ISSN:0975-9646

Monika Pathania et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 5 (3) , 2014, 3483-3486

An Efficient Technique of Noising and De-Noising Medical Images Using Support Vector Machine

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***Abstract*— Medical imaging technology is becoming an important component of large number of applications such as diagnosis, research, and treatment. Medical images like X-Ray, CT, MRI, PET and SPECT have minute information about heart brain and nerves. These images need to be accurate and free from noise. Noise reduction plays an important role in medical imaging. Various methods of noise removal such as: filters, wavelets and thresholding based on wavelets. Although these methods produced good results but still have some limitations. Considering and analyzing the limitations of the previous methods our research presents neural networks as an efficient and robust tool for noise reduction. In our research we use SVM as the learning algorithm which follows the supervised learning. The proposed research use both mean and median statistical functions for calculating the output pixels results in terms of PSNR and MSE.**

Keywords— ***Noising, De-noising, Medical images and SVM***

I. INTRODUCTION

Image processing is a form of signal processing for which the input is an image such as a photograph or video frame and the output of image processing may be either an image or the image parameters. Image is a two dimensional function of two real variables. Image= f(x, y) where, x and y are the spatial coordinates known as pixels and f is the amplitude. Before, processing an image is converted into the digital form. The digitization includes; sampling of images and quantization of the sampled values. Therefore after converting the image into bit information the processing is performed. The processing technique may be image enhancement; image reconstruction and image compression. Image is processed in two ways:

1. Spatial domain: Spatial domain, refers to the image plane itself; it is based on the direct manipulations of the pixels in the image.
2. Frequency domain: In frequency domain, image is processed in form of sub bands. All types of transformations are applied in frequency domain. e.g DWT, DFT etc.

Therefore the purpose of image processing is divided into five groups:

1. Visualization: Observe the objects that are not visible.
2. Image Sharpening and Restoration: To create a better image.
3. Image Retrieval: Seek for the image of interest.
4. Measurement of the Pattern: Measure various objects in an image.
5. Image Recognition: Distinguish the objects in an image.

It is the use of computer algorithms to perform image processing on digital images. It is a field of digital signal processing; digital image processing has many advantages over analog signal processing [1,2]. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build- up of noise and signal distortion during processing. Images are defined over two dimensions digital image processing may be modeled in the form of multidimensional systems. Therefore digital image processing allows the use of much more complex algorithms. Medical imaging is the technique and process used to create images of the human body for clinical purposes and diagnosis (medical procedures seeking to reveal; diagnose or examine disease) or medical science. Therefore imaging of removed organs and tissues can be performed for medical reasons; such procedures are not usually referred to as medical imaging. A discipline and in its widest sense; it is part of biological imaging and incorporates radiology; nuclear medicine; investigative radiological sciences; endoscopy; medical thermography; medical photography and microscopy (e.g. for human pathological investigations). Then measurement and recording techniques which are not primarily designed to produce images; such as electroencephalography (EEG), magneto encephalography (MEG), Electrocardiography (EKG) and others; but which produce data susceptible to be represented as maps; can be seen as forms of medical imaging .Radiation exposure from medical imaging in 2006 made up about 50% of total ionizing radiation exposure in the USA. Therefore in the clinical context; "invisible light" medical imaging is generally equated to radiology or "clinical imaging" and the medical practitioner responsible for interpreting (and sometimes acquiring) the images is a radiologist. Then "Visible light" medical imaging involves digital video or still pictures that can be seen without special equipment. The Dermatology and wound care are two modalities that utilize visible light imagery. And diagnostic radiography designates the technical aspects of medical imaging and in particular the acquisition of medical images. [2,10]

II. NOISE

Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is generally regarded as an undesirable by-product of image capture. And although these unwanted fluctuations became known as "noise" by analogy with unwanted sound they are inaudible and actually beneficial in some

applications, such as dithering. The characteristics of noise depend on its source. Therefore filter or the operator which best reduces the effect of noise also depends on the source . Many image-processing packages contain operators to artificially add noise to an image.
Different types of noise present in images which is given below:
1. Amplifier Noise
2. Salt and Pepper Noise and
3. Speckle Noise

