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A UNIQUE PROPOSED MULTIMODAL MEDICAL IMAGE FUSION METHOD FOR TWO-STAGE GUIDED IMAGE FILTERING

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ABSTRACT

In almost all vision and image processing systems, picture fusion is critically significant. The research presents to combine the anatomic imaging (SPECT) and Functional Imaging (MRI) employs a new proposed fusion approach with the aid of the most popular guided filter. In the proposed system, most of the features of the sources are preserved with the nature of preserving curves by image statistics. Along with this, other significant features of the image like linear edges and their orientation are retrieved by modulated guided filtering methods. The evaluations of the proposed approaches have been performed based on the image fusion metrics such as Entropy, correlation coefficient, Mean and STD information. The proposed methods produced good quality of fused images. It can be proved that proposed models can be considered as an efficient system in terms of image fusion compared to the conventional approaches with respect to the various qualitative evaluations.

Keywords: Medical image fusion, guided filtering, image statistics.

1. INTRODUCTION

An essential component of a patient's overall diagnosis is medical imaging. It encompasses a variety of radiological imaging methods, including X-rays, MRI, CT, PET, and single-photon emission computed tomography (SPECT), among others. Better anatomical visualisation and analysis of the patient's body is made possible by imaging modalities, which increases survival rates. Medical imaging is an essential component in many clinical applications nowadays [1].

Medical imaging tests are non-invasive test techniques that aid in the diagnosis of diseases or injuries so that a course of therapy can be planned. It is commonly expected that effective merging of the useful data from the photographs be necessary because the information (info) received from a few adopted images is typically of a free character. The fundamental step in this merging process is called "Registration" and involves adding the necessary modes for spatial alignment. After that, a fusion process is required for a unified perspective of the required data.

An example of the use of registering different modes may be seen in the designing of radiation diagnostics [2], whereas CT is currently used virtually exclusively. Combining CT and MRI would improve results because the first is more suited for characterization of tumour tissue (and is inherently more advantageous to gentle tissue counterpoint) and the second is required for precise dose of radiation calculating.Data fusion is the process of merging information from several sources to portray large amounts of data in the most effective or compact way possible to allow improved description and decision-making. The best example of a data fusion system is the human brain [3–4].

Even the human eye can extract many useful features of a situation by looking at the picture more than once. This is an example of the usage of repeated in the development of radiation diagnostics [2]. A two-dimensional quantity is an image. You might think of it as a fusion of illumination and reflection. Reflectance, or the amount of light reflected back from the same item, is referred to as illumination, which is defined as light from the source falling on the object. Using a sensor array, the visual data contained in a scene can be recorded as a digital image. The sensor array's components will all be of the same modality. Consequently, the term "single sensor image capture" is used to describe image capture employing a sensor array. Several sensor arrays that operate in various wavelength ranges may be used to examine the specifics of a scene. Simply put, this is referred to as multi sensor image capture. It should be noted that in the discussion that follows, the word "sensor" is used in place of a sensor array.

2. LITERATURE REVIEW

Pyramids and Wavelets, including the Gaussian Pyramid (GP), Non Sub Sampled Counter Let Transform (NSCT), Laplacian Pyramid (LP), Discrete Wavelet Transform (DWT), and Stationary Wavelet Transform (SWT), are commonly used MSD approaches for fusing the images in earlier works. In [7], a method for merging pictures using NSCT-DWT is proposed. This method uses NSCT decomposition and reconstruction. The NSCT, on the other hand, is thought to be inadequate for accurately capturing the images' contrast and shape. A method based on the union DWT [8] transform with a variety of attributes for precisely fusing the key characteristics from the source medical images. By using NSCT, the source medical image is initially mapped into their performances.

The contrast and outline feature maps are then extracted from the source images at each scale, and a successful fusion strategy is used to combine the coefficients of the pyramid. In order to obtain a fused image, the inverse pyramid reconstruction process is finally used. However, the image fusion metrics employed in this only evaluate the quality of the fused images from a limited perspective, making it difficult to determine which non-subjective parameter has been significantly changed. The most used MS fusion strategy is the DWT. Due to its superior simultaneous representation of spatial and spectral information, it offers far better fusion outcomes than the pyramid transforms.

