Color Medical Imaging Fusion Based on Principle Component Analysis and F-Transform[1]

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Abstract—In last years, various medical image fusion algorithms have been proposed to fuse medical image. But, most of them focus on fusing grayscale images. This paper proposes a qualified algorithm for the fusion of multimodal color medical images. The technique of F-transforms has mainly been employed as a fusion technique for images obtained from equal or different modalities. The restriction of fused color mixing RGB, substitution method is resolved by incorporating F-transform and color mixing RGB. The proposed method significantly outperforms the traditional methods in terms of both visual quality and objective evaluation, with improved contrast and overall intensity. The proposed method provides better visual information than the gray ones and more adaptable to human vision. Additional, PCA is functional on the two-level decomposition to maximize the spatial resolution. Experimental evaluation demonstrates that the proposed algorithm qualitatively outperforms many existing state-of-the-art multimodal image fusion algorithms.

Keywords: Image fusion, computed tomography, magnetic resonance imaging, F-transform, color mixing RGB

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1. INTRODUCTION

The Medical imaging considered as an important role in medical analysis and diagnosis. Different medical imaging techniques such as computed tomography (CT), magnetic resonance imaging (MRI) and positron emission tomography (PET) provide different perspectives of the human body. For example, CT images provide perfect contrast of bones and additional dense structures to the surrounding tissue, whereas MRI provides excellent soft-tissue contrast. On the other hand, PET provides a concept of functional characteristic. Therefore, an enhanced understanding of a patient's condition can be achieved through the use of different imaging modalities. In the medical imaging field, the different images can get of the same part of the same patient with different imaging devices, and the information provided by a variety of imaging modes is often complementary [6]. Image fusion is the process of integrating information from two or more images of an object into a single image. The resultant image should be more informative and suitable for visual perception or computer examination.

In present day technology, images from a single sensor may not always be sufficiently accurate to represent all required information of a particular organ, whereas the images from different modality carry complimentary but important information. The benefits are even more profound in combining anatomical imaging modalities with functional ones. For example, PET/CT in lung cancer, MRI/PET in brain tumors, SPECT/CT in abdominal studies and ultrasound images/MRI for vascular blood flow. Outcome of CT/MRI image fusion has been shown to be able to assist in planning surgical procedure. It is beneficial for assisting neurosurgery of temporal bone tumors [1]. The disadvantage of CT/MRI image fusion in gray color is that both bone and fat are bright. Therefore, it will be difficult to distinguish between them. However, the most common multimodal medical images such as MRI, CT, and PET can provide a grayscale representation for a view. Coloring is an image enhancement technique [2, 3], which helps physicians to isolate relevant tissues and groups different tissues together. Color fused by spatial relationships is very useful in many clinical areas. Biological research evidence that human eyes are more sensitive to color [4] and resolution of color image is higher than a gray image. Thus, the color mapping in the fusion process of those images is an interesting and important issue.

Medical image fusion typically employs the pixel level fusion techniques. Many image fusion methods have been proposed for combining different modality images. Some of them are based on Bayesian and neural network approaches [5]. Substitution methods such as principle component analysis (PCA) [6–8],

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averaging weighted, color mixed RGB [9] and intensity hue saturation (HIS) [6, 10]. Transform domain such as multiresolution decomposition, which introduces spatial features from the high-resolution images into the multispectral (color) images. For example, wavelets [11], curvelet [12], and contourlet transform [7]. One of the most common techniques used for the fusion of two images is the color overlay substitution method [13]. The color overlay substitution method, one image is showed semi-transparently on top of the other image. This can be implemented in many ways such as the addition of images or averaging of the source images. In color mixing [9, 13, 14], any number of one-channel images (N) can be used, and a fused RGB image can be created. It was found that image fusion based on color mixing methods, average or magnitude maximum method reduced the contrast of features uniquely presented in either of the source images [15]. They also reduce the overall intensity therefore; it cannot provide a good outcome. Thus, there is a need for an algorithm that can handle contrast and overall intensity. The algorithm might be necessary to be able to scale the intensity of the fused image. Image fusion based on Fuzzy-transform (F-transform) can handle contrast and overall intensity.

The F-transform [16] is an efficient intelligent method to handle uncertain information. It represents those natural phenomena which can observe in our real lives. F-transform has already been proposed for multimodality image fusion by [17–19]. Perfilieva [20] shows that the F-transform technique is a promising and efficient method for image fusion. In this paper, coloring fusion algorithm for multimodality medical image based on F-transform and color mixing RGB is proposed. Experimental results show that the proposed color fusion algorithm provides an effective way to enable more accurate analysis of multimodal images.

