



# PET/CT Fusion using Pixel Level Adaptive Weighted Alpha Blending

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**Abstract**— Cancer is one of the primary causes of morbidity and mortality in the developing countries. To infer complex decisions during diagnosis and treatment planning, multi-modality imaging plays an important role. So, accurate anatomic localization of functional abnormalities is desirable. This paper aims to combine the low resolution functional information representing the metabolic activity of tissues from the PET image on the top of detailed, high-resolution anatomical information in the CT image. The paper proposes a new method called adaptive-weighted alpha blending at pixel level for the fusion of PET and CT images. The proposed method is compared with some of the pixel-level spatial domain image fusion algorithms using the non-reference image quality, image fusion and error metrics. It is found that the proposed method excels in performance over the other methods.

**Keywords**— Adaptive Image Fusion, Non-Reference Metrics, PET/CT Fusion, Medical Image Fusion, Alpha Blending

## I. INTRODUCTION

The ultimate objective of medical image fusion is to combine the information from multi-modality images into a single image for easy diagnosis and treatment planning. Mostly, an individual medical imaging system reveals either internal structures hidden by the skin and bones or biological processes taken place within in the body at cellular and molecular levels. For example, CT provides fine detail about bony structures and less detail about soft tissues. Whereas, MRI affords detailed images of organs, soft tissues, bones and almost all other internal body structures. PET offers the information about the metabolic changes in the cells of the body. SPECT shows how blood flows to tissues and organs. The complementary nature of medical images motivated the imaging systems to combine Single Photon Emission Tomography (SPECT) or Positron Emission Tomography (PET) with Computed Tomography (CT) or Magnetic Resonance Imaging (MRI). These dual modality combinations provide both anatomic-metabolic information that can be used for improved diagnostic assessment and treatment planning.

Image fusion can be performed in spatial domain or in transform domain. In the spatial domain, individual pixel values of the source images are manipulated to get the resultant image. In the transform domain, the source images are converted to multiscale image representation. The fusion process is taken place at the transformed representation and the resultant fused image can be obtained by inverse transformation. In both the domains,

the fusion operation can be performed at pixel, feature or at decision level [1].

In this paper, a pixel-level adaptive-weighted alpha blending method is proposed for PET/CT images. The proposed method dynamically calculates the weight or alpha value for each and every pixel in the image based on the metabolic activity information that is measured by the PET image. Then the fusion image is obtained as the adaptive-weighted alpha blending of both PET and CT images. The proposed method is objectively compared with some of the spatial domain methods such as simple average and Principal Component Analysis (PCA) using non-reference image-quality, fusion and error metrics. The proposed method produces better results both subjectively as well as objectively.

## II. PET/CT TECHNOLOGY

PET is being increasingly used for diagnosis, staging and follow-up of several prominent diseases like malignancies. PET is also useful to differentiate malignant from benign lesions and in the follow-up of patients after chemotherapy or surgical resection of tumour.

### A. PET Technology

The basic principle of PET imaging is the injection of a substance containing positron emitter, the subsequent detection of emitted radiation using the detector, and the computation of a digital image that represents the distribution of the radiotracer in the body [2]. A radionuclide is a non-stable nuclide which decays upon time. Upon decaying, it emits a positron. This emitted positron travels a short distance along the tissues in the body. After some time, it loses energy as a result of exiting or ionizing nearby atoms. Once it has lost nearly all kinetic energy, it annihilates with an adjacent electron. This annihilation process results in pair of photons. The emission of these photons is detected and recorded by the detector. The raw data from the detector ring is stored in the form of sinogram. This is subsequently followed by image reconstruction. The reconstruction produces the cross-sectional images from the raw data (sinogram) representing the radioactivity distributions in the tissues of the body.

PET has the ability to capture the images of changes in the body's metabolism caused by actively growing malignant tissues. But its capability is limited by poor anatomic details. So correlation with any of the anatomical imaging such as CT or MRI is required.

