



Noise Reduction Models in Neural Networks: A Review

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Abstract— This paper describe the development of the neural network models for the noise reduction. These types of the networks used to enhance the performance of multimedia images by reducing the effect of noise. To remove the blurriness and noise from multimedia objects, the Recurrent and Multilayer backpropagation networks can be used. With the help of Gradient descent backpropagation (traingd) and Gradient descent with momentum backpropagation (traingdm) the performance of multimedia images can be increased by removing the effect of noise.

Keywords— Noise reduction, recurrent neural networks, multi-layer backpropagation, neural networks, robust ASR.

I. INTRODUCTION

An Artificial Neural Network is an information processing system that is based on human nervous systems, such as the brain and process information. The key element of this system is the novel structure of the information processing system. It is the composition of large number of highly interconnected processing elements (neuron) working in unison to solve specific problems.

Image noise is an unwanted information in an image that can occur at any moment of the time such as during image capture, transmission or processing. In order to remove the noise from the distorted image, we must have the knowledge about the nature of noise must be known otherwise noise removal cause the image blurring. The original meaning of "image noise" was "blurring images" that can be captured from the videos. Image noise is random (not present in the object imaged) variation of brightness or color information in images, and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of a scanner or digital camera.

In image noise there are the different neural networks models (Recurrent network, multi-layer backpropagation, Recurrent Neural Networks for Noise Reduction in Robust ASR) have been compared to minimize the effect of noise. In this paper, two different NN architectures are employed. These are Recurrent Neural Networks (RNNs) and MultiLayer Neural Networks (MLNNs). Both networks are trained with five training algorithms. The training functions used are:

- 1) Gradient descent backpropagation (traingd)
- 2) Gradient descent with momentum backpropagation (traingdm)
- 3) Gradient descent with adaptive lr (learning rate) backpropagation (traingda)
- 4) Gradient descent w/momentum and adaptive lr backpropagation (traingdx)
- 5) Levenberg Marquardt backpropagation (trainlm).

This research is an attempt to employ ANN for the enhancement of the measured corrupted images and reduce the noise. The main contribution includes the following:

- The input training sequences to the designed NNs are assumed to be a composition of the desired image plus an additive white Gaussian noise. This assumption speeds up the learning process and improves the approximation of the desired model [2].
- The development and comparison of NN architectures for use in noise reduction applications.
- A comparison of modeling performance using multi-layer and recurrent NNs.
- An examination of the relationship between training performance and training speed with the training algorithm used for a given NN architecture.

II. RECURRENT NEURAL NETWORK

The human brain is a type of recurrent neural network *i.e.* network of neurons with feedback connections. It can be learned by different methods such as behaviors, sequence processing tasks, algorithms and programs that can't be learned by traditional machine learning methods. The designed RNN is called Elman network. Elman networks are two-layer backpropagation networks, with the addition of a feedback connection from the output of the hidden layer to its input. This type of feedback path allows Elman networks how to learn, how to recognize and generate temporal patterns as well as spatial patterns in ANN's.

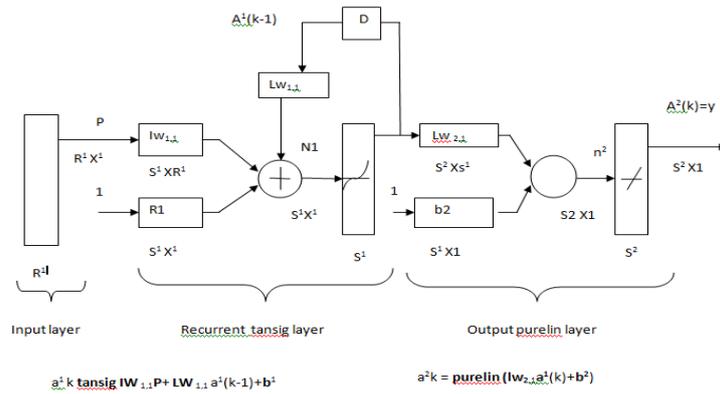


Figure 1. The architecture of Elman network

The Elman network constructed has tansig neurons in its hidden (recurrent) layer, and purelin neurons in its output layer, shown in Figures 2 and 3, respectively. The numbers of neurons in the hidden and output layers are 10 and 1, respectively. The hidden units and the output unit also have biases. These bias terms act like weights on connections from units whose output is always 1. The bias gives the network an extra variable, and so the network with bias is expected to be more powerful than those without [10]. This combination is special in that two-layer networks with these transfer functions can approximate any function (with a finite number of discontinuities) with arbitrary accuracy.

Elman network performs the following:

1. The input units receive the first input.
2. Both the input units and context units (group of units that receives feedback signals from the previous time step [8]) activate the hidden units.
3. The hidden units also feedback to activate the context units (copying the content of the hidden unit).
4. The output units is compared with a teacher input (desired output) and backpropogation of error is used to incrementally adjust the connection strength.