2. COLOR MIXING RGB

Baum [9, 13] proposed a multimodal medical fusion technique based on color mixing RGB. Color mixing RGB is a technique that can be employed to take any number of one channel images, N, and create a fused color image, usually defined in RGB (red, green, blue). Channel mixing is constructed by

$$[S_1\ S_2\ S_3\ .....S_i] = \begin{bmatrix} R_1 & G_1 & B_1 \\ R_2 & G_2 & B_2 \\ R_3 & G_3 & B_3 \\ \vdots & \vdots & \vdots \\ R_i & G_i & B_i \end{bmatrix} = [R\ G\ B] \quad \text{for} \quad i = 1,\ldots,N, \tag{1}$$

where R, G, B represented the red, green, and blue channels in the displayed image, respectively; S_i presents the intensity in the ith source image; R_i, G_i, B_i are the weighting factors for the red, green, and blue channel, respectively. They control the influence of source i to each of the output channels.

The source intensities are standardized from zero to one. Channel mixing is equivalent to taking the intensity axis of source i and lying it along the line segment, formed by connecting (0, 0, 0) to (R_i, G_i, B_i) in the RGB color space. The output image is formed by collecting the projections of each of these onto the red, green, and blue axes.

3. F-TRANSFORM

The proposed for the F-transform (an abbreviated name for the fuzzy transform) came from fuzzy modeling Perfilieva [20]. The purposed was to show that, similarly to conventional transforms (Fourier and wavelet). The F-transform is given by a matrix of elements in correspondence with a finite vector of its Fptransform components. The F-transform of a 2D grayscale image u that is considered as a function $u : [0, M] \times [0, N] \to [0, 255]$. It is supposed that the image is defined at points (pixels) that belong to the set P, where the discrete function $u : P \to \mathbb{R}$ of two Variables. Moreover, let fuzzy sets $A_k \times B_l$, $k = 1, \ldots, n$, $l = 1, \ldots, m$, where $0 < n \le N$, $0 < m \le M$ establish a fuzzy partition of $[1, N] \times [1, M]$. The F-transform of u corresponds to the matrix of F-transform components is:

$$F[u]_{nm} = \begin{pmatrix} F[u]_{11} & \cdots & F[u]_{1m} \\ \vdots & \vdots & \vdots \\ F[u]_{n1} & \cdots & F[u]_{nm} \end{pmatrix}. \tag{2}$$

The coefficients $F[u]_{nm}$ are called *components* of the F-transform. Each component $F[u]$ is a local mean value of u over a support set of the respective fuzzy set $A_k \times B_l$. The F-transform of u (with respect to the chosen partition) is an image of the mapping $F[u]: \{A_1, \ldots, A_n\} \times \{B_1, \ldots, B_m\} \to \mathbb{R}$ defined by:

$$F[u]_{nm} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} u(i,j)A_k(i)B_l(j)}{\sum_{i=1}^{N}\sum_{j=1}^{M} A_k(i)B_l(j)}. \tag{3}$$

The fuzzy partitions of $[1, N]$ is defined as largest partition $F[u]_{11}$ *and* u_{11} is *the respective inverse* F-*transform*. The finest partition $F[u]_{nm}$ is the fuzzy partitions of *fuzzy sets* $A_k \times B_l$, *such that for all* $k = 1, \ldots, N$ *and* $l = 1, \ldots, M$. The inverse F-transform of u is a function on P, which is represented by the following inversion formula:

$$u_{nm}(i, j) = \sum_{i=1}^{n}\sum_{j=1}^{m} F[u]_{kl} A_k(i)B_l(j), \qquad (4)$$

where $i = 1, ..., N, j = 1, ..., M$. It can be shown that the inverse F-transform u_{nm} approximates the original function u on the domain P. The F-transform technique, leading to one-level or higher-level decomposition of an image; the technical specifics proof of these decompositions can be found in [16]. The one level decomposition is as the following representation of u on P:

$$u(x, y) = u_{nm}(x, y) + e(x, y), \qquad (5)$$

$$e(x, y) = u(x, y) - u_{nm}(x, y), \quad \forall(x, y) \in P, \qquad (6)$$

where $0 < n \le N$, $0 < m \le M$, and u_{nm} is the inverse F-transform of u and e is the respective residuum. The pixels are processed one by one in a technique that appropriate basic functions are initiate for each of them. If function is smooth, then the error function $e(x, y)$ is minor, and the one-level decomposition (5) is adequate for our fusion algorithm. However, images generally hold various types of degradation that disrupt their smoothness. As a result, the error function $e(x, y)$ in (5) is not negligible, and the one-level decomposition is insufficient for our purpose. Therefore, continue with the decomposition of the error function e in (5) [20]. The decompose into its inverse F-transform $e_{n'm'}$ (with respect to a finer fuzzy partition of $[1, N] \times [1, M]$ with $n' : n < n' \le N$ and $m' : m < m' \le M$ basic functions, respectively) and a new error function e'. Hence, the second-level decomposition of u is found.

4. THE PROPOSED FUSION ALGORITHM

When using proposed method to combine CT, PET, and MRI images, there would be two sources and six weights of mixed color. Our objective is to merge both images to obtain as much information as possible. It is known that different imaging modalities are employed to represent different anatomical morphologies. The proposed algorithm is summarized as follows.

1. Image registration is the procedure of transforming to align images including features into one coordinate system. Image registration technique employed is as [21].

2. The CT, PET, and MRI images are registered. The input images c_i, $i = 1, ..., K$, $K = 2$.

3. Apply color mixed algorithm and manually select the color matrix for fusion using the F-transform. For each source image, there are three matrices that are of the same size as the source image. They represent the three bands; red, green, and blue.

4. Choose only one weighted matrix from each source image for fusion using F-transform. The other matrices are processed by using color mixed approach.

5. Create the fuzzy partitions $A_1^{(1)}, ..., A_n^{(1)}$ and $B_1^{(1)}, ..., B_m^{(1)}$ of $[1, N]$ and $[1, M]$, respectively.

6. Decompose input images c_1 and c_2. The F-transform algorithm using two-level decomposition is derived from the one developed in [18].

7. For all $i \in I$, compute the direct and the inverse F-transforms of each input image c_i and obtain: $[c_i]_{11}, ..., F[c_i]_{nm}$, the F-transform components of c_i and $c_{i_{nm}}$, the inverse F-transform of c_i. Compute the error functions: $e_i = c_i - c_{i_{nm}}$. Identify values $e_i(x, y)$, $(x, y) \in P$, with the F-transform components $F[e_i]_{xy}$ of e_i with respect to the finest partitions of $[1, N]$ and $[1, M]$.

8. Apply the fusion operator κ to the respective F-transform components of c_i, $i \in I$. Assuming I and J are the elements of the principal eigenvector, which are calculated by analyzing the original input image c_1 and c_2 for corresponding image coefficients, we obtain, weight factor PCA as in [7]. Fusion operator $\kappa : \mathbb{R}^{\kappa} \to \mathbb{R}$ defined as follows

$$\kappa(x_1, \ldots, x_K) = x_p, \quad \text{if} \quad |x_p| = PCA(|x_1|, \ldots, |x_K|)$$

$$\kappa(F[c_1]_{11}, \ldots, F[c_\kappa]_{11}) = \kappa_{11}^{(1)} \qquad (7)$$

$$\ldots\ldots\ldots\ldots\ldots\ldots$$

$$\kappa(F[c_1]_{nm}, \ldots, F[c_\kappa]_{nm}) = \kappa_{nm}^{(1)}$$

and obtain the fused F-transform components of a new image $\kappa_{11}^{(1)}, ..., \kappa_{nm}^{(1)}$.This process is repeated (step 7) for new error function and obtain the fused F-transform components of a new error function $\kappa_{11}^{(2)}, ..., \kappa_{nm}^{(2)}$. The process is repeated for second level decomposition.

9. Reconstruct the fused image from the inverse F-transforms with the fused components of the new image and the fused components of the new error function.

