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Automatic Noise Identification Using GLCM Properties

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***Abstract-** A neural network based noise identification which takes different feature values as input and classification of noise as output. Noise identification is performed using GLCM properties. On the basis of noise, appropriate filter is selected to get better results. The results of experiments using proposed method shows better identification of noise than those suggested in recent works.*

***Keywords-** Noise, GLCM properties, ANN, Back propagation neural network, Additive noise, Multiplicative noise, Impulsive noise.*

I. INTRODUCTION

Noise is an unwanted signal that generates random variation in brightness and color information of image. It can be occurred in image acquisition process. Thus, it is necessary to process the image for detecting and removing noise before it can be further used. Noise results in blurring and degradation of quality of image. Noises are complex signal which alters information. It is difficult to differentiate between the true image and corrupted image. Denoising is a process of removing noise from image. A digital image can be represented as a 2-dimensional array of data, $s(x,y)$ where (x,y) represents the pixel location . The pixel value corresponds to the brightness of the image at location (x,y) [1]. The most frequently used image types are gray-scale, binary and color images [3]. There are different type of noises Gaussian, speckle, salt and pepper, Poisson and uniform. Each type of noise has its own characteristics which makes it different from others. Automated noise identification system reduces manual burden. For making the system automated, it should learn the reaction of different parameters for different noises process and can be easily implemented using ANN. In this work, identify the nature of noise from observed image, so that appropriate filter can be applied. The approach used in this paper has been organized in following manner, section 2 describes different type of noises present, section 3 represents GLCM Properties used for classification, section 4 describes GLCM properties which is used to make feature set, section 5 proposed noise identification method, section 6 describes result and section 7 gives conclusion and direction for future work.

II. NOISE MODELS

On the basis of mathematical operations noises are classified as additive, multiplicative and impulsive in nature which encountered in most images.

Additive noise is primarily caused by thermal noise (fundamental noise), which comes from reset noise of capacitors. **Addition** also finds applications in image morphing [2]. Additive noise follows the rule as mentioned in equation (1):

$$w(x,y) = s(x,y) + n(x,y) \qquad (1)$$

where, $s(x,y)$ is the original signal, and $n(x,y)$ is the noise which is added and $w(x,y)$ is the distorted image by noise. Gaussian noise, Uniform noise is come under category of additive noise.

Multiplicative noise gives a magnified view of area. Thus, there is a higher random variations observed in an image. This type of noise has more intensity in brighter region than darker region. This noise is signal dependent and gives more distorted image. The mathematical model for multiplicative noise type is shown in equation (2):

$$w(x,y) = s(x,y) * n(x,y) \qquad (2)$$

where, $s(x,y)$ is the original signal; $n(x,y)$ is noise introduced signal; $w(x,y)$ is corrupted signal at pixel location (x,y). Speckle noise is of multiplicative type.

Impulsive or intensity spike noise is typically seen in digital images. This noise has dark pixels in bright regions and bright pixels in dark regions. It is caused by analog-to-digital converter errors, bit errors in transmission etc. it can be shown mathematically as:

$$f(i,j) = \{ r(i)\ with\ probability, y(j)\ with\ probability\ 1-r\} \qquad (3)$$

where, y(j) is gray level of a true image y at pixel location (i, j); f(i,j) is gray level of the noisy image f at pixel (i, j); r(i) is random number and r is noise ratio. Salt and Pepper is an example of impulse noise.

A. Gaussian noise

Gaussian noise is uniformly distributed over the signal. All pixel values in noisy image is sum of pixel value in true image and a random Gaussian distributed noise value. As name suggests, this type of noise has a Gaussian distribution, which has bell shaped pdf (probability distribution function). Fig. 1 is an example of Gaussian noise.

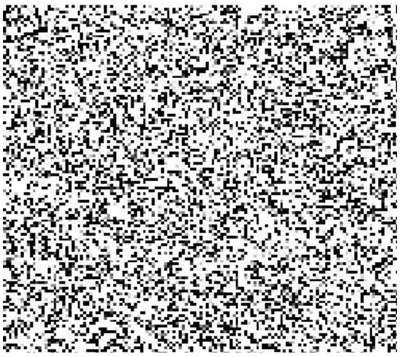

Fig. 1: Gaussian noise with m=1.5 and v=10.

