Multi dose Computed Tomography Image Fusion Based on Hybrid Sparse Methodology

Anuyogam Venkataraman, Javad Alirezaie - *Senior Member IEEE*, Paul Babyn and Alireza Ahmadian- *Senior Member IEEE*

***Abstract*— With the increasing utilization of X-ray Computed Tomography (CT) in medical diagnosis, obtaining higher quality image with lower exposure to radiation has become a highly challenging task in image processing. In this paper, a novel sparse fusion algorithm is proposed to address the problem of lower Signal to Noise Ratio (SNR) in low dose CT images. Initial fused image is obtained by combining low dose and medium dose images in sparse domain, utilizing the Dual Tree Complex Wavelet Transform (DTCWT) dictionary which is trained by high dose image. And then, the strongly focused image is obtained by determining the pixels of source images which have high similarity with the pixels of the initial fused image. Final denoised image is obtained by fusing strongly focused image and decomposed sparse vectors of source images, thereby preserving the edges and other critical information needed for diagnosis. This paper demonstrates the effectiveness of the proposed algorithm both quantitatively and qualitatively.**

***Key words*— sparse fusion, dictionary, principal component analysis, sparse representation, signal to noise ratio, Dual Tree Complex Wavelet Transform dictionary**

I. Introduction

Multiple images of the same scene can be captured by varying image contrast, image focus or by using different sensors. It can be very challenging to perceive the complete picture of a scene from these captured source images. Image fusion algorithms can integrate the information obtained from different source images, even when they originate from differing sensors, are out of focus or of differing resolution.

Medical Imaging has revolutionized medical diagnosis with the arrival of cross-sectional imaging modalities such as computed tomography (CT). The increasing use of CT however raises concern of potential patient harm from excessive radiation exposure. Reducing the dose of radiation used in CT results in a lower signal to noise ratio and may obscure critical details necessary for precise diagnosis. Hence effective denoising algorithms to significantly increase Peak Signal to Noise Ratio (PSNR) are needed. An effective fusion algorithm able to combine multiple images of the same scene obtained with variable radiation exposure may lead to overall improved image quality and offer a means to reduce overall radiation needs. Challenges to be addressed while fusing multimodal images are given in [1]. The proposed algorithm is developed for fusing multi dosage CT images with consideration to the following: 1) The fused image should preserve all the critical information and edges needed for diagnosis. 2) Artifacts and blocks should not be introduced in fused image. 3) Noise and unimportant information should be suppressed thereby enhancing the quality of low dose CT images.

Sparse representation of signals is now possible utilizing many different Greedy approaches [2], including: 1. Matching Pursuit (MP) [2] 2. Orthogonal Matching Pursuit (OMP) [2], and 3. Stage wise Orthogonal Matching Pursuit (St OMP) [3]. These techniques are used to represent signals with the fewest number of non-zero coefficients. Dual Tree Complex Wavelet Transform (DTCWT) fusion [4] is a state-of-the-art image fusion method which involves integrating the high frequency coefficients by maximum fusion rule and low frequency coefficients by weighted average rule. DTCWT fusion enhances the reconstruction quality using short linear phase filters. Sparse fusion preserves important information but high spatial resolution is lacking. This paper proposes a new algorithm inspired by [5] which employs the determination of focused regions from the source images and initial fused image. The uniqueness in our proposed algorithm is that the initial fused image, focused region determination and further processing are all implemented in the sparse domain utilizing a DTCWT Dictionary. In this paper, we demonstrate the robustness of our algorithm by comparing the results with DTCWT and Sparse fusion methods.

II. Methodology

A. *Dual Tree Complex Wavelet Transform*

Shift variance property of DWT motivates the need for complex extended DWT. DTCWT, introduced by Kingsbury [7], was used with filters and resulted in good shift invariance, directional selectivity and reduced over completeness. Complex filters are applied separately to rows and columns of an image which produces six bandpass bands at each decomposition level that are aligned at ±15, ±45 and ±75 degrees. Complex filters help in interpreting one wavelet as the real part and the other wavelet as the imaginary part of complex-valued 2D wavelet. This complex nature provides approximate shift invariance perpendicular to wavelet orientation. These properties can be seen in

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figure.1. DTCWT is vaguely represented as the union of four real orthonormal bases of two DTCWT trees, though DTCWT is not actually the union of four orthonormal bases.