10. Rebuild the three channel bands (Red-Green-Blue) for fused image.

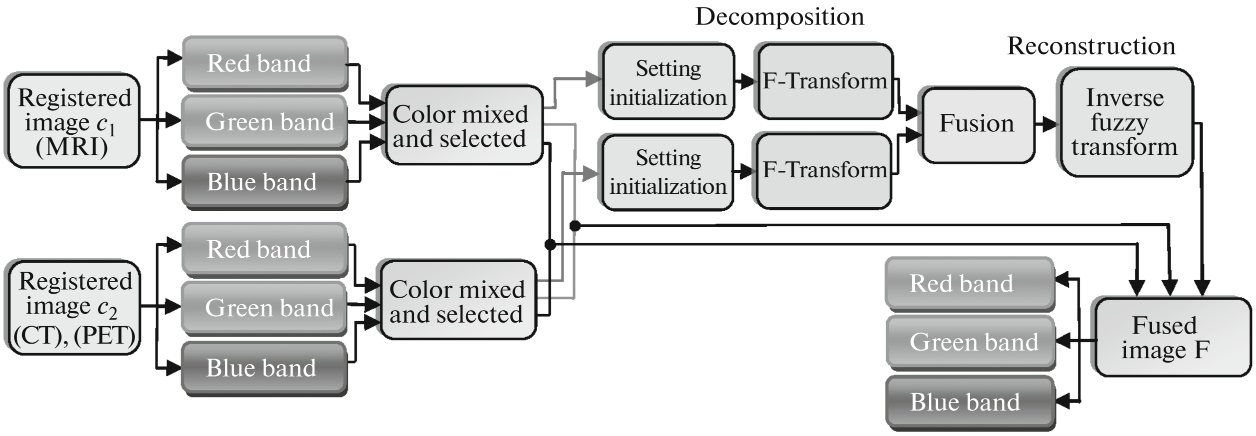

Fig. 1. The block diagram of the proposed color image fusion algorithm.

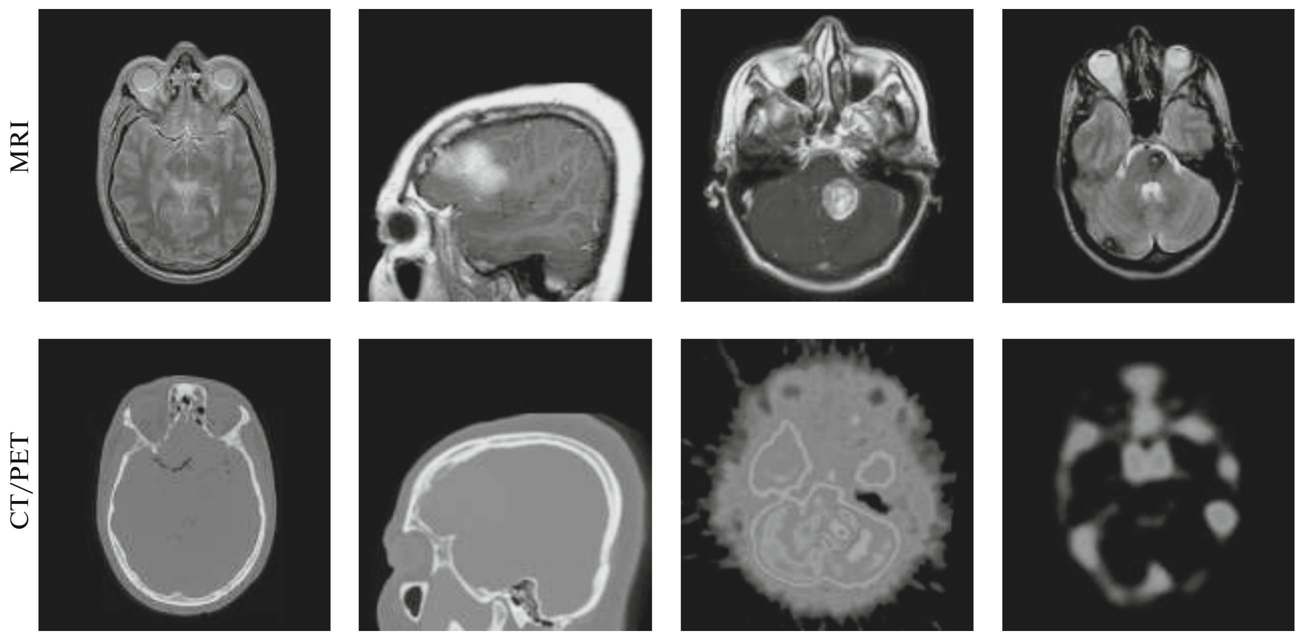

Fig. 2. Original multimodality image dataset 1, 2, 3, and 4.