B. Speckle noise

Speckle noise is of multiplicative type. This type of noise occurs in almost all imaging systems such as Laser and SAR imagery [5]. v= variance whose default value is 0.04. Fig. 2 shows noise with v=0.04

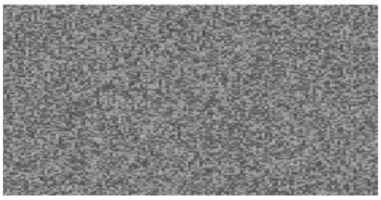

Fig. 2: Speckle Noise

C. Salt and Pepper noise

Salt and Pepper is caused most probably due to errors in data transmission. The corrupted pixels set alternatively to pepper (minimum) or to the salt (maximum) value, giving the image a "salt and pepper" like appearance. For an 8-bit image, the typical value for pepper noise is 0 and for salt noise are 255. The salt and pepper noise is due to malfunctioning of pixel elements in the camera sensors, faulty memory locations, timing errors in the digitization process. Salt and Pepper noise with a density of 0.05 is shown in Fig. 3.

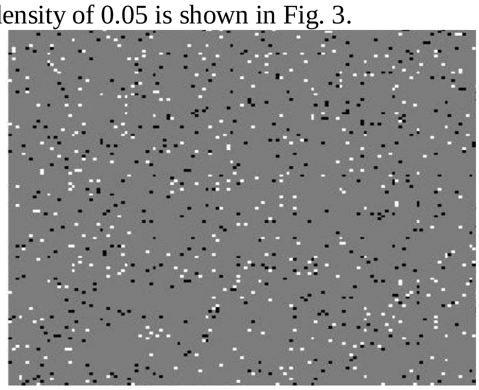

Fig. 3: Salt and Pepper noise

D. Poisson noise

Poisson noise or shot noise is a type of electronic noise that occurs when the finite number of particles carries energy. Shot noise in electronic devices consists of unavoidable random statistical fluctuations of the electric current in an electric conductor [4]. Fig. 4 shows the Poisson noise in image.

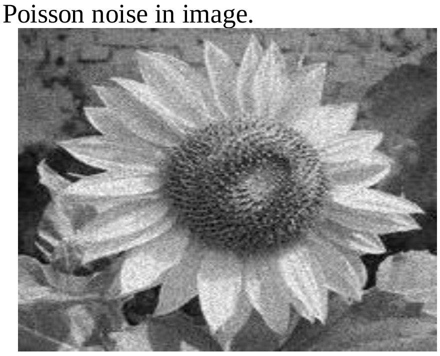

Fig. 4: Poisson noise

E. Uniform noise

Uniform noise is signal dependent is caused by quantizing the pixels of an image. It is not easily encountered in real world imaging systems, but it provides useful comparison with Gaussian noise. It gives poor estimation of mean of uniform distribution, so nonlinear filters were used. Fig. 5 shows Lena image with uniform noise.

Fig. 5: Image with uniform noise

III. FEATURE SET

GLCM (Gray Level Co-occurrence Matrix) [6] estimates the second-order statistics of image which considers the relationship among pixels or group of pixels (basically two). Haralick [2] suggested using gray level co-occurrence matrix. The method is based on joint probability distributions on pair of pixels. GLCM shows how often each gray level occurs at each pixel in an image located at a fixed position relative to each other. GLCM properties such as correlation, contrast, entropy, energy, homogeneity have been used as feature set in this work.

Feature(1): Energy provides sum of squared elements in GLCM. It is also known as uniformity or angular second moment [7]. It is 1 for constant image. Equation 4 shows how to calculate energy is:

$$energy = \sum_i \sum_j g_{ij}^2 \tag{4}$$

where, g_{ij} is the graylevel co-occurrence matrix. Energy is the most important discriminating factor. All noises give different set of values for energy due to which classification is possible.

Feature (2): Entropy measures the disorder or complexity of an image. The entropy is large when image is not texturally uniform and GLCM elements have very small values. Complex textures have high entropy and is inversely proportional to energy.

Feature (3): Correlation returns a measure of how correlated a pixel is to its neighbor over the whole image. It measures joint probability occurrences of specified pixel pairs [8]. Correlation is given by equation:

$$correlation = \left(\sum_i \sum_j [(ij) - g_{ij} - u_x \, u_y) \Big/ std.dev.(x) std.dev.(y)] \right. \tag{5}$$

where, u_x and u_y are the mean of g_x, g_y.

Feature (4): Contrast returns a measure of the intensity contrast between a pixel and its neighbor over the whole image [8]. It measures local variations in GLCM. Contrast is given by:

$$contrast = \sum_i \sum_j (i-j)^2 g_{ij} \tag{6}$$

Feature (5): Homogeneity returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. It effects strongly for classification and it is given by:

$$homogeneity = \sum_i \sum_j \left({}^{1}\!/_{1+(i-j)^2} \right) \cdot g_{ij} \tag{7}$$

IV. BACK PROPAGATION FEED FORWARD NEURAL NETWORK (BPN)

Neural network is used because of its ability to capture and represent complex input and output relationship among data. ANN models prove to be a competitive alternative to traditional classifier for many practical classification problems.