An innovative method for MRI and PET image augmentation and fusion utilising NLAF-PCA was presented in [9]. To improve the quality of the input photos, anisotropic filters are first used to pre-process the source medical images, which are damaged and unreadable for a variety of reasons. Then, using PCA for brain areas with differing degrees of activity, these improved images are combined. In compared to other medical fusion techniques, it produced less accurate results with lessened colour distortion and without losing any anatomical information.

IGNLA (Guided Nonlinear Anisotropic Filtering with Image Statistics Based Fusion Algorithms) is a method that suffers from shift variance, aliasing, and lack of directionality, as reported by the authors in [10]. To get over the shift variance restriction, authors in [11] introduced the on weighted parameter adaptive dual channel PCNN (WPAD-PCNN) and sparse representation based medical picture fusion strategy. For the fusion of medical images, parameter adaptive PCNN (PA-PCNN) approaches have recently been developed, which extract more spectral characteristics in varied orientations than conventional neural networks [12]. However, it also has a problem with lack of focus.

Ant colony optimization-based ensemble empirical mode decomposition (ACO-EEMD), which was reported in [13], uses productive image fusion to get around these restrictions. Directionality and shift invariance The main advantages of ACO-EEMD over other wavelet transform variations like DWT and SWT are Novel Methods to Improve Diagnostic Details in Medical Images via Registration and Fusion Techniques selectivity, which reduces the artefacts introduced by these two versions.

By segmenting the features of registered source pictures with watershed transform, either simultaneously or independently, the authors of [14] focus on feature level image fusion based on Multiscale decomposition (MSD) with local energy maxima, which is used to build region maps. New Sum of Modified Anisotropic Laplacian (NSMAL) was first introduced in [15] to analyse the properties and address constraints-related concerns. The photos are then combined using the determined region characteristics. a fusion strategy in which the input images were first decomposed using NSMAL, and then the maximum and local energy fusion laws were used to integrate the results at various frequencies, low and high.

In [16], authors merged NSST with biologically inspired neurons like PCNN to create a two-stage NSST-PCNN based fusion system for medical imaging. Source images are first re-sliced and co-registered, and in the second stage, NSST is used to fuse those co-registered images. Authors established multi-resolution and nonparametric density models (MRNDM) in [17] by utilising a weight adjustment model to address concerns with mutual information in this technique. It makes use of the MRNDM's approximate shift-invariance property, which is essential for the fusing of the subbands. As a result, the multi-level procedure avoids information loss. On the other hand,

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more fused picture coherent structures are encoded using phase information availability.
By developing the fuzzy clustering-based decomposition (FCD) method for multi-exposure image fusion, which minimises the ghosting effect, and in hierarchical multivariate Gaussian Conditional Random Field (CRF) mode, the authors of [18-19] improve the fusion. By decomposing the input images with rich PCA [20] and estimating the weights after assuming the characteristics of local sparse inputs, principle component and sparse matrices are generated.

3. PROPOSED METHOD

The suggested Fusion approach can combine data from two or more multimodal photos to create a single image that is more informative than any of the applied input images. Figure 1 depicts the suggested fusion strategy. The specific procedure is as follows:
The proposed method can be capable of performing the fusion of different multi modal image combinations such as MRI and SPECT fusion, MRI and CT fusion and MRI and PET fusion. Thus here A is considered as MRI image. The B is color image of type SPECT or PET, so it is applied to RGB2YUV operation. While BU and BV are the differentiated chromium blue and chromium red components, they will also be beneficial for the YUV2RGB conversion since they contain the major source of the input picture B. The BF is the luminance or brightness output component, which contains the main source of the input image B.