### III. ALPHA BLENDING

Alpha blending is the process of convex combination of foreground image with a background image allowing for transparency and producing a new blended image. The degree of transparency of the foreground image may range from complete transparent to complete opaque. If the foreground image is completely transparent, the blended image will be the background image. Conversely, if the transparency is completely opaque, the blended image will be the foreground image. In addition, the degree of transparency can also range between these extremes, in which case the blended image is computed as a weighted average of the background and foreground images [3]. Then the alpha blending of two images is given by

$$F = I_1 * (1 - \alpha) + I_2 * \alpha \quad (1)$$

Where  $I_1$  is the background image,  $I_2$  is the foreground image,  $F$  is the resultant blended image and ' $\alpha$ ' is the blending factor or degree of transparency from the background image to the foreground image and it may take values as given below:

$$\alpha = \begin{cases} 0, & \text{if fully transparent} \\ 1, & \text{if fully opaque} \\ 0 < \alpha < 1, & \text{otherwise} \end{cases} \quad (2)$$

For the color image alpha blending, the gray images are first converted into RGB images. Then, the alpha blending operation is performed for each of the color channels R, G and B separately and it is represented as

$$F_{RGB} = I_{RGB1} * (1 - \alpha) + I_{RGB2} * \alpha \quad (3)$$

### IV. PET/CT FUSION

The PET/CT multi-modality imaging system results in series of slices in DICOM format. The PET slice size is 128x128 and CT slice is 512x512. After reconstruction, these slices must be preprocessed for attenuation correction, artifacts reduction, contrast enhancement and co-registration. The CT image represents the anatomical structure and PET image is a pixel by pixel representation of the radiotracer concentration on the tissues in the body. In PET image, each pixel represents the absorption of glucose substance by the tissues. Since the malignant tissues are metabolically active than the normal tissues, they absorb more glucose. Hence in the PET image, the pixels that represent the metabolically active malignant tissues have high intensity value. Whereas, the pixels that represent the metabolically inactive normal tissues have low intensity value. When PET DICOM images are converted to JPEG format, the gray value of each pixel is reversed. The pixels with smaller intensity value represent the malignant tissues and the pixels with larger intensity values are normal tissues and are shown in Fig. 1.

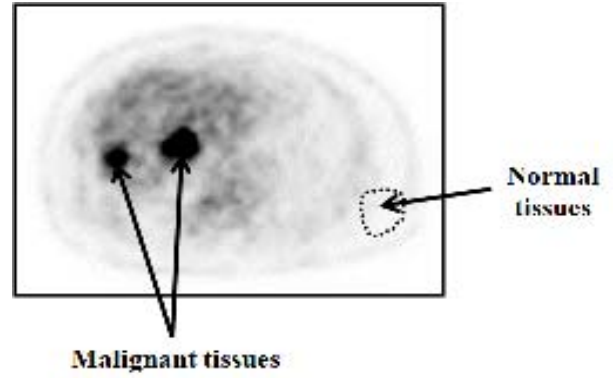


Fig. 1 PET image of a neck

For PET/CT fusion using alpha blending, CT image is considered as the background image and PET image as the foreground image. The degree of blending between these two images depends on the glucose absorption rate dictated by the pixels of PET image. If the pixel represents the normal tissue, it should be made transparent as seen through to the background CT image. Whereas, the pixels corresponding to the malignant tissues needed to be set as opaque. So the adaptive weight or adaptive alpha value which determines the transparency of pixel has to be calculated for each and every pixel in the PET image.

In the PET image, the pixels of normal tissues have high intensity values and the pixels of malignant tissues have low intensity values. Let  $I_1$  as the CT image,  $I_2$  as the PET image and ' $\max$ ' is the largest intensity value in the PET image. Then the adaptive weight or adaptive alpha value ' $\alpha$ ' is calculated as the ratio between the maximum intensity and the difference between the pixel value and the maximum intensity value and it is given by

$$\alpha_{i,j} = (\max - I_2(i, j)) / \max \quad (4)$$

Then the adaptive alpha blending of PET and CT images are performed using the formula given below:

$$F_{i,j} = I_{i,j} * (1 - \alpha_{i,j}) + I_{i,j} * \alpha_{i,j} \quad (5)$$

For the malignant tissues, the alpha value is nearer to 1, for the normal tissues the alpha value is close to 0.