Figure 1 shows the block diagram of the proposed coloring image fusion algorithm-based F-transform. The observer can adjust the weighting of color matrices to create a variety of fused images and also to make the fusion technique interactive.

5. EXPERIMENTAL RESULTS

The proposed method has been implemented and verified on medical images provided by Hospital Universiti Sains Malaysia (HUSM). Forty groups of human brain images have been selected (Fig. 2, shows four groups only). All images have the same size of 512 × 512 pixels, with 256-level grayscale, where the multimodal medical images are assumed to be perfectly registered, pixel-by-pixel. The registration technique employed is as described by Al-Azzawi [21]. The proposed algorithm systems were implemented in MATLAB software package and tested on an Intel Core i7-4500U, 2.4 GHz. Clinical MR, T1 image volumes were acquired with an echo time (TE) of 11 ms and a repetition time (TR) of 420 ms. The PET/CT images were acquired using a GE lights speed plus scanner, Siemens scanner and the MR images, using a GE Signa Horizon 1 T scanner. The proposed algorithm for the fusion of CT, PET, and MRI images is tested and compared to the traditional color mix RGB [13] fusion algorithm and wavelet fusion method (DWT) [22]. Objective evaluations of fused images are

Table 1. Objective evaluations of the fusion algorithms

Dataset	Algorithm	mean $Avg_{k=\mathrm{R,G,B}}$	PSNR to MRI in dB	PSNR to CT/PET in dB
Dataset 1	Proposed	3.979	44.716	44.517
	Wavelet	3.586	41.358	41.359
	Color mixed	3.449	29.410	29.410
Dataset 2	Proposed	3.814	50.659	50.545
	Wavelet	3.837	46.559	49.701
	Color mixed	3.183	43.345	38.249
Dataset 3	Proposed	5.719	34.401	34.420
	Wavelet	5.680	31.764	31.782
	Color mixed	5.677	28.482	28.497
Dataset 4	Proposed	4.345	46.880	45.879
	Wavelet	4.038	38.824	38.724
	Color mixed	4.235	33.509	33.508

important in comparing the performance of different algorithms [23]. Furthermore, evaluation methods are needed to compare "good" or "bad" fused images. Two indicators are used for evaluation of the performance of the fusion algorithms. They are average gradient [24] and peak signal to noise ratio [25]. Comparison is also made based on the visual quality of the fusion result.

A. Average Gradient

Average gradient is used to calculate the performance of the fused image [24] and reflects the clarity of the fused image. The overall image fusion performance measure can be described as:

$$Avg_k = \frac{1}{(M-1)(N-1)} \times \sum_{x=1}^{M-1}\sum_{y=1}^{N-1}\sqrt{\frac{1}{2}\left(\frac{\partial F_k(x,y)}{\partial x}\right)^2 + \frac{1}{2}\left(\frac{\partial F_k(x,y)}{\partial y}\right)^2}, \tag{8}$$

where $F_k(x,y)$ is the pixel value of the fused image at position (x, y). The average gradient reflects the clarity of the fused image. It can be used to measure the spatial resolution of the fused image. Higher value of average gradient shows a higher spatial resolution.

B. Peak Signal to Noise Ratio

The peak signal to noise ratio PSNR of the fusion result is defined as follows:

$$PSNR = 20\log_2\left(f_{\max}\Big/\left(\frac{1}{3}\right)\sum_k\sqrt{\frac{\sum_{x=1}^{N}\sum_{y=1}^{M}(R_k(x,y)-F_k(x,y))^2}{M\times N}}\right), \tag{9}$$

where $k = R, G, B$, $F_k(x,y)$, and $R_k(x,y)$ are the pixel values of the fused and original images at position (x, y), respectively. In this paper $N = 512$, $M = 512$, $f_{\max}$ equals to 255 where it is the maximum scale value of the pixels in the fused image. The higher value of the *PSNR*, means a better performance of the fusion algorithm.