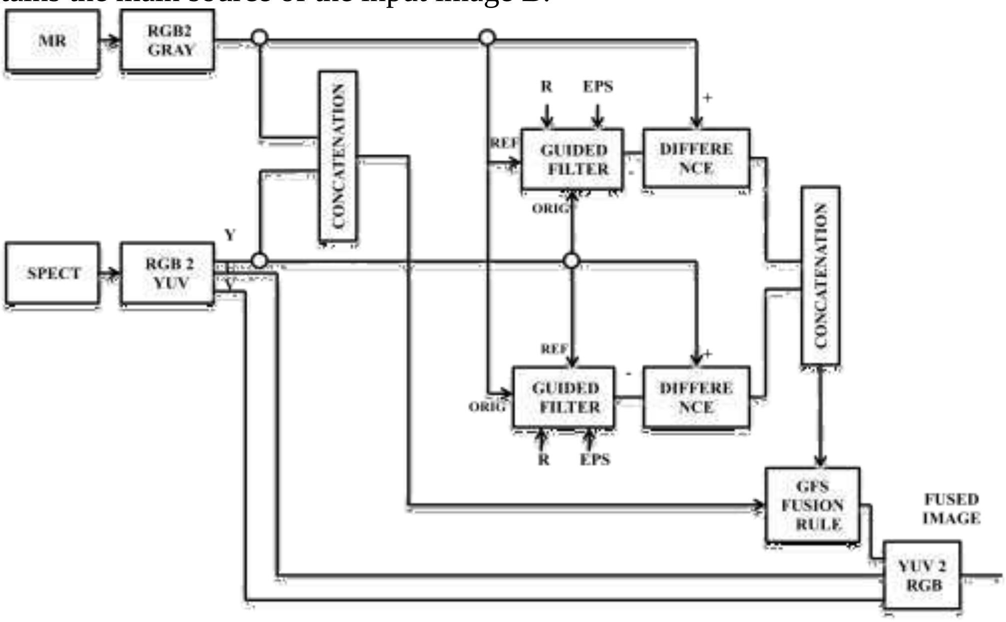


Fig 1: Proposed image fusion block diagram.

The RGB2YUV conversion as follows

$$V = 0.299*R + 0.587*G + 0.114*B \quad (1)$$

$$U = -0.1473 *R - 0.289*G - 0.436*B \quad (2)$$

$$Y = 0.615* R - 0.514*G -0.100*B \quad (3)$$

The RGB2 Gray conversion as follows

$$Out=0.2989 * R + 0.5870 * G + 0.1140 * B \quad (4)$$

Guided filter Fusion (GFF): The saturation of a color described the intensity of color in the photograph which would be useful to produce well exposed pixels in the fused image. When image is captured at long exposure setting the color details present in the brightly illuminated areas becomeless saturated. A desaturated photograph will look washed out and has overly faded colors. The approach proposed in the thesis would avoid desaturated pixels by producing the weight map with saturation measure. The saturation measure is computed for k^{th} source image as the standard deviation within the R, G, and B channel, at each pixel.
Contrast is determined by the difference in luminance or color within the same field of view that makes an object distinguishable. The response of HVS is more sensitive to contrast than absolute luminance. In other words, the maximum contrast of a photograph can be determined by the ratio

of the luminance of the brightest color (white) to that of the darkest color (black), which is known as contrast ratio or DR. In order to measure local contrast, GFF used isotropic derivative operator . The isotropic derivative of an image I(x,y) having two independent variables, denoted by $A^2(x, y)$ is defined as:

$$A^2 I\,(x,y) = \frac{d^2 I(x,y)}{dx^2} + \frac{d^2 I(x,y)}{dy^2} \qquad (5)$$

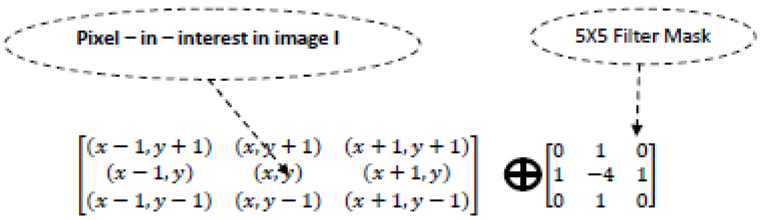
For digital images, the second order derivative in the x-direction is estimated as:

