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An Optimized Preprocessing Decision for Multispectral MRI- Based Applications

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Abstract: Medical imaging refers to technique and process used to create images of human body for clinical purpose .Image processing techniques in medical imaging are used to analyze the symptoms of the patients with ease. Medical images often consist of random noise and which are affected during acquisition and it spread over the image. In such situation it is very difficult to diagnosis the particular disease. The overall noise characteristic in an image depends on many factors, which include sensor type, pixel dimensions, temperature, exposure time, and ISO speed. Therefore it is necessary to remove the noise from the image. Real images are often degraded by noise and this noise can occur during image transmission and digitization. The key function of preprocessing is to improve the image in ways that increase the chances for success of the other processes. This paper evaluates different types of preprocessing filters and proposes a new type of preprocessing. Many of these methods use the information of a single image without taking into consideration the intrinsic multispectral nature of MR images, the proposed a new technique reduce random noise in multispectral MR images by spatially averaging similar pixels using information from all available image components to perform the preprocessing process. One of the main goals in the image pre-processing is to remove the redundant information as much as possible using simple and high-speed methods. Experimental results demonstrate that the performance of the proposed image preprocessing method is superior to that of other spatial-type filters.

Keywords: Medical Imaging, Preprocessing, Spatial filters, Multispectral MRI Image, Noise removal.

I. INTRODUCTION

The magnitude of signal intensity changes that cause the detection of brain activation using MRI is small, requiring multiple repetitions to detect stimulus- correlated signal variations. This limits the flexibility of the patterns that can be used for fMRI experiments [3, 11]. Therefore removing baseline drifts, which are emanating from the scanner or incurred by the aliasing of physiological pulsations, is crucial. Physiological noise can be reduced by straightforward measures that include gating and post-hoc filtering [2] or external monitoring and retrospective estimation [4]. These include CSF flow and spontaneous low-frequency fluctuations, the latter hypothesized to be related to spontaneous neuronal activity.

The MR scanner itself is likely an ample source of noise. The low frequency drifts in cadavers found in regions of high spatial intensity changes, not only at the edges of the brain, but also the in folding’s of cortex, accurately where fMRI activations are localized [8]. Thus, removing baseline drifts plays an important role in pre-processing data prior to statistical analysis for fMRI studies performed at both clinical and high (4T) field Linear and higher order polynomial [7, 12]. Wavelets have been used on several occasions for removing noise from MR images and fMRI data has detrending methods that are commonly used in fMRI data analysis, and extend this varied approach to the voxel level. While some have looked at nonlinear and frequency domain filters [4], many works [6, 19, 20, 21] have been reported on image de-noising using nonlinear filters. This paper focuses exclusively on a comparison of fairly easy to implement linear models and propose a new preprocessing algorithm.

A. Effect of Noise in Digital Image Processing:

Noise is often introduced during the analog-to-digital conversion process as a side-effect of the physical conversion of patterns of light energy into electrical patterns.

One kind of noise which occurs in all recorded images to a certain extent is detector noise. This kind of noise is due to the discrete nature of radiation, the fact that each imaging system is recording an image by counting photons [9]. Real images are often degraded by some error this is called Noise. In the digital image noise can occur during image transmission and digitization [17]. Image sensors are affected by environmental condition during image digitization and by quality of elements. In acquiring image with a CCD camera, light levels & sensors temperature are major factors affecting the amount of noise in the resulting images [1]. Noises may be dependent or independent of image content. Images are corrupted during the transmission due to interference in the channel used for transmission. The noise of an image gives it a gray appearances and mainly the noise is evenly spread and more uniform. MRI Brain images are prone to a variety of types of noise [16]. The overall noise characteristics in an image depends on many factors, which include sensor type, pixel dimensions, temperature, exposure time, and ISO speed [18].

II. MATERIALS AND METHODS

Many existing filters used in MRI work using a single image component or volume without taking into consideration the multispectral intrinsic nature of MR studies. A typical MR study is comprised by many different types of images of the same patient (for example T1, T2, PD, etc.) where after a preprocessing process each voxel can be seen as vector with as many components as image types in the study. The Simulated T1-weighted and protondensity (PD) and T2-weighted (T2) MRI volumes were acquired [15] from the brain web database.