B. Orthogonal Matching Pursuit

An overcomplete dictionary contains linear combination of atoms. Dictionaries which are constructed using predefined set of functions are analytical dictionaries while adaptive dictionaries are constructed to fit a given signal. For our experiment, we use KSVD dictionary [12] to learn high dose images for the best possible sparse representation. KSVD is an iterative procedure with mainly 2 stages. In the first stage, the signal to be trained is sparsely represented using Matching Pursuit algorithm. We use OMP for our experiment. In second stage, the dictionary is updated for best representation of the signal. In this section, we briefly explore the Orthogonal Matching Pursuit algorithm to achieve sparsest representation. These sparse coding algorithms are constructed based on the premise that Dictionary D of size n×k is already known. For effective results, we use DTCWT (Dual tree Complex Wavelet Transform) dictionary [6] for our experiment. Four times overcomplete representation of DTCWT is transformed into one with very few non-zero coefficients by OMP. The signal $S \in \mathbb{R}^d$ is sparse represented as $s \in \mathbb{R}^k$, given the dictionary $D \in \mathbb{R}^{d\times k}$. In iterative OMP framework, next atom to be added is the atom which has highest correlation to the residual at each stage until the stopping criterion is met.

The mathematical formula for solving this constraint problem is given by

$$\operatorname{argmin}_s \|S - Ds\|_2^2, \text{subject to } \|s\|_0 \le N \quad (1)$$

$$\operatorname{argmin}_s \|s\|_0, \text{subject to } \|S - Ds\|_2^2 \le \epsilon \quad (2)$$

Where N is the number of non-zero coefficients. Equation 2 represents the definition for solving the error constrained problem.

Pseudo Algorithm of Joint Sparse Fusion

Given: Dictionary D, signals S1andS2, and error threshold ϵ

1) Sparse Representation of each signal:
- Initialize residual r^0=S-Ds^0 , index set I^0={} and main iteration is k=k+1(initial k=0). Using the ideal solution $z_i = d_i^T r^{k-1}/\|d_i\|_2^2$, Calculate the error $e(i) = \min_x \|d_i z_i - r^{k-1}\|$ for all *i*.
- Update stage: Augmenting the index set $I^k = I^{k-1} \cup \{i_0\}$ (find i_0 of $e(i)$: $\forall 1 \le i \le m$ and $e(i_0) \le e(i)$.
- Update the solution $s^k(i_0) \mathrel{+}= z_i$ and residual.
- If stopping criterion is met, $s = s^k$; else, apply another iteration.

2) Fusion Stage:
- Fuse *S1*and *S2* sparse vectors using PCA.

III. Proposed Fusion Algorithm

Proposed method employs DTCWT dictionary and Sparse transformation fusion. An attempt is made to effectively use the advantages of sparse fusion. Firstly Joint sparse fusion methodology is adopted to obtain initial fused image. Secondly, the focused regions are detected, which is the similarity between initial fused image and source images. Fusion process is carried out in sparse domain by making use of the source images and focused region image. Workflow of proposed methodology is given in figure 2.

1) Initial fused image I_f is obtained by adopting joint sparse fusion methodology as proposed in our previous work [13]. From registered multiple images in an ensemble having one common component and multiple innovative components $\{I_i\}_{i=1}^{i}$, fused image is obtained. Innovative component has more chances to contain noise. Orthogonal Pursuit Methodology is adopted to decompose the innovative components to sparse vectors $s_1, s_2, s_3, \dots s_i$. Decomposed vectors are fused using PCA (Principal Component Analysis) [8]. Covariance matrix C_s of sparse vectors for fusion is calculated through

$$C_s = \operatorname{cov}(I_s) = \operatorname{cov}([\alpha_1(:), \alpha_2(:)]) = \frac{1}{i-1} I_s . I_s^* \quad (3)$$