$$\frac{d^2 I(x,y)}{dx^2} = I(x+1\,,y) + I(x-1\,,y\,) - 2I\,(x,y) \qquad (6)$$

From Equation (7), two-dimensional Laplacian operator can be obtained by summing Equation (5)and Equation (6) as:

$$A^2 I\,(x,y) = I\,(x+1,y) + I(x-1,y) + I(x,y+1) + I(x,y-1) - 4I(x,y) \qquad (7)$$

This Equation (8) can be implemented in an image by convolving the image with the following 5-by-5mask:



If the image is of pixel intensities are between 0 and 1. A correctly exposed picture is one that has intensities not near zero (under-exposed) or one (over-exposed). Therefore, a pixel is said to be well- exposed if intensity value is close to 0.5 [113]. The weight intensity value (Ù˜) of each pixel at (x,y) location based on how close it is to 0.5 using a Gauss curve:

$$EX\,(x,y) = e^{\left(-\frac{(i-0.5)^2}{2\sigma}\right)} \qquad (8)$$

where σ ′ equals 0.2 in GFF implementation, which can control the quality of the fused image. When computing the weights in GFF, the fusion performance will be worse when the value of σ is too large or too small. In this paper, the default parameters is set as σ ′ = 0.2. In order to balance the brightness in fused image, we have found that σ ′ = 0.2 generates reasonably good results for most of the cases. To account for multiple color channels, GFF apply the Gauss curve to each R, G, and B channel separately, and multiply the results for computing final exposedness measure EX_k The weight map

function used in GFF approach is computed as the product of three quality metric

$$W_k^{gff}(x,y) = SA_k(x,y) \times CO_k(x,y) \times EX_k(x,y) \qquad (9)$$

In GFF based exposure fusion framework, the fused BL $BL^{gff}(x, y)$ is computed as the weighted sum of the BLs obtained from GF $BL_1^{gff}(x, y)$, BL_2^{gff} (x,y),..... $BL_N^{gff}(x, y)$ obtained across N input exposures. GFF uses the pyramid approach proposed, which generate Laplacian pyramid of the BL

$LB_k^{gff,l}(x, y)$ and Gaussian pyramid of weight map functions $GW_k^{gff,l}(x, y)$ estimated from three quality measures. The Laplacian pyramid and Gaussian pyramid of BLs and weight map function are computed in similar manner as computed in ADF approach, respectively. Here l (0<l<k) refers to the number of levels in the pyramid and k (1<k<N) refers to the number of input

images. The Laplacian pyramid of $k_{th} BL$ $(LB_k^{\mathbf{gff},l}(x, y))$ is multiplied with the corresponding Gaussian pyramid of weight maps ($GW_k^{gff,l}(x, y)$) nd summed over k yield modified and fused Laplacian pyramid
$L_F^{gff,l}(x, y)$:

$$L_F^{gff,l}(x,y) = \sum_{k=1}^{N} LB_k^{gff,l}(x,y) GW_k^{gff,l}(x,y) \qquad (10)$$

The $BL_F^{gff}(x, y)$ that contains well exposed pixels is reconstructed by expanding and summing each

level of modified and fused laplacian pyramid :

$$BL_F^{gff}(x,y) = \sum_{l=0}^{d} L_F^{gff,l}(x,y) \qquad (11)$$

The DLs computed in Equation (12) across all the input exposures are linearly combined to producefused detail layer $DL_F^{gff}(x, y)$ that yields combined texture informat ion:

$$DL_F^{gff}(x,y) = \frac{\sum_{k=0}^{N} \gamma f_k(DL_k^{gff}(x,y))}{N} \qquad (12)$$