A. Noise Reduction Using Filters

In image processing filters are mainly used to suppress either the high frequencies in the image, which is smoothing the image, or the low frequencies, that is enhancing or detecting edges in the image. An image can be filtered either in the frequency or in the spatial domain. The first involves transforming the image into the frequency domain, multiplying it with the frequency filter function and re-transforming the result into the spatial domain [13]. The filter function is shaped so as to attenuate some frequencies and enhance others. A simple lowpass function is 1 for frequencies smaller than the cut-off frequency and 0 for all others. The corresponding process in the spatial domain is to convolve the input image f(i,j) with the filter function h(i,j). This can be written as shown in equation 1.

$$g(i, j) = h(i.j) \otimes f(i, j) \qquad (1)$$

Gaussian noise can be reduced using a spatial filter. But, while smoothing an image, not only the noise reduces, but also the fine-scaled image details because they also correspond to blocked high frequencies. The most effective basic spatial filtering techniques for noise removal include: mean filtering, median filtering and Gaussian smoothing. Crimmins Speckle Removal filter can also produce good noise removal. More sophisticated algorithms which utilize statistical properties of the image and noise fields exist for noise removal.

For salt and pepper noise conventional lowpass filtering, the mean filtering or Gaussian smoothing is relatively unsuccessful because the corrupted pixel value can vary significantly from the original and therefore the mean can be significantly different from the true value. A median filter removes drop-out noise more efficiently and at the same time preserves the edges and small details in the image better. Conservative smoothing can be used to obtain a result which preserves a great deal of high frequency detail, but is only effective at reducing low levels of noise.

B. Mean Filter

Mean filtering is a simple, instinctive and easy to implement method of smoothing images, which reduces the amount of intensity variation between one pixel and the next. It is often used to reduce noise in images. The idea of mean filtering is simply to replace each pixel value in an image with the mean value of its neighbors, including itself. This has the effect of eliminating pixel values which are unrepresentative of their surroundings. Mean filtering is usually thought of as a convolution filter. Often a 3×3 square kernel is used, as shown in Fig.1, although larger kernels can be used for more severe smoothing. The small kernel can be applied more than once in order to produce a similar but not identical effect as a single pass with a large kernel.

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

Figure 1. Mean Filter Kernel

If we increase the size of the mean filter to 5×5, we obtain an image with less noise and less high frequency detail.

The two main problems with mean filtering,

a. A single pixel with a very unrepresentative value can significantly affect the mean value of all the pixels in its neighborhood.
b. When the filter neighborhood spans an edge, the filter will interpolate new values for pixels on the edge and so will blur that edge. This may be a difficult if sharp edges are required in the output.

Both of these problems are tackled by the median filter, which is often a better filter for reducing noise than the mean filter, but it takes longer to compute. In general the mean filter acts as a low pass frequency filter and therefore, reduces the spatial intensity derivatives present in the image.

C. Median Filter

The median filter is normally used to reduce noise in an image, similar to the mean filter. It often does a better job than the mean filter of preserving useful detail in the image. Similar to the mean filter, the median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighboring pixel values, it replaces it with the median of those values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value. If the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is used. Fig.2 illustrates an example calculation.

123	125	126	130	140
122	124	126	127	135
118	120	150	125	134
119	115	119	123	133
111	116	110	120	130

Neighbourhood values:
115, 119, 120, 123, 124
125,126,127,150
Median Value: 124

Figure 2. Median Filter Kernel

Calculating the median value of a pixel neighborhood as illustrated in Fig.2, the central pixel value of 150 is rather unrepresentative of the surrounding pixels and is replaced with the median value: 124.

D. Gaussian Smoothing

The Gaussian smoothing operator is a 2-D convolution operator that is used to blur images and to remove noise. It is similar to the mean filter, but it uses a different kernel that represents the shape of a Gaussian hump. This kernel has some special properties which are detailed below.

The Gaussian distribution in 1-D has the form as in equation 2:

$$G(x) = \frac{1}{\sqrt{2\Pi\sigma}} e - \frac{x^2}{2\sigma^2} \qquad (2)$$

Where σ is the standard deviation of the distribution. Let us assume that the distribution has a mean of zero which indicates that, it is centered on the line x=0). The distribution is illustrated in Fig.3.