III. MEDICAL IMAGE DE-NOISING

The arrival of digital medical imaging technologies such as positron emission tomography (PET), magnetic resonance imaging (MRI), computerized tomography (CT) and ultrasound Imaging has revolutionized modern medicine. Today, many patients no longer need to go through invasive and often dangerous procedures to diagnose a wide variety of illnesses. The widespread use of digital imaging in medicine today; the quality of digital medical images becomes an important issue. To achieve the best possible diagnosis it is important that medical images be sharp; clear; and free of noise and artifacts. The technologies for acquiring digital medical images continue to improve; resulting in images of higher and higher resolution and quality, removing noise in these digital images remains one of the major challenges in the study of medical imaging, because they could mask and blur important subtle features in the images, many proposed de-noising techniques have their own problems. Image de-noising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. Noise modelling in medical images is greatly affected by capturing instruments; data transmission media; image quantization and discrete sources of radiation. Therefore different algorithms are used depending on the noise model. Then most of images are assumed to have additive random noise which is modelled as a white Gaussian noise. Medical images such as magnetic resonance imaging (MRI) and ultrasound images have been widely exploited for more truthful pathological changes as well as diagnosis. They suffer from a number of shortcomings and these includes: acquisition noise from the equipment; ambient noise from the environment; the presence of background tissue; other organs and anatomical influences such as body fat; and breathing motion. Noise reduction is very important; as various types of noise generated limits the effectiveness of medical image diagnosis [7,8].
There are different techniques to de-noising from the medical image which given as:
1. Filter techniques
2. Wavelet techniques

A. FILTER

In image processing filters are mainly used to suppress either the high frequencies in the image that is smoothing the image , or the lower frequencies that is enhancing or detecting edges in the image. The image can be filtered in frequency domain or in the spatial domain. In spatial domain there are two types of filters namely linear filters and non linear filters.

B. WAVELET TRANSFORM

Noise reduction using the wavelets is performed by first decomposing the noisy image into wavelet coefficients that is approximation and the detail coefficients. Then by selecting a proper thresholding values that detail coefficient are modified based on the thresholding function. Finally the reconstructed image is obtained by applying the inverse wavelet transform on modified coefficients. Basic procedure for all thresholding methods is [6]:
1. Calculate the Discrete Wavelet Transform (DWT) of the image.
2. Threshold the wavelet components
3. Compute the IDWT to obtain the de-noised image.

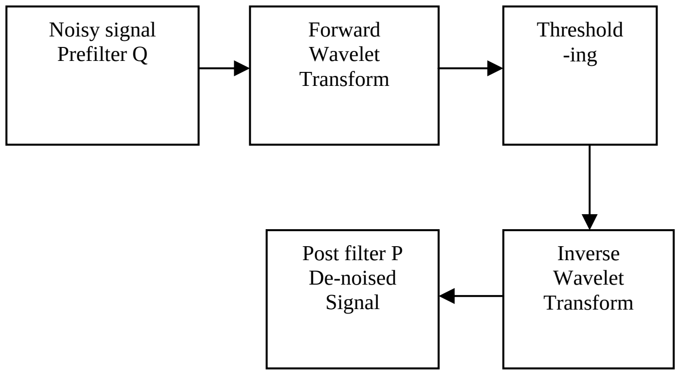

Figure 1: wavelet based de-noising

C. Discrete Wavelet Transform

At last DWT of image signal produces a non-redundant image representation; which provides better spatial and spectral localization of image formation; compared with other multi scale representations such as Gaussian and Laplacian pyramid recently; Discrete Wavelet Transform has attracted more and more interest in image de-noising. The DWT can be interpreted as signal decomposition in a set of independent; spatially oriented frequency channels. Therefore signal S is passed through two complementary filters and emerges as two signals; approximation and Details. It is called decomposition or analysis. Components can be assembled back into the original signal without loss of information. These processes are called reconstruction or synthesis. Mathematical manipulation; this implies analysis and synthesis; is called discrete wavelet transform and inverse discrete wavelet transform. Image can be decomposed into a sequence of different spatial resolution images using DWT. Therefore in case of a 2D image; an N level decomposition can be performed resulting in 3N+1different frequency bands namely; LL; LH; HL and HH. The sub-image a1 is formed by computing the trends along rows of the image followed by computing trends along its columns. Therefore the same manner; fluctuations are also created by computing trends along rows followed by trends along columns. Then next level of wavelet transform is applied to the low frequency sub band image LL only. Therefore Gaussian noise will nearly be averaged out in low frequency wavelet coefficients. And only the wavelet coefficients in the high frequency levels need to be threshold [9].