Hence, the pixels that represent malignant tissues are extracted from PET image and are overlaid on the CT image in their respective positions using adaptive-weighted alpha blending and the normal tissues are made transparent to show the anatomic details.

For color alpha blending of PET/CT images, first both the gray scale intensity images are converted to RGB images. Then the gray color map is assigned to the background CT image and hot or jet or other color maps are assigned to the foreground PET image. Now by considering the pixel value of the CT and PET image as the index value for the Color Look Up Table (CLUT), the value of each of the color channels (R,G,B) for the fused image is calculated using eqn. (3) and the adapted alpha value  $\alpha_{i,j}$ .

## V. RESULTS AND DISCUSSIONS

An ideal image fusion algorithm should results in a clear, quality and an error-free image and also it must possess as much information from the source images. In most applications, the ground truth image is not available for evaluation. Hence this paper considers the following non-reference image quality metrics such as Entropy (EN), Spatial Frequency (SF), Standard Deviation (SD), Variance (VARI), Average Gradient (AG), Edge Intensity (INT), Shannon Entropy (SH) and non-reference image fusion metrics such as Fusion Factor (FF), Fusion Symmetry (FS) [5], Peak Signal to Noise Ratio (PSNR), Xydeas and Petrovic metric ( $Q^{(A,B/F)}$ ), Fusion Quality metric ( $Q(A,B,F)$ ), Overall Mutual Information (MI), Correlation (CORR), Correlation Coefficient (CC), Structural Similarity Index (SSIM) and non-reference error metrics such as Root Mean Square Error (RMSE), Percentage Fit Error (PFE), Normalized Absolute Error (NAE) [4].

In general, the image quality metrics measures the clarity, contrast and sharpness of an image, whereas the fusion and correlation metrics computes how much information is derived from the source images or how much the fused image is correlated to the source images. The error metrics estimates the degree of distortions or deviations or the degree of blur that may occur in the resultant fused image as a result of fusion process. For an efficient algorithm, the image fusion metrics should score higher value, the image fusion metrics other than fusion symmetry should be higher and the error metrics should be lower. As the value of each of these quality metrics widely differ in the range, to bring them in the uniform range and to confer equal importance while evaluation, the above mentioned non-reference metrics are statistically normalized using the linear mapping function [6].

### A. PET/CT Data

The CT and PET images of axial view of a neck are considered as source images. The source images and the fused images of various methods are shown in Fig. 2. The CT image shows the anatomical details such as bone structure with clear outline and high contrast. Whereas, the PET image demonstrates the metabolic activity of the tissues of a neck. Here, the PET image 1b shows the identification of the significant metabolic activity of necrotic mass lesion in the base of the tongue on the left side extending to the left tonsillar fossa and to left parapharyngeal region as pointed in the figure which is missing in CT image. For accurate diagnosis and correct localization of malignant tissues, these two details from CT image and PET image must be combined as a single image. The images 2a, 2b and 2c are the resultant images of simple average, PCA, gray image adaptive-weighted alpha blending. The resultant images incorporate both anatomical information and metabolic information in the same image.

The images of color alpha blending are shown in Fig 2. The image 3b shows the color alpha blend with jet color map, 4a shows the color alpha blend with hot color map and 4b shows the color alpha blend with hsv color map. Since the malignant tissues are differentiated using various colors

from normal tissues, it is more helpful for the physician during diagnosis.