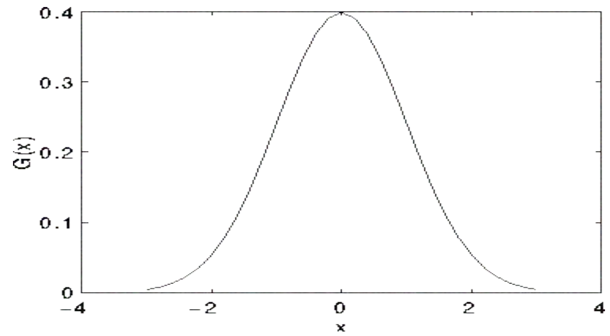


Figure 3. 1-D Gaussian distribution with mean 0 and σ =1

In 2-D, an isotropic Gaussian has the form as in equation 3:

$$G(x, y) = \frac{1}{2\prod \sigma^2} e - \frac{x^2 + y^2}{2\sigma^2} \qquad (3)$$

This distribution is shown in Fig.4.

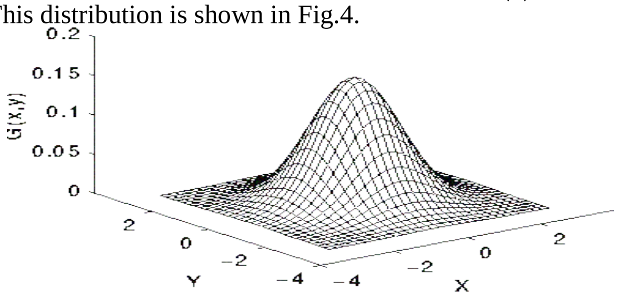


Figure 4. 2-D Gaussian distribution with mean (0,0) and σ =1

The idea of Gaussian smoothing is to use this 2-D distribution as a point-spread function, and this is achieved by convolution. Fig.5 shows a suitable integer-valued convolution kernel that approximates a Gaussian with a σ of 1.0.

1	4	7	4	1
4	16	26	16	4
7	26	41	26	7
4	16	26	16	4
1	4	7	4	1

1/273

Figure 5. Discrete approximation to Gaussian function with σ =1.0

Once a suitable kernel has been calculated, then the Gaussian smoothing can be performed using standard convolution methods. The effect of Gaussian smoothing is to blur an image, in a similar fashion to the mean filter. The degree of smoothing is determined by the standard deviation of the Gaussian. The Gaussian outputs a weighted average of each pixel's neighborhood, with the average weighted more towards the value of the central pixels. This is in contrast to the mean filter's uniformly weighted average. Because of this, a Gaussian provides gentler smoothing and preserves edges better than a similarly sized mean filter. One of the principle validations for using the Gaussian as a smoothing filter is due to its frequency response. Fig.6 shows the frequency responses of a mean filter with width 5 and also of a Gaussian filter with σ = 3.

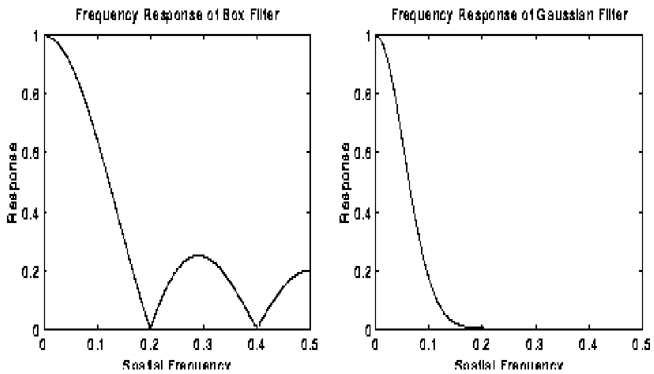


Figure 6. Frequency responses of Box (mean)filter (width 5 pixels) and Gaussian filter (σ = 3 pixels). The spatial frequency axis is marked in cycles per pixel, and hence no value above 0.5 has a real meaning.

Both filters attenuate high frequencies more than low frequencies, but the mean filter exhibits oscillations in its frequency response. The Gaussian on the other hand shows no oscillations. Actually, the shape of the frequency response curve is itself half a Gaussian. So by choosing an appropriately sized Gaussian filter we can be fairly confident about the range of spatial frequencies are still present in the image after filtering, which is not the case of the mean filter.

