Enhanced Total Variation Model Image Fusion using Hybrid Filters and Adaptive Median Method

K.Elaiyaraja, M. Senthil Kumar, B. Chidambararajan

Abstract: ***In order to obtain a thorough and perfect description of the object, need to integrate information from different modalities of the same image. Image restoration causes artifacts and parameter regularizations issues. In the existing Total Variation method, adaptive functional directives are used. These stuffs are based on limited divergence of fused images. These method causes staircase effects. The Enhanced Total Variation (ETV) model is proposed to solve staircase effects and artifacts issues. An Adaptive Median Method (AMM) is proposed to maintain image details and de-noises effectively without creating any staircase effects. Experimental results are produced by using this method for restoration of images. This proposed method has robustness and produce effective result compared to other variation methods for image fusion or restoration.***

Index Terms – Total Variation, Hybrid Filter, Adaptive Median Method, Image Fusion, Enhanced Total Variation

I. INTRODUCTION

The image fusion is a technique used to diagnose for treatment. Each report from different modality provides limited data only [1]. For example, CT image (Computed Tomography) gives detailed reports of dense structure and its distortion will be on bones and implants. The major issue we are facing in CT image is that it cannot provide or detect physiological effects [2].

Soft tissue information can be obtained from MR (Magnetic Resonance) image [3]. Fusion image is a concept of integrating images from various modalities to attain the same object of exact and complete description [4][5]. Noisy images from medical tools are unbreakable if the images are captured imperfectly. Noise in images leads to wrong diagnose as it creates artifacts in images. Noise is the biggest obstacle for extracting features of an image [4]. So many reasons discovered for noise occurrence in multi-modality images. This noise images lead to low level photon absorption, loss of data while extracting features.

The ultimate aim for image fusion is to extract meaningful information from various images of the same object captured from different modalities and transported to a single image without any loss of information [6][7]. The quality of an image is based on the performance of extracting information [8].

Related Works:

The n number of fusion techniques has been proposed in order to fetch the edge details of an image, various techniques were used [9]. Fusion images are processed based on three levels namely low level (Data level), Intermediate level (Feature level) and High level (Decision level).

Pixels based fusions are the examples of Data level fusion. In this fusion level, the pixels are derived from various multi-modal images. Here, the fusion processes are measured quantities comprised directly. In the intermediate fusion level, the significant features like edges and texture are extracted and in the decision level fusion, decisions from various experts are combined together for fusion.

Fuzzy transform [10], DWT (Discrete Wavelet Transform) [11], FWT (Fractional Wavelet Transform) [12], Filters [13], NCT (Non-subsampled contourlet transform) [14] etc. are some of the techniques used to extract information from images. These methods are inefficient while removing noise as it affects features of images [15].

Averaging method can be used to lessen noises in multimodality images [16]. But effective extraction is not attained by this approach. [19]. In Gaussian model [20], SR (Sparse Representation) [21] model were proposed for fusion images. In SR method, coefficients are represented with the help of dictionary [17]. Uniting those coefficients using fusion rules and reconstruction of those united coefficients are the methods of obtaining fusion image in Sparse Representation method.

Wavelet transform [23][24] based algorithms are used to get effective images with ringing effect. De-noising is an important key factor to obtain a perfect fused image. In that way, Total Variation (TV approach) [18] is an approach to evaluate fused image pixels and retain the significant information of an image while applying de-noising techniques. The Total Variation method is a popular model for suppressing noises and overcomes the weakness of Sparse Representation models issues. The main drawback of applying this approach is creating staircase effect [27]. Enhanced Total Variation method (ETV) is proposed to overcome the staircase effect.

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II. PROPOSED METHOD

The main function of an image fusion is removing and reducing noise. In this proposed method noisy images of multimodal are integrated and into single image which preserves significant details such as flow of blood, structures of dense and soft tissue [22]. Defective image is an unavoidable fact while capturing images from modalities. Preserving or maintain significant details of an image while removing noise is a challenging task. The progression of proposed method represents in the subsequent contents.