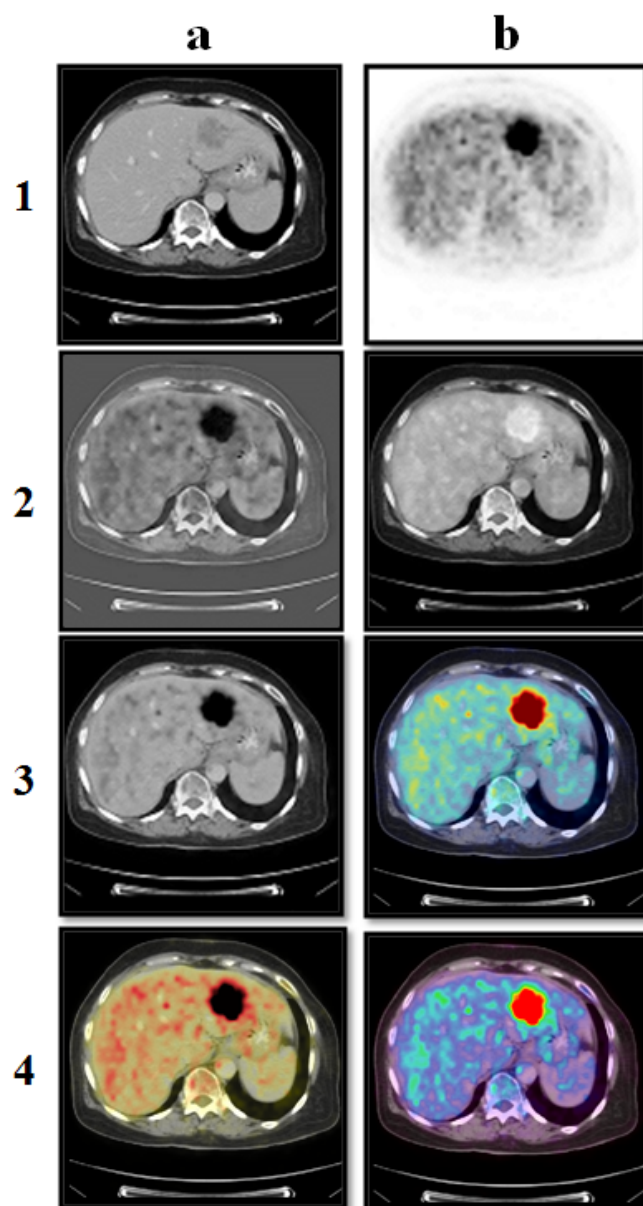


Fig. 2 Source and Fused Images of PET/CT Data Set  
Source Images: 1a) CT Image, 1b) PET Image Output Images: 2a) Simple Average, 2b) PCA, 3a) Gray Image alpha blend, 3b) alpha blend with jet map 4a) alpha blend with hot map 4b) alpha blend with hsv map

### B. Qualitative Analysis

The qualitative analysis by human perception depicts that the fused image obtained from the adaptive-weighted alpha blending is better than simple-average and PCA method in terms of both content and clarity. Also, the output images from color alpha blending shows its usefulness in terms of display for easy diagnosis.

### C. Quantitative Analysis

The resultant fused images 2a, 2b and 3a of simple average, PCA and gray-level alpha blending are compared quantitatively using various non-reference image quality, image fusion and error metrics.

1) *Image Quality Metrics*: As the quality of the fused image is very important, the objective quantitative analysis of the resultant images are performed with the non-reference image quality metrics ENT, SF, SD, VARI, AG, INT and SH. The obtained and normalized values of these non-reference image quality metrics are shown in Table I. The normalized values shows that the adaptive-weighted alpha blending method scores the higher values than other methods for all the metrics. The subjective evaluation of these resultant images also says that the adaptive-weighted alpha blending method results in a clear image with sharper edges and with good contrast level.

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TABLE I  
COMPARISON OF IMAGE FUSION METHODS USING IMAGE QUALITY METRICS

Metrics		Simple Average	PCA	Adaptive-Weighted Alpha Blend
EN	Obtained	5.16	5.20	5.25
	Normalized	80.63	89.24	100.00
SF	Obtained	9.81	11.70	13.67
	Normalized	47.65	73.28	100.00
SD	Obtained	31.35	71.24	73.81
	Normalized	18.36	95.06	100.00
VARI	Obtained	982.93	5447.56	5474.95
	Normalized	10.64	99.46	100.00
AG	Obtained	2.47	3.14	3.82
	Normalized	34.49	67.00	100.00
INT	Obtained	26.66	34.08	35.20
	Normalized	46.93	93.04	100.00
SH	Obtained	5.16	5.25	30.52
	Normalized	2.42	2.77	100.00