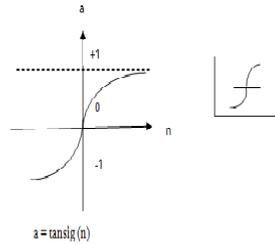


Figure 2. Tansig transfer function

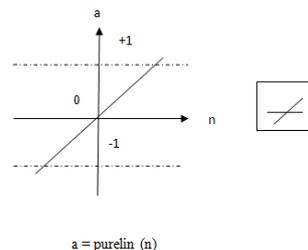


Figure 3. Pureline transfer function

III. MULTILAYER BACKPROPAGATION NEURAL NETWORK

A Multilayer Backpropagation NN is designed with three layers as shown in Figure 4. The feed forward network has two hidden layers of tansig neurons followed by an output layer of purelin neurons. The numbers of neurons in the first and second hidden layers. The hidden units and the output unit also have biases. These bias terms act like weights on connections from units whose output is always 1.

Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationship between input and output vectors. The back propagation model is multilayered since it has distinct layers. The neurons within each layer are connected with the neurons of the adjacent layers through directed edges. There are no connections among the neurons within the same layer.

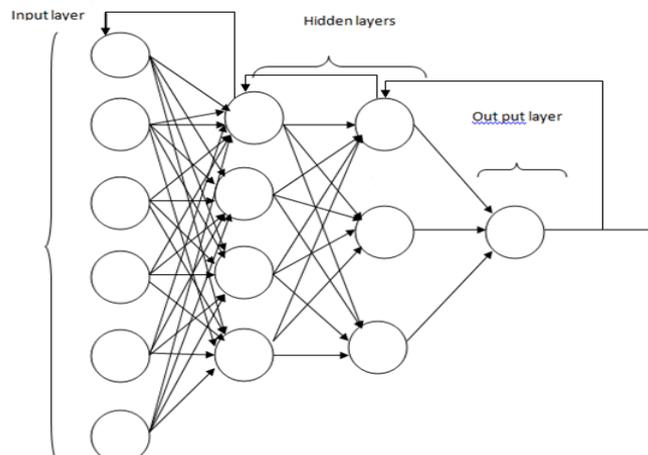


Figure 3. The Architecture of Multi-layer Back propagation neural network

1. Gradient descent backpropagation (traingd)

The batch steepest descent training function is traingd. The weights and biases are updated in the direction of the negative gradient of the performance function. To train a network using batch steepest descent, we can set the network trainFcn to traingd, and then call the function train. There are seven training parameters associated with traingd algorithm given below :-

- o Epochs
- o Show
- o Goal
- o Time
- o min_grad
- o max_fail
- o lr

2. Gradient descent with momentum backpropagation (traingdm):

Gradient descent with momentum, implemented with traingdm, allows a network to respond not only to the local gradient, but also to recent trends. Like a lowpass filter, momentum also allows the network to ignore small features in the error surface. Without momentum a network can get stuck in a shallow local minimum. With the help of momentum a network can slide through such a minimum.

Gradient descent with momentum depends on two training parameters. The parameter lr indicates the learning rate like a simple gradient descent. The parameter mc is the momentum constant that defines the amount of momentum. mc is set between 0 (no momentum) and 1 (lots of momentum). A momentum constant of 1 results in a network that is completely insensitive to the local gradient and therefore, does not learn properly.

3. Gradient descent with adaptive lr (learning rate) backpropagation (traingda)

In adaptive learning some changes can be made in the training procedure by using traingd. Initially network output and error are calculated. At each epoch new weights and biases are calculated using the current learning rate. Then at last new outputs and errors are calculated.

As with momentum, if the new calculated error exceeds the old calculated error by more than a predefined ratio, max_perf_inc (typically 1.04), then the new weights and biases are ignored. In addition, the learning rate is decreased (typically by multiplying by lr_dec = 0.7). If the new error calculated is less than the old error, the learning rate is increased (typically by multiplying by learning_rate_inc = 1.05).

4. Gradient descent w/momentum and adaptive lr backpropagation (traingdx)

The function traingdx combines adaptive learning rate with momentum training. It is applied in the same way as traingda, except that it has the momentum coefficient (mc) as an additional training parameter. Traingdx can be used to train any network as long as its weight, net input, and transfer functions have derivative functions. Backpropagation algorithm is used to calculate the derivatives of performance perf with respect to the weight and bias variables X. Each variable is adjusted according to gradient descent with momentum.

5. Levenberg Marquardt backpropagation (trainlm)

Another objective is to evaluate the performance of LMBP as a hybrid IQM. To achieve these objectives, a number of objective assessments was conducted and compared to a corresponding subjective assessment. Afterward, this measurement data were combined and used as the input vectors to Levenberg - Marquardt Back-propagation network.

The application of Levenberg Marquardt backpropagation: This algorithm is the fastest method for training moderate-sized feed-forward neural networks (up to several hundred weights). This algorithm has an efficient implementation in MATLAB software. The matrix equation solution can be built-in function, so its attributes become more pronounced in a MATLAB environment [10].