where γ is the user defined parameter to control amplification of texture details (typically set to 5) and
`$f_k(.)$ is the nonlinear function to achieve detail enhancement while reducing noise and artifacts near strong edges due to over-enhancement. GFF follow the approach of to reduce noise across all DLs.
Finally, the detail enhanced fused images $I_F^{gff}(x, y)$ easily computed by simply adding up the fusedBL $BL_F^{gff}(x, y)$computed in Equation (13) and the manipulated fused DL $DL_F^{gff}(x, y)$ in Equation (4.23):

$$I_F^{gff}(x,y) = BL_F^{gff}(x,y) + DL_F^{gff}(x,y) \qquad (13)$$

5. EXPERIMENTAL ANALYSIS

The analysis and outcomes of the suggested fusion procedure are described in this section. For quicker running times, all experiments were carried out in the high-speed CPU environment of MATLAB 2018a. Results from tests are based on various combinations of MR, SPECT, and PET image datasets.

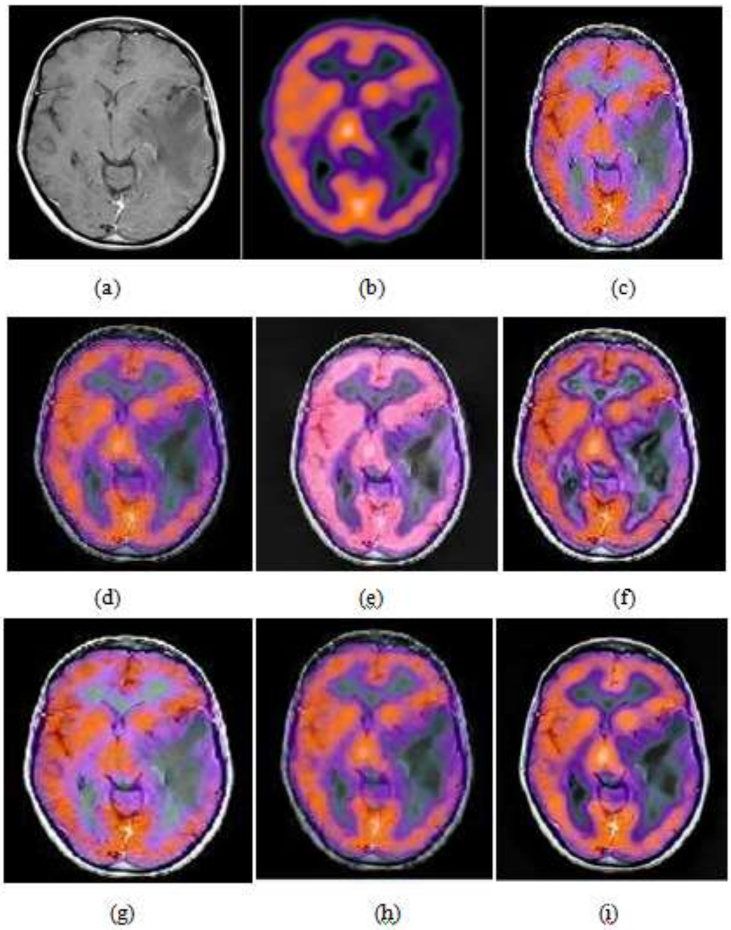


Fig.2. Fusion of SPECT-TC images and MR-Gad

The acquired fused results of the suggested fusion approaches for the MR-Gad & SPECT-TC datasets, respectively, were shown in Figure 2. The CNN-PCA [24] fused output is degraded in local minima regions, according to observations of the fused output. The WPADC-PCNN [11] fused output is unable to fully realise the global features. Due to the pulsed response in NSST-PCNN [16], the fused output luminance component is significantly more dominating than the chroma components. The tissues are overbrightened because of the overintensity of the PA-PCNN [12] fused output. The IGNLA [10] fused output has inappropriate weight changes in the luma and chroma components, and the ACO-EEMD [13] fused output has greater patches of darkness. Thus, it is evident that the suggested fusion improves the visual quality of the image without lowering its quality, thereby providing greater visual information. The performance evaluation of the MR-Gad and SPECT-TC dataset, as well as the visual results of the fusion of the MR-T2 and SPECT-TC, is shown in Table 1. In comparison to the existing literatures ACO-EEMD[13],NN-PCA[14],WPADC-PCNN[11],NSST-PCNN[16],PA-PCNN[12] and IGNLA[10], our suggested TSMSD fusion generates optimal values for all the quality measures, which are underlined in bold.