The BPN is the best known and widely used learning algorithm in training feed-forward multilayer NN's. The feed forward NN refer to network consisting of a set of sensory units (source nodes) that constitute the input layer, at least one hidden layer and an output layer [9]. The input data propagates through the network in a direction i.e. forward, from left to right and on layer-by-layer (input-hidden-output) basis. Back-Propagation is a multi-layer feed forward (BPNN), supervised learning algorithm network based on gradient descent learning rule. This NN provides a computationally efficient method for changing weights in feed-forward network to learn a training set of input-output data [8]. Being a gradient descent learning method, it minimizes the total squared error of the output computed by the network. The aim is to train the network to achieve a balance between the ability to respond correctly to the input patterns that are used for training and the ability to provide good response to the input. A typical BPN of input layer, one hidden layer and output layer is shown in Fig. 5

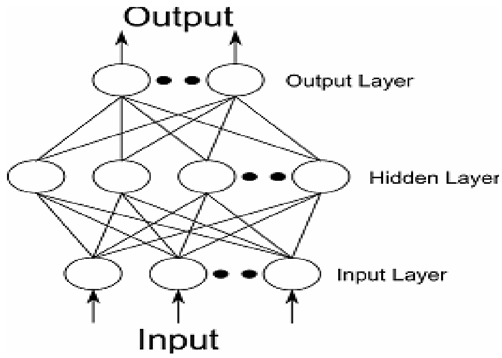

Fig. 5: Neural network

V. PROPOSED METHOD

The steps of algorithm to classify noise are detailed in Fig. 6. There are five major steps involved to make an automated system for identification. They are image acquisition, preprocessing of image, calculate GLCM, feature extraction and classification. Initially, images are acquired then preprocessing is done then for making NN GLCM features are calculated. Finally, the training as well as testing performed quite well with feed forward BPN network and then confusion matrix is calculated to know the accuracy of the system.

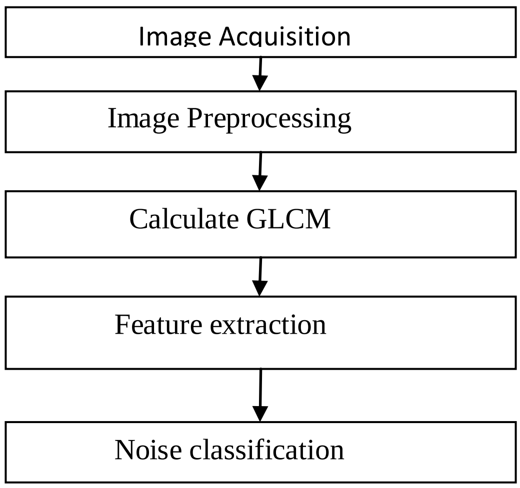

Fig.6: Block Diagram of proposed method.

VI. EXPERIMENTAL RESULTS

The Berkeley database has been used to test the database. Out of 1000 images of dataset, 500 images are used for drawing BPNN and 500 are used for testing. Then, the dataset is made to train network of 500 images (i.e. 100 images of Gaussian, 100 images of speckle, 100 images of Salt and Pepper, 100 of Poisson and 100 of uniform). All experiments were carried out using MATLAB®, Version 7.11.0 (R2010b) with Image Processing toolboxes and Neural Network toolboxes. After training NN on 500 images, parameters such as Performance goal, No. of epochs and time are observed.

Table I
PARAMETERS FOR NEURAL CLASSIFIER

Parameters	
Performance Goal	0.687
No. of epochs taken to meet the performance goal	1000
Time taken to learn	0.12

The confusion matrices given in Table II give the percentage of images classified correctly by BPN. Testing result shows 97 percent, 98 percent, 95 percent, 97 percent, 96 percent accuracy for Gaussian, Speckle, Salt and Pepper(S&P), Poisson and Uniform respectively.

Table II
CONFUSION MATRIX-PERFORMANCE ANALYSIS OF BPN

	Gaussian	Speckle	S&P	Poisson	Uniform
Gaussian	97	0	0	0	0
Speckle	0	98	1	1	0
S&P	1	1	95	2	0
Poisson	0	0	3	97	0
Uniform	3	1	0	0	96

VII. CONCLUSION

In general purpose of classification of noise has been achieved by using BPN network. A maximum accuracy of 98 percent was found for speckle noise followed by accuracy of 96 percent, 97 percent, 95 percent and 97 percent for those of uniform, Gaussian and Salt & Pepper, Poisson noises respectively. Each noise behaves different on different properties. The future work will concentrate to identify more type of noises on the basis of this system.

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