Let x(i,j), where i,j be the coordinates of source image. Then, $x_1(i,j)$, $x_2(i,j)$… $x_n(i,j)$ where i,j is the subset of t.

$$z_n(i,j) = x_n(i,j)\, z(i,j) + z_n^t(i,j) \text{ where } 1 \le n \le m \longrightarrow \ (1)$$

x_n represents the window(i,j) and it is the subset of 0 and 1. The n^{th} image at position (i,j) represents gain as well as noise. The following variation model is used along with proposed method in order to suppress noise and increase efficiency.

$$a = (e - n^{\alpha} e)^2 - - - - - \rightarrow (2)$$

$$b = |\nabla e|^{m(|\nabla e|)} - - - - - \rightarrow (3)$$

$$T_e = minimum\left(\iint a\,dx\,dy + \lambda \iint b\,dx\,dy\right) - - - \rightarrow (4)$$

Where n=$(n_1, n_2, \ldots . n_n)^{\alpha}$ and $n_n \in [0,1]$ is the function of weight obtained from source image and λ value will be greater than 0 and lesser than 1.Variation is solved by using gradient descendent method [25]. The following equation is represented as Euler-Lagrange equation shown in below.

$$u - w^T u - \lambda\nabla.\left[q(|\nabla u|)\frac{\nabla u}{|\nabla u|}\right] = 0 - - - - - \rightarrow (5)$$

Next challenging task of this proposed method is constructing weight function. This function highlights important features of images from sources without any interference due to noise. Source images are processed in two ways. In the first way, the significant details are extracted. Then, weightage calculations and refinements are done. In the second way, softened images are obtained by using the adaptive median method. To subdue noise without any staircase effect, different values are taken adaptively in order to create isotropic transmission. The proposed method is applied after calculating weight function along with adaptive fraction order. The refined images and softened images are applied to Enhanced total variation model. In this proposed model refined and softened images are fused together. Finally, the targeted image is achieved. By applying this proposed method, the following pros are given.

- Nose free images can also be used for image fusion
- In order to improve the efficiency of extracting important details or features of images, hybrid based filters are used in this method. So, noise interference are blocked while extraction.
- The main advantage of proposed method is avoiding staircase effects and efficiency improvements.

The following diagram shows the overall architecture of this proposed method.

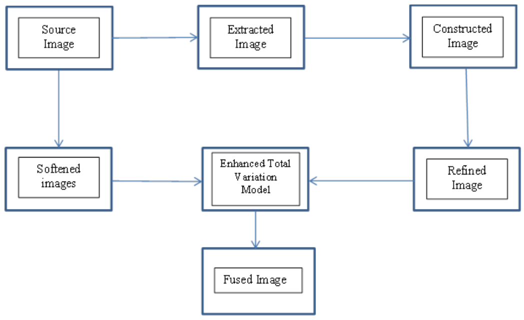

Figure1: Architecture diagram of proposed system

a. Feature Extraction using hybrid method:

Different kinds of noise are exists in images from various modalities. Extracting feature is difficult as the characteristics of feature and noise are same. For extracting features of images, the combination of greedy and genetic algorithm based filter is used in this proposed method.

Search procedures are used to select features of images. An 'n' number of procedures are available and proposed for extracting the features of source image. Here, the combination of greedy stepwise [25] method and genetic algorithms were used as hybrid method. This method increases the accuracy and reduces the manipulation time. In this extracting method, the following significant details were retrieved. Cluster shade, Autocorrelation, Difference variance, contrast, homogeneity etc. The hybrid algorithm for extracting features is given below [26]. The following figure represents the structure of hybrid extraction method using in proposed model.

n € (x1,x2,x3,….xn)

Select W using genetic algorithm, where W<N

Select subset value of (Z) using Greedy steps where Z<N.

W? Z

(Z,W)<N for classification purpose.

Fig. No. 2 Structure of Hybrid extraction method

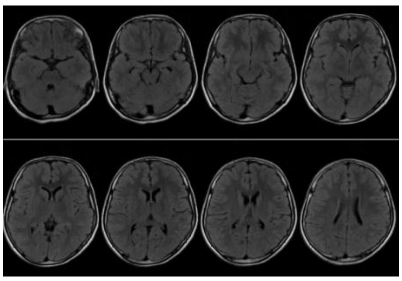

Fig. No. 3 Source Images

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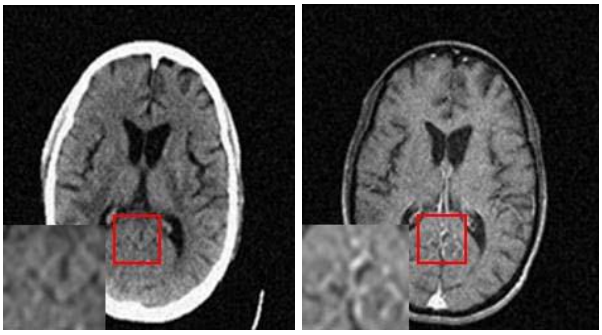