2) *Image Fusion Metrics*: The fused image should be enriched in information i.e. it should possess analytical information from CT image and also the functional information from PET image. Therefore, the information derived from each of the source image are measured using the non-reference image fusion metrics FF, FS, PSNR, Q(A,B/F), Q(A,B,F), MI, CORR, CC, SSIM for the fusion methods and is given in Table II. These metrics uses some means of correlation that exist between the input and output images. For an ideal image, all the fusion and correlation metrics should be high and the fusion symmetry should be low. From the table, it is well known that, the adaptive-weighted alpha blending fusion method scores higher values for all the non-reference image fusion metrics and lower value for fusion symmetry metric. It indicates that proposed algorithm extracts as much information from the source images than the other methods.

TABLE III  
COMPARISON OF IMAGE FUSION METHODS USING IMAGE FUSION METRICS

Metrics		Simple Average	PCA	Adaptive-Weighted Alpha Blend
FF	Obtained	0.41	0.64	0.72
	Normalized	19.24	79.16	100.00
FS	Obtained	0.34	0.36	0.13
	Normalized	91.39	100.00	1.00
PSNR	Obtained	14.97	17.51	17.77
	Normalized	66.84	96.92	100.00
Q(A,B/F)	Obtained	0.01	0.02	0.03
	Normalized	1.00	50.50	100.00
Q(A,B,F)	Obtained	0.09	0.21	0.27
	Normalized	31.46	77.15	100.00
MI	Obtained	12.95	13.90	13.96
	Normalized	68.05	98.10	100.00
CORR	Obtained	0.01	0.02	0.04
	Normalized	1.00	34.00	100.00
CC	Obtained	87.18	101.03	97.03
	Normalized	81.45	100.00	94.64
SSIM	Obtained	0.01	0.36	0.37
	Normalized	1.00	97.25	100.00

3) *Error Metrics*: The errors that occur in the resultant images are evaluated with the non-reference error metrics such as RMSE, PFE and NAE. The obtained and normalized values of these metrics are shown in Table III.

TABLE IIIII  
COMPARISON OF IMAGE FUSION METHODS USING ERROR METRICS

Metrics		Simple Average	PCA	Adaptive-Weighted Alpha Blend
PMSE	Obtained	107.82	93.40	91.95
	Normalized	28.72	3.53	1.00
PFE	Obtained	16787.91	14066.62	13602.02
	Normalized	32.62	5.61	1.00
NAE	Obtained	245.99	137.74	137.61
	Normalized	51.51	1.06	1.00

From the table, it is evident that the adaptive-weighted blending fusion method scores small value for all these metrics when compared with the other methods. This depicts that the error that occurs in the fused in less only for the adaptive-weighted average fusion method and also it is deviated from the source images only a little when compared with others fusion methods.

The above discussions proved that the proposed adaptive-weighted average algorithm is the superior among the other methods.

## VI. CONCLUSIONS

This paper implements a new pixel level adaptive-weighted alpha blending method based on the metabolic activity rate for the fusion of PET and CT images. It is found that the performance of the proposed algorithm is better than the other spatial domain algorithms both objectively and subjectively. Color image alpha blending is more helpful for the visual interpretation since the malignant tissues are highlighted from normal tissues that bring out diagnosis and accurate localization of diseases easier. Other blending methods such as poisson blending, laplacian pyramid blending and mixed gradient blending may also be adopted. Further, the adaptive alpha-weights are calculated only based on the pixel intensity value of PET image which reflects the glucose absorption rate. But in practical, the glucose absorption rate depends on other factors like arterial blood radioactivity concentration, patient's body weight, sugar level, the time interval between the intrusion of radiotracer substance and scan etc. So the other factors that affect the absorption of glucose by the tissues may also be considered for accurate calculation of adaptive alpha weight.

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