6. RESULTS AND DISCUSSION

The proposed algorithm for the fusion of CT, PET, and MRI images is tested and compared to the wavelet fusion method and traditional color mixed RGB method [13]. Table 1, shows the objective evaluations of the fusion algorithms. It is observed from the values of average gradients that the proposed algorithm can

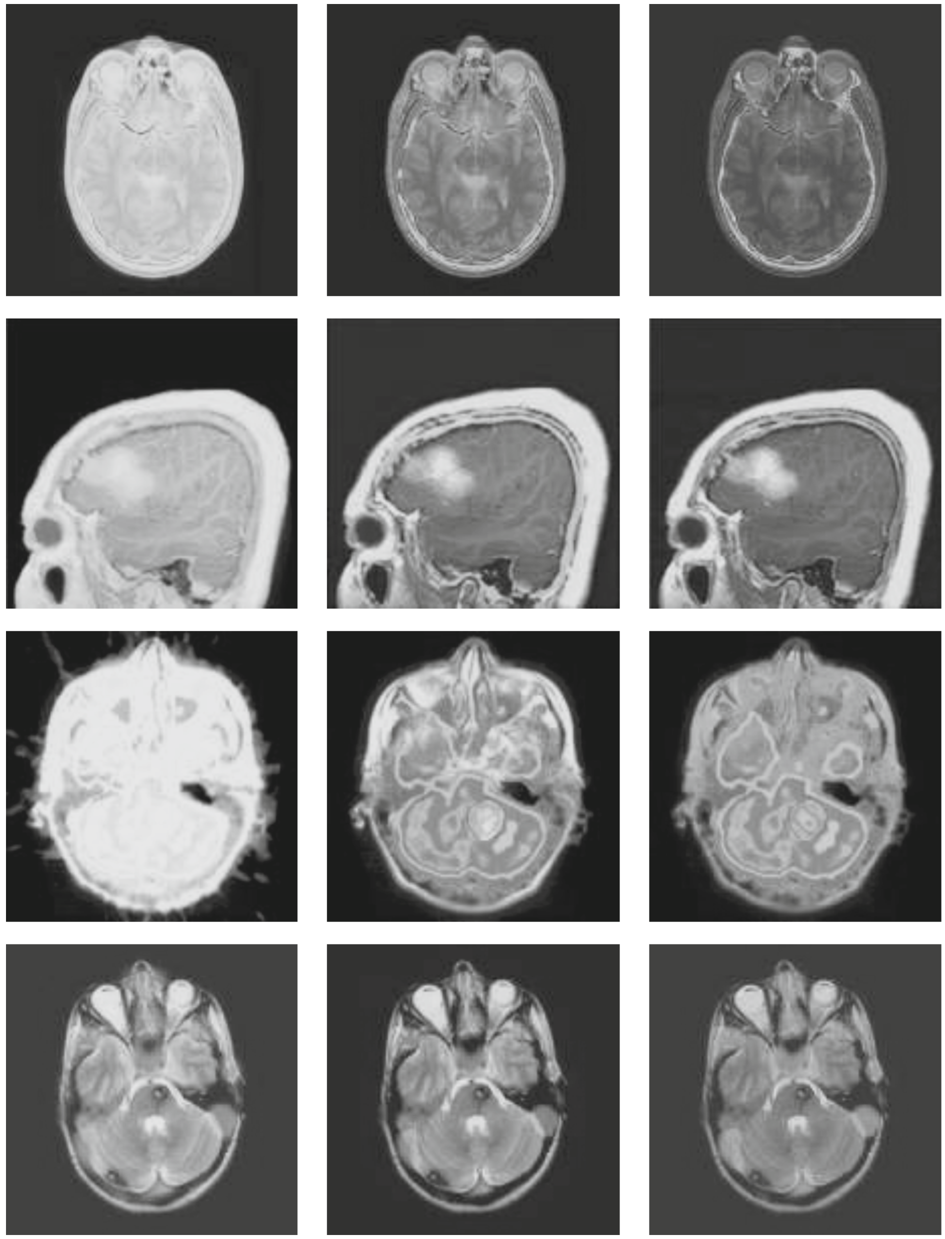

Fig. 3. Color fusion results on test Original multimodality image dataset 1, 2, 3, and 4 using color mixed RGB, wavelet and proposed method based on F-transform.

preserve high spatial resolution characteristics of the high-resolution source image. In addition, the spectral distortion introduced to the proposed fusion method is less than the wavelet method and traditional color mixed RGB method. Furthermore, the calculated *PSNR* demonstrate that the proposed method preserves more spatial features with less spectral distortion compared with other fusion algorithms. For the two-human brain medical image sets, the corresponding fused images are shown in Fig. 3. It can be easily seen that image fusion based on wavelet performs better than traditional method. However, the best image fusion result is obtained by applying the proposed fusion algorithm. Clearly the proposed method based on F-transform gives a better visual quality than the wavelet fusion and color mixed RGB.

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