Fig. No. 4 Images with noises added up to 14.36 dB

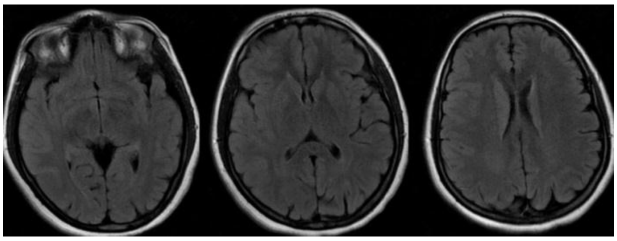

Fig. No. 5 Softened Images

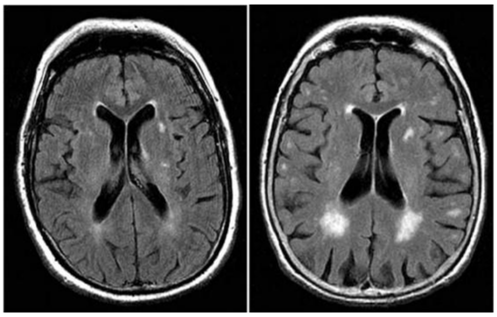

Fig. No. 6 Feature Extracted Images

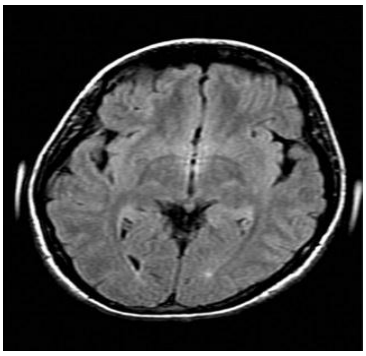

Fig. No. 7 Fused Resultant Image

b. Image Construction:

The weight map of an image is considered as an important feature. In this constructed image stage, the weightage of objects were calculated [28]. The weight map is estimated with the help of $Weight(i,j) =$

$$\begin{cases} 1 \; x_n(i,j) = t_1(i,j), t_2(i,j,) \dots t_n(i,j) & -----\rightarrow (6) \\ 0 \;\; Otherwise & \end{cases}$$

Numbers of images from the sources are represented as n. $x_n(i,j)$ is denoted for feature value at the position of i and j. Weights calculated from this images using above method are obviously noisy (0) as well as hard (1) and which also causes artifact effects in the fused image. The noise of an image is the main source for creating this artifact [36]. The dynamic non–local mean method is used to avoid the noise.

c. Enhanced Total Variation model:

For image processing, the Total Variation (TV) model is widely preferred. This method can suppress noise. But this method causes staircase effect which affects smooth edges and regions [27]. In [28], the fractional directive is taken as the value of 2 in order to avoid staircase effect. But the result is blurring at the edges. In this proposed enhanced total variation method can de-noise the images without any staircase effects. The adaptive median method (AMM) constructs the images without any noises. In this method, different values are taken to suppress noise and also retaining the edges of objects. The structure of proposed method is shown in this below figure.

a=WindowSize$_{medium}$ - WindowSize$_{minimum}$,b=WindowSize$_{medium}$-WindowSize$_{maximum}$
if a>0 && b<0, goto Step6.
else
increase WindowSize
if WindowSize<=S$_{maximum}$, Then Repeat Step1.
else
Generate resultant WindowSize$_{i,j}$
a= WindowSize$_{i}$j - WindowSize$_{minimum}$
b= WindowSize$_{i,j}$ - WindowSize$_{maximum}$
if a>0 && b<0
Generate resultant WindowSize$_{i,j}$
else
Generate resultant WindowSize$_{medium}$

Fig. No. 8 Structure of Enhanced Total Variation model

Experiments and Discussion:

The following measurements are used to analyze the performance of this proposed method with other methods [29][30][31][32].