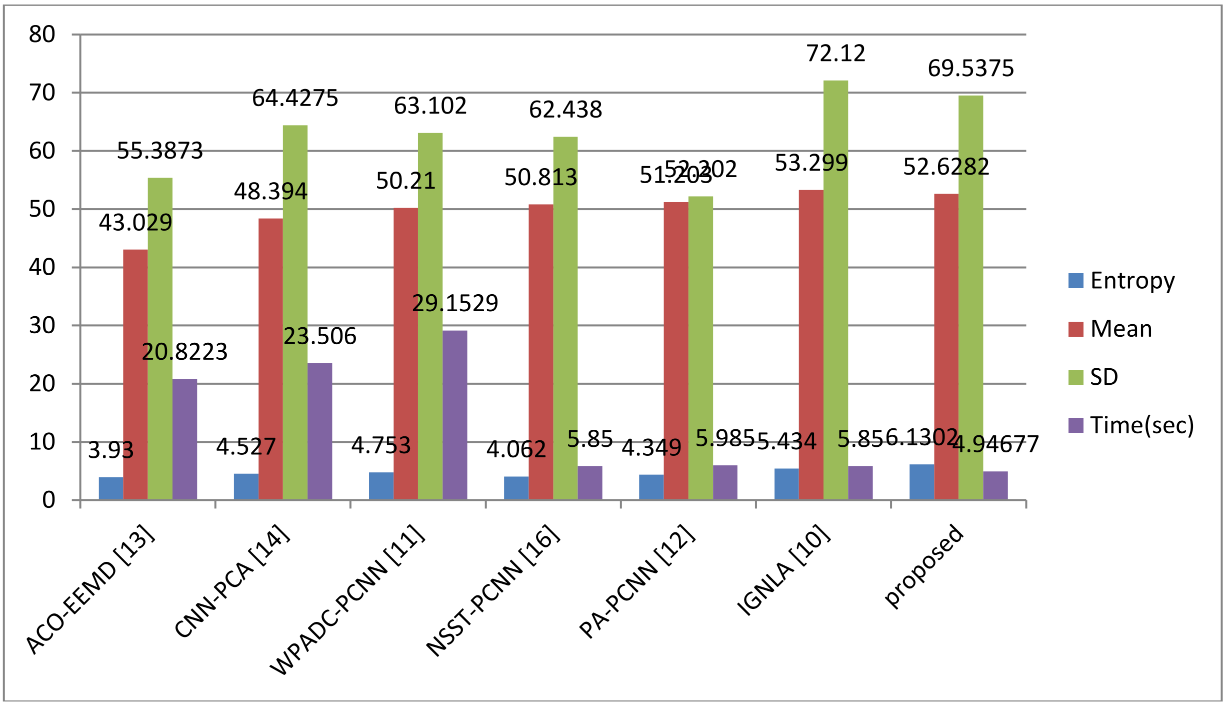


Figure.3. Gathered performance measures for the fusion approach that is currently being used and proposed for MR and SPECT datasets.

CONCUSSION

In this work the edge-preserving property of guided filter is extended to BL and DL decomposition, which has applicability to avoid false texture detail extraction in DL computation. The multi layers will be decomposed based on guided filter is utilized to extract the superior features for detail fusion of images. In the present method, the Fusion approach is used for the fusion of BLs, and the utilization of contrast, saturation and well-exposedness for the calculation of weight map is investigated. An alternate approach for DL enhancement using non-linear function has been developed. This work can be extended to implement the detection and classification brain tumors from the fused output image.

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