E. Conservative Smoothing

Conservative smoothing is a noise reduction technique that derives its name from the fact that it employs a simple, fast filtering algorithm that sacrifices noise suppression power in order to preserve the high spatial frequency detail which is sharp edges in an image. It is explicitly designed to remove noise spikes which is isolated pixels of exceptionally low or high pixel intensity which is salt and pepper noise and is, therefore, less effective at removing additive noise which is Gaussian noise from an image. Conservative smoothing simply ensures that each pixel's intensity is bounded within the range of intensities defined by its neighbors.

This is accomplished by a procedure which first finds the minimum and maximum intensity values of all the pixels within a windowed region around the pixel. If the intensity of the central pixel lies within the intensity range spread of its neighbors, it is passed on to the output image unchanged. if the central pixel intensity is greater than the maximum value, it is set equal to the maximum value; if the central pixel intensity is less than the minimum value, it is set equal to the minimum value. Fig.7 illustrates this idea.

123	125	126	130	140
122	124	126	127	135
118	120	150	125	134
119	115	119	123	133
111	116	110	120	130

Neighbourhood values:
115, 119, 120, 123, 124
125,126,127,150
Max: 127, Min: 115

Figure 7. Conservatively smoothing a local pixel neighborhood. The central pixel of this figure contains an intensity spike (intensity value 150). In this case, conservative smoothing replaces it with the maximum intensity value (127) selected amongst those of its 8 nearest neighbors.

If the result of conservative smoothing on the image segment is compared with the result obtained by mean filtering and median filtering, it produces a more subtle effect than both the former (whose central pixel value would become 125) and the latter (124). Thus the conservative smoothing is less corrupting at image edges than either of these noise suppression filters.

F. Thresholding Method

Generally thresholding is used as in preprocessing but thresholding has a problem. The threshold value should be decided so automated systems may confront this problem. The shape of histogram can be modeled as Gaussian function but the shape of histogram is affected by illumination [5, 10]. There is no guarantee that a histogram has Gaussian function shape and well separated clusters. The major problem associated with thresholding is that it is less possible to know which cluster has useful information. Some clusters can be noise or some clusters may contain useless information. It is very difficult to decide a proper threshold value which makes method less effective.

III. THE PROPOSED PREPROCESSING ALGORITHM

Step 1: combine the 3 image data set.
Step2: create Six-dimensional feature vector
Step 3: Estimate the standard deviation and mean independently for each slice.
Step 4: Subtract the feature vector by mean and divide by standard deviation.
Step 5: The preprocessed image output is a normalized image with eliminated error.