(i) Entropy:

The entropy values are obtained by using the following calculation method. Here, the ratio is represented by m_i/m and m represents the aggregate pixel value.

$$e_t = -\sum_{i=0}^{x-1} \frac{m_i}{m} \log \frac{m_i}{m} \quad where\ 1 \le n \le x - 1 -----\rightarrow (7)$$

(ii) GBI:

GBI is the expansion of Gradient-Based Index. The GBI value is generated by the following syntax.

$$GBI = \frac{\sum_{m=1}^{x} \sum_{n=1}^{y} \left(q^{\alpha}(m,n) \tau^{a}(m,n) + q^{\beta}(m,n) \tau^{b}(m,n) \right)}{\sum_{i=1}^{x} \sum_{j=1}^{y} \left(\tau^{a}(m,n) + \tau^{b}(m,n) \right)} -----\rightarrow (8)$$

(iii) Correlation:

$$C_{rn} = \frac{2 \sum_{m=1}^{x} \sum_{n=1}^{y} (\alpha_{mn})(\beta_{mn})}{\sum_{m=1}^{x} \sum_{n=1}^{y} (\alpha_{mn})^2 + \sum_{m=1}^{x} \sum_{n=1}^{y} (\beta_{mn})^2} --\rightarrow (9)$$

(iv) SNR:

SNR stands for Signal-to-Noise Ratio. It is calculated by

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$$SNR = 10\log_{10}\left[\frac{\sum_{m=1}^{p}\sum_{n=1}^{q}(x_{mn})^2}{\sum_{m=1}^{p}\sum_{n=1}^{q}(x_{mn}-y_{mn})^2}\right] \dashrightarrow (10)$$

The rows and columns are represented as p and q respectively. The pixel values are denoted as x and y in the range of m and n for the reference and targeted image.

(v) Root-Mean-Square-Error:

$$r_e = \sqrt{\frac{\sum_{m=1}^{x}\sum_{n=1}^{y}(\alpha_{mn}-\beta_{mn})^2}{x \times y}} \dashrightarrow (11)$$

III. EXPERIMENTAL SETUP & RESULTS

The different multimodal images are taken and the proposed method is applied on that images. The proposed method is verified by the experiments established from three kinds of aspects. Computer generated noises are added and the levels are obtained by SNR calculation. As per [30], the noise intensities are obtained by using SNR calculation. The proposed method is evaluated by applying several levels of SNR. The proposed method is compared with other fusion techniques. Six levels of decompositions used where low pass sub-band for average scheme and band pass sub-band for absolute scheme. Different multimodal images are taken to apply this experiment setup and performances are evaluated. The selective images are given above.

In this proposed method, w and z are used in hybrid filter for altering sequences. The w and z parameter alters the noise suppression degree and also protects edge information. If the values of w and z are too high, obviously the edges of image are over smoothed. But noises are suppressed excellently. The tradeoff scalar (between fidelity and smoothness) is represented as λ in (5).

The performance of the proposed method is shown Figure 3 if λ is constant and n is different values. The entropy, correlation and GBI value increased gradually while increasing the value of n. Similarly SNR value increased gradually if λ value is increased when n is constant.

Experimental Results and Discussion:

The proposed method applied in a single data set. Since dataset images are available at [33], registration technique for images are not required. Registration technique not applied before fusion process. Figure 3 shows noise added Images up to 14.36 dB. These noises are simulated using ZMWG (Zero Mean White Gaussian) noise and these noises given to source images. Different kinds of SNR levels used for the validation of robustness. The SR method suppresses noises effectively. But in the fused images, the edges are smoothed. Whereas in NGMF over smooth significant information and makes unclear. The TVPL method retains the edge information along with staircase effects. In AFTV method, it avoids staircase method with less efficient as multi-scale alternating-sequence filter used. The proposed method preserves features of source image without having any staircase effects along with improved efficiency. The quantitative measurements of various fused images obtained from different methods are shown in the following table.

Key	SR	NGMF	TVPL	AFTV	ETV (Proposed method)
SNR	6.51	6.19	6.62	6.77	6.83
En	23.86	22.25	21.02	24.84	25.01
RMSE	23.88	20.39	23.10	18.23	17.86
CORR	0.97	0.98	0.97	0.99	0.99
GBI	0.61	0.56	0.54	0.64	0.73

Table 1: Assessment of different methods used for image fusion

It is apparent from table 1 that the proposed method performance is better than other techniques. In the following comparison chart, it shows sharpness improvements and the structure visibility of images obtained from the proposed method. Overall, the finest results yield by proposed method. The Signal to noise ratio value is increased when compare to other methods. The entropy and Root mean square error values are gradually increased when compared with other methods. Noticeably, the correlation value has not changed. In this proposed method, the correlation parameter has not retained the same value when compared with AFTV method. Other than correlation, other parameters are noticeably increased and could see the efficiency as the values are high than other methods. The variations of proposed methods can see in the following charts.

