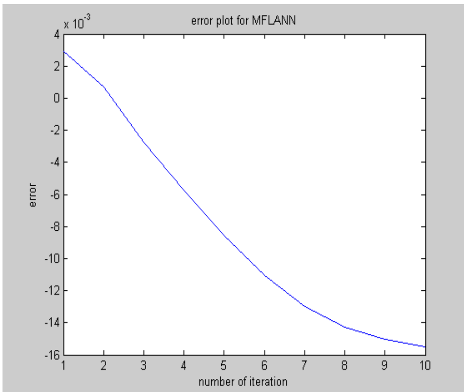
IMAGE PASS THROUGH M-FLANN

Experiment-2

In this experiment its tried to cancel noise by using M-FLANN network. First the noisy Cameraman image is pass through the single layer neural network and the target be the original cameraman image. Image is corrupt with Gaussian noise of mean 0 and variance 0.01. After passing through M-FLANN network the image obtain will be shown here. It is clear from result that image obtain is objectively better.

Experiment3

In this experiment computer simulations are carried out to evaluate the performance of Modified Functional link neural network with trigonometric functional expansion for denoising of image corrupted with Salt and Pepper Noise of 10 percent density.



4.11 Conclusion:

It has better convergence speed than MLP. It has no hidden layer, is computationally cheap and has small number of interconnection weights and biases, which makes it suitable for on-line applications. Also, M-FLANN makes use of linear terms, just as used in FLANNs and is able to approximate linear as well as nonlinear functions. From the results obtained in the work, it is concluded that the M-FLANN is computationally cheap and has small convergence times and denoise an digital image more efficiently than MLP.M-FLANN improves upon the approximation ability of FLANN. Therefore, it is expected that M-FLANN is likely to re-ignite the interest of research community in FLANNs.

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