T1	T2	PD	MEAN OF T1	MEAN OF T2	MEAN OF PD

Figure 8. Six – Dimensional Feature Vector

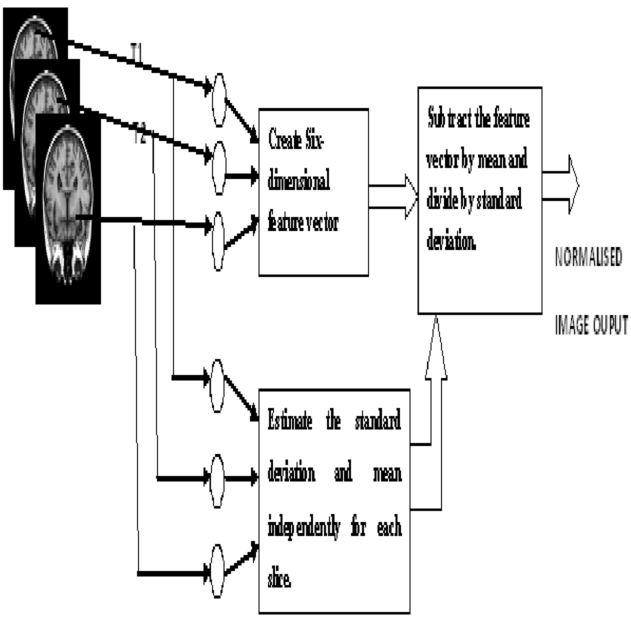


Figure 9. Preprocessing Process

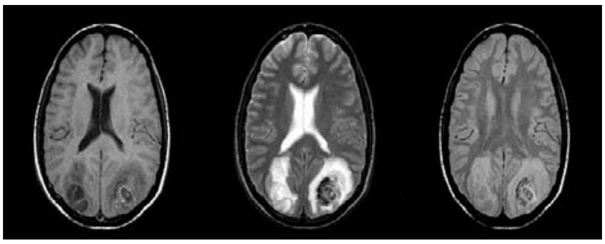
An important part of any image processing system is represented by the pre-processing phase. This phase could imply contrast enhancement techniques or methods for removing the noise. Preprocessing aims at improving the quality of each input image and reducing the computational burden for subsequent analysis steps Specifically, since skull and other extrameningeal tissues are usually of scarce clinical interest in most MRI studies, they were discarded, along with the background, as described by the preprocessing technique proposed in [4, 6].Subsequently, each voxel in the input image is assigned a six-dimensional feature vector as shown in Fig.8, which comprises the gray level intensities of the corresponding pixel in the three channels which are T1, T2 and PD, as well as the mean intensities calculated in a 3x3 neighborhood of the pixel in each channel. The preprocessing process is illustrated in Fig.9. This aims at compensating the effects of random noise, while minimizing the loss of resolution.

Normalization is a process that changes the range of pixel intensity values. An alternative is to scale each feature vector element according to the standard deviation of this measurement across the entire image. This effectively normalizes measurements with respect to the current image providing in variances to attributes such as image contrast. All feature vectors are normalized prior to segmentation by subtracting the mean and dividing by the standard deviation, where the mean and standard deviation are estimated independently for each slice.

IV. RESULTS AND DISCUSSION

Preprocessing of the raw data before the application of test statistics helps to extract the signal and can vastly improve signal detection. In this section, the results obtained using simulated MR images are illustrated. The use of simulated images eases the task of validating a segmentation method as a reproducible. The simulated datasets are obtained from the Brain web institution1 [15]. All multichannel datasets comprise of 8- bit gray level T1-weighted, T2-weighted and PD-weighted images with 1.0 mm slice thickness. Three reference slices were selected.

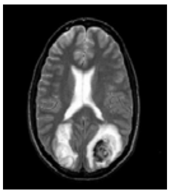
The visual comparison of the resultant images can lead us to the subjective evaluation of the performances of selected pre-processing filters and the proposed pre-processing algorithm. A representative slice and its corresponding output for different filter outputs are illustrated in Fig.10.



(a) T1 **(b) T2** **(c) PD**

(d) mean filter **(e) median filter**

(f) Conservative smoothing



(g) Gaussian filter

(h) proposed algorithm

Figure 10. Comparison of selected preprocessing filters and proposed preprocessing algorithm results with Brain MR Images

From the results it is clear that the proposed pre-processing algorithm performs best and it holds the pixel value, removes the noise and enhances the image as a whole.

V. CONCLUSION

The main finding of this paper is to find a suitable filter among several preprocessing filters used to suppress different noises and enhancing the image commonly used for fMRI data analysis, the proposed technique performed best. It has been demonstrated that using multicomponent images to de-noising image series presents important benefits over single image techniques due to the increased data redundancy. The implementation of the proposed method in the 3D case can potentially improve the results by increasing the number of similar pixels in the local surrounding volume and by using a more specific local similarity volume. The major limitation of linear filtering, namely that a weighted average smoothing process tends to reduce the magnitude of an intensity gradient. Rather than employing a filter which inserts intermediate intensity values between high contrast neighboring pixels, a non-linear noise suppression technique can be employed, such as the median filtering or conservative smoothing, to preserve spatial resolution by re-using pixel intensity values already in the original image. The real utility of conservative smoothing and median filtering is in suppressing salt and pepper, or impulse, noise. A linear filter cannot totally eliminate impulse noise, as a single pixel which acts as an intensity spike can contribute significantly to the weighted average of the filter. Non-linear filters can be robust to this type of noise because single outlier pixel intensities can be eliminated entirely. Conservative smoothing works well for low levels of salt and pepper noise. However, when the image has been corrupted such that more than 1 pixel in the local neighborhood has been effected, conservative smoothing is less successful. In conclusion, this paper compares several linear and non-linear filters for analyzing Brain MRI data. The proposed preprocessing methodology reveals new information that appears to be a good trade-off with respect to computation time and noise removal.

Comparison of these linear algorithms to nonlinear or frequency domain filters. But the proposed algorithm for preprocessing provides better result which shows that it is effective in noise removal than any other linear and non-linear filters existing. The application of the proposed methodology in other imaging techniques can also be tested and has to be addressed with further research.

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