IV. SUPPORT VECTOR MACHINE

The Support Vector Machine (SVM) is a state-of-the-art classification method introduced in 1992 by Boser, Guyon, and Vapnik. The SVM classifier is widely used in bioinformatics (and other disciplines) due to its highly accurate; able to calculate and process the high-dimensional data such as gene expression and exibility in modeling diverse sources of data .SVMs belong to the general category of kernel methods. Therefore a kernel method is an algorithm that depends on the data only through dot-products. This is the case; the dot product can be replaced by a kernel function which computes a dot product in some possibly high dimensional feature space. Therefore this has two advantages: First; the ability to generate non-linear decision boundaries using methods designed for linear classifiers. And second; the use of kernel functions allows the user to apply a classifier to data that have no obvious fixed-dimensional vector space representation. Thus prime example of such data in bioinformatics are sequence; either DNA or protein; and protein structure. Using SVMs effectively requires an understanding of how they work. When training an SVM the practitioner needs to make a number of decisions: how to preprocess the data, what kernel to use; and finally; setting the parameters of the SVM and the kernel [1]. Uninformed choices may result in severely reduced performance. Thus aim to provide the user with an intuitive understanding of these choices and provide general usage guidelines. And all the examples shown were generated using the PyML machine learning environment; which focuses on kernel methods and SVMs.

A. PRELIMINARIES: LINEAR CLASSIFIERS

Support vector machines are an example of a linear two-class classifier. This section explains what that means. The data for a two class learning problem consists of objects labeled with one of two labels corresponding to the two classes; for convenience we assume the labels are +1 or -1. In what follows boldface x denotes a vector with components xi. This notation xi will denote the ith vector in a data set, f(x_i; y_i) gn_i =1, where y_i is the label associated with xi. A key concept required for defining a linear classifier is the dot product between two vectors; also referred to as an inner product or scalar product. The vector w is known as the weight vector; and b is called the bias. And consider the case b = 0first. The set of points x such that wTx = 0 are all points that are perpendicular to w and go through the origin | a line in two dimensions, a plane in three dimensions, and more generally, a hyper plane [2]. The bias b translates the hyper plane away from the origin. The hyper plane fx : f(x) = wTx + b = 0divides the space into two: the sign of the discriminant function f(x) denotes the side of the hyper plane a point is on. The boundary between regions classified as positive and negative is called the decision boundary of the classifier. The decision boundary defined by a hyper plane is said to be linear because it is linear in the input examples. A classifier with a linear decision boundary is called a linear classifier. Conversely, when the decision boundary of a classifier depends on the data in a non-linear the classifier is said to be non-linear.

B. KERNELS: FROM LINEAR TO NON-LINEAR CLASSIFIERS

In many applications a non-linear classifier provides better accuracy. And linear classifiers have advantages; one of them being that they often have simple training algorithms that scale well with the number of examples [9, 10]. This begs the question: Can the machinery of linear classifiers be extended to generate non-linear decision boundaries? Furthermore, can we handle domains such as protein sequences or structures where a representation in a fixed dimensional vector space is not available? The naive way of making a non-linear classifier out of a linear classifier is to map our data from the input space X to a feature space F using a non-linear function.

This approach of explicitly computing non-linear features does not scale well with the number of input features: when applying the mapping from the above example the dimensionality of the feature space F is quadratic in the dimensionality of the original space. And this result in a quadratic increase in memory usage for storing the features and a quadratic increase in the time required computing the discriminant function of the classifier. Therefore this quadratic complexity is feasible for low dimensional data; but when handling gene expression data that can have thousands of dimensions; quadratic complexity in the number of dimensions is not acceptable. These Kernel methods solve this issue by avoiding the step of explicitly mapping the data to a high dimensional feature-space.