IV. REMOVING NOISE FROM IMAGE BY FILTERING

Image noise is an unavoidable side-effect occurring as a result of image capture, more simply understood as inaudible, yet inevitable fluctuations. In a digital camera, if the light which enters the lens misaligns with the sensors, it will create image noise. If sometime noise is not so obviously visible in a picture, some kind of image noise is bound to exist. Every type of electronic device receives and transmits some noise and sends it on to what it is creating.

When the images are transmitted over channels, they are corrupted with impulse noise due to noisy channels. This impulse noise consists of large positive and negative spikes [3]. The positive spikes have values much larger than the background and thus they appear as bright spots, while the negative spikes have values smaller than the background and they appear as darker spots. Both the spots for the positive and negative spikes are visible to the human eye. Also, Gaussian type of noise affects the image. Thus, filters are required for removing noises before processing. There are lots of filters in the paper to remove noise. They are of many kinds as

- 1) linear smoothing filter
- 2) median filter,
- 3) wiener filter
- 4) Fuzzy filter.

In this filtering technique, the three primaries (R, G and B) are done separately. It is followed by some gain to compensate for attenuation resulting from the filter. The filtered primaries are then combined to form the colored image [4]. This process is very simple. This approach is shown in figure 1.

1) Linear Filters:

The most common, simplest and Fast kind of filtering is achieved by linear filters. The linear filter replaces each pixel with a linear combination of its neighbours and convolution kernel is used in prescription for the linear combination s.

Linear filtering of a signal can be expressed as the convolution .

$$y(t) = \int_{-\infty}^{\infty} (h(r) \cdot x(t - r) dr)$$

of the input signal x(n) with the impulse response h(n) of the given filter, i.e. the filter output arising from the input of an ideal Dirac impulse .Now from fig. it is clear that image filtering is done by applying function and when we apply linear filtering then each pixel is replaced by linear combination of its neighbour.

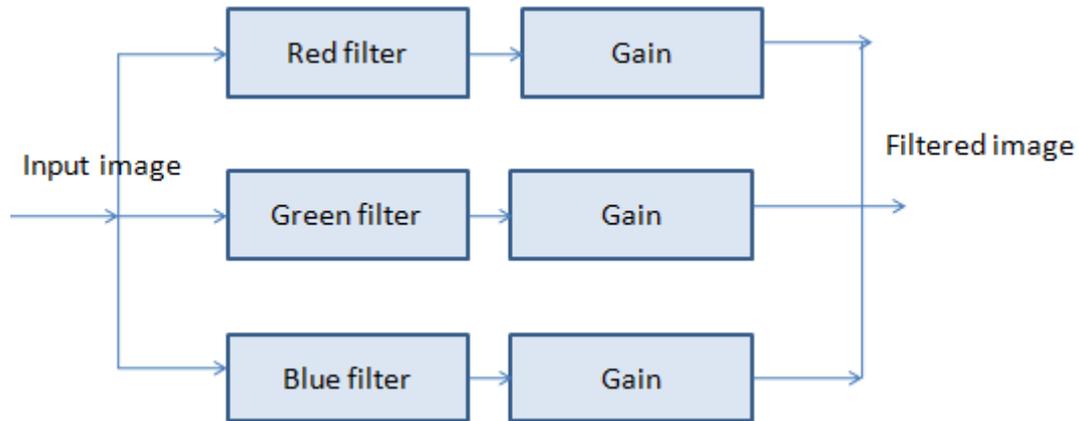


Figure 4. Filtering the three primaries separately

2) Non-Linear Filters

A variety of nonlinear median type filters such as weighted median, rank conditioned rank selection, And relaxed median have been developed to overcome this shortcoming.

3) Median Filter:

In image processing ,The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical preprocessing step to improve the results of later processing (for example, edge on an image). Median filtering is mostly used in image processing because, under certain conditions, it preserves edges of the images while removing noise.

Median is a non-linear local filter whose output value is the middle element of a sorted array of pixel values from the filter window. Since median value is robust to outliers, the filter is used for reducing the impulse noise. Now we will describe median filtering with the help of example in which we will placed some values for pixels.

4) Fuzzy Filter :

Fuzzy filters provide promising result in image-processing tasks that cope with some drawbacks of classical filters. Fuzzy filter is capable of dealing with vague and uncertain information [7]. Sometimes, it is required to recover a heavily noise corrupted image where a lot of uncertainties are present and in this case fuzzy set theory is very useful. Each pixel in the image is represented by a membership function and different types of fuzzy rules that considers the neighbourhood information or other information to eliminate filter removes the noise with blurry edges but fuzzy filters perform both the edge preservation and smoothing .Image and fuzzy set can be modeled in a similar way [8]. Fuzzy set in a universe of X is associated with a membership degree. Similarly, in the normalized image where the image pixels ranging from {0, 1, 2... 255



Original image

Figure5. : Results of the proposed filtering Technique

V. CONCLUSION

Many algorithms can be implemented to reduce the noise. In this paper we have done the comparison between different algorithms for noise reduction. So, we conclude that median filtering approach is the best approach that can be easily implemented. The median filter is demonstrably better than another algorithms at removing noise because it preserves edges for a given, fixed window size. So, median filtering is very widely used in image processing.

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