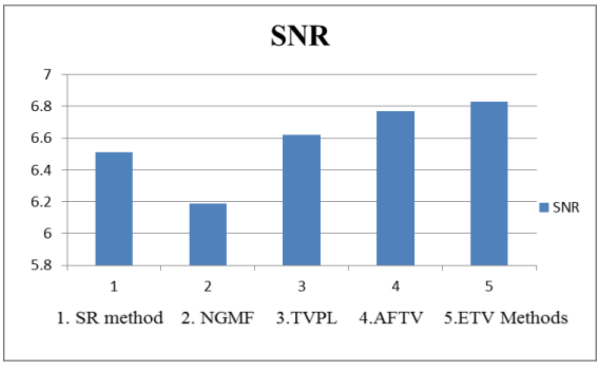

Figure 7: SNR comparison chart with various methods

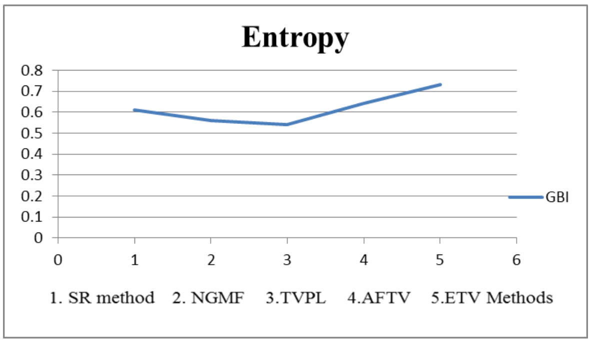

Figure 8: Comparison chart of Entropy with other methods

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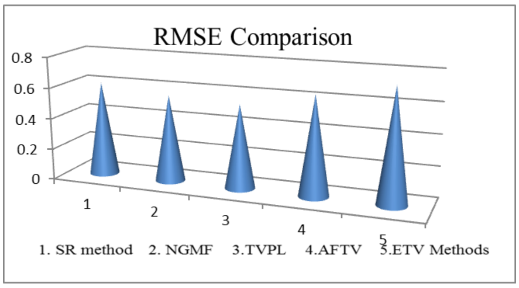

Figure 9: Comparison chart of RMSE with other methods

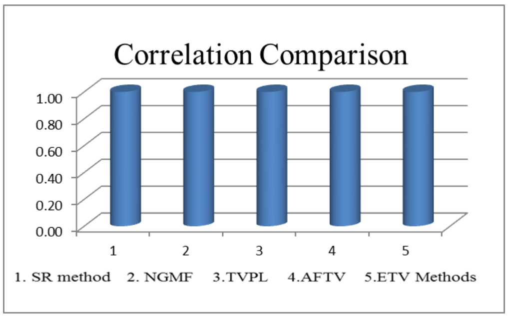

Figure 10: Comparison chart of Correlation with other methods

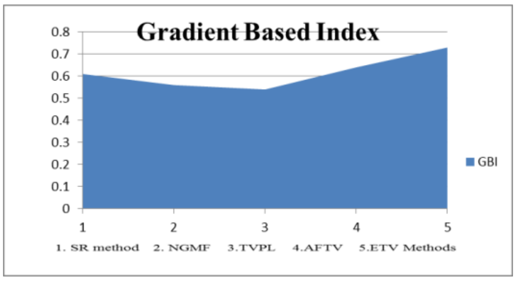

Figure 11: Comparison chart of Gradient based index with other methods

IV. CONCLUSION

An enhanced variation model for image fusion and de-noising has been proposed. The hybrid filter is initially integrated multimodal fusion imaging by using adaptive median method. This method extracts the significant details from the source images without any noise interferences. Furthermore, the ETV constraints are used to suppress noise with improved efficiency and overcome the drawbacks of Total variation methods. This experiment shows that this proposed method gives solutions for general things and applied successfully on noisy and noise free source images. Additionally this proposed method suppresses noises greatly without any loss of important details of source image from different modalities. Parameter adaptability can be used for future research purpose.

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