Gaussian kernel is defined by:

$$K(\mathbf{x_i}, \mathbf{x_j}) = \exp\left(-\frac{\left\|\mathbf{x_i} - \mathbf{x_j}\right\|^2}{2\sigma^2}\right) \quad (1)$$

Where k > 0; is a parameter that control the width of Gaussian distribution. It plays a similar role as the degree of the polynomial kernel in controlling the exibility of the resulting classifier. We saw that a linear decision boundary can be kernelized i.e. its dependence on the data is only through dot products. In order for this to be useful, the training algorithms need to be kernelizable as well [6]. It turns out that a large number of machine learning algorithms can be expressed using kernels | including ridge regression, the perceptron algorithm, and SVMs. This kernel nonlinearly maps samples into a higher dimensional space so it, unlike the linear kernel, can handle the case when the relation between class labels and attributes is nonlinear.

V. CONCLUSIONS

Image de-noising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. Medical images like X-Ray, CT, MRI and PET, SPECT have minute information about the heart brain and nerves. These images suffer from a lot of short comings including the acquisition of noise from the equipment, ambient noise from the environment and the presence of background tissue, other organs and anatomical influences such as body fat and breathing motion. Noise reduction therefore becomes very important. Therefore the main techniques of image de-noising are filters wavelets and neural networks. The SVM based approach is a powerful and effective method for image de-noising. Wavelet transform outperforms the filters because of its properties like sparsity, multi resolution and multi scale nature and proved promising as they are capable of suppressing noise while maintaining high frequency signal details. But the limitation with wavelet transform was that the local scale- space information of the image is not adaptively considered by the standard wavelet thresholding methods. At last in this research; we studied the existing methods of image de-noising, understand the limitations of the existing techniques and describe an efficient technique to reduce the noise. Regarding this, we will work on the Support Vector Machine (SVM).

ACKNOWLEDGMENT

Thanks to my Guide and family member who always support, help and guide me during my dissertation. Special thanks to my father who always support my innovative ideas.

REFERENCES

[1] Abuzoum Mohamed Saleh *"Efficient analysis of medical image de-noising for MRI and Ultrasound Images"*, (2012

[2] Akutagawa Mastake, ChanYongjia, Katayama Masato, Yohsuke Kinouchi, Qinyu Zhang,*"Additive and multiplicative noise reduction by back propagation neural network"*, Proceedings of the 29th Annual International Conference of the IEEE EMBS Internationale, Lyon, France August 23-26, 2007 IEEE(2007).

[3] Al-Sobou Yazeed A. (2012) *"Artificial neural networks as an image de-noising tool"* World Appl. Sci. J., 17 (2): 218-227, 2012

[4] Dr. T.Santhanam, S.Radhika, *"Applications of neural networks for noise and filter classification to enhance the image quality"*, IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 5, No 2, September 2011 (IJCAI 2011).

[5] E.Salari, S. Zhang ,*"Image de-noising using neural network based non-linear filter in wavelet domain"*, 0-7803-8874-7/05/IEEE(2005)

[6] F.Marvasti, N.sadati, S.M.E Sahraeia, *" Wavelet image De-noising based on neural network and cycle spinning"* 1424407281/07/IEEE(2007).

[7] Gupta Manoj, KumarPapendra, KumarSuresh (IJCA-2010) *"Performance comparison of median and the weiner filter in image de-noising."*

[8] KaurJappreet, KaurManpreet, KaurManpreet, KaurPoonamdeep *"Comparative analysis of image de-noising techniques."* (IJETAE2012)

[9] Leavline E.Jebamalar Sutha S, Singh D.Asir Anton Gnana (IJCA-2011) *"Wavelet domain shrinkage methods for noise removal in mages."*

[10] Mr. S. Hyder Ali, Dr.(Mrs.) R. Sukanesh, Ms. K. Padma Priya *" Medical image de-noising using neural networks"*.

[11] Rehman Amjad, Sulong Ghazali, Saba Tanzila *"An intelligent approach to image denoising"*, (JATIT 2005-2010).

[12] Sontakke Trimbak R, Rai RajeshKumar, *"Implementation of image de-noising using thresholding techniques"*, IJCTEE.

[13] Toshihiro Nishimura, Masakuni Oshiro, *"US Image Improvement Using Fuzzy NeuralNetwork with Epanechnikov Kernel"*, 978-1-4244-4649-0/09/ ©2009 IEEE