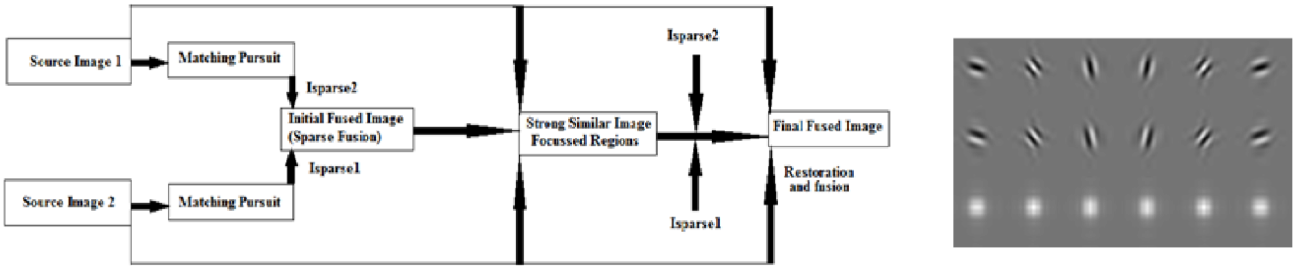
Eigen sparse vector is used as weightings for innovative sparse vectors to be fused. PCA fusion of sparse vectors uses Eigen sparse vector as weightings of innovative sparse vectors. Resultant I_f of sparse fusion and common component is fused adopting weighted average scheme proposed by Burt [9]. In our experiment, we have customized OMP sparse coding algorithm for fusion purposes.

2) In case of multi dosage images, pixels of initial fused image are compared with the pixels of source images. Pixels in all the source images that have greater similarity with the initial fused image are appropriately placed in focused regions. The similarity between source images and the initial fused image is measured in terms of certain quality metrics like RMSE, Correlation, Entropy and SNR. The above mentioned quality metrics are calculated for each pixel within M×N window between source images and initial fused image. Entropy shows the amount of important details available in the M×N window. RMSE for focused region can be calculated by,

$$RMSE = \sqrt{\frac{1}{m\times n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left[I(i,j) - I_f(i,j)\right]^2} \quad (4)$$

3) Overlapping patches are used to construct the strong similarity image which has focused regions. Overlapping patches are used to overcome thin protrusions, gulfs and breaks. Instead of overlapping patches, morphological opening and closing can also be employed to smoothen object contour.

4) Further processing is required to retain the edge information and to get rid of artifacts. Final fused image I_{final}



(a) (b)

Figure1. (a) Work flow of the proposed fusion algorithm stage. (b) Wavelets associated with the orientation of DTCWT.

is obtained by processing Sources images, initial fused image and strong focused image again in sparse domain.

IV. Experimental Results

Experiment is conducted to evaluate the performance of proposed algorithm by comparing the quantitative and qualitative results with other state-of-the art fusion methods such as DTCWT fusion and Sparse fusion. Qualitative assessment is done through visual inspection. Performance of the proposed algorithm is analyzed by implementing the algorithm over multi dosage images. The results are then compared with those of the existing fusion methods. Our experiment is carried out with the assumption that the source images are already registered. Medical image fusion needs high level of accuracy as it's used for diagnosis. Proposed method seems to be precise, both visually and quantitatively.

Since it requires an expert for subjective analysis of resultant image, contrast plot and certain quantity metrics are used to evaluate the performance of the proposed algorithm [11]. We have considered 4 metrics for analysis: PSNR, Correlation, RMSE and SSIM. PSNR is Peak Signal to Noise Ratio which is used to measure the reconstruction quality of fused image. PSNR of the fused image I_f is calculated using the standard formula:

$$PSNR(I_f) = 10\log_{10}\left(\frac{M^2}{MSE}\right) \quad (5)$$

Where M is the maximum possible pixel value of the image and MSE is the Mean Square error. SSIM [10] is the Structure Similarity Index which provides structural information of objects in the image.

Figure 2 and Figure 3 shows a high dose and low dose CT image of a phantom taken in helical mode. Exposure of high dose images used here are 500R.

Low dose image in Figure 2 seems to be very noisy and the noise hides some details. Circle on the top left is not clear. Our proposed algorithm is implemented to fuse 60% dose image and 90% dose image. Results of fusion using various methods are shown in Figure 2. Visually, Fusion result of prosed method and high dose image is very similar. Edges of the outer circle in DTCWT fusion image has some artifacts which is very clearly shown in contrast plot. Contrast plot of proposed method and sparse method is very similar to the contrast map of high dose image.

It is very obvious that proposed method outperforms quantitatively since it has the lowest RMSE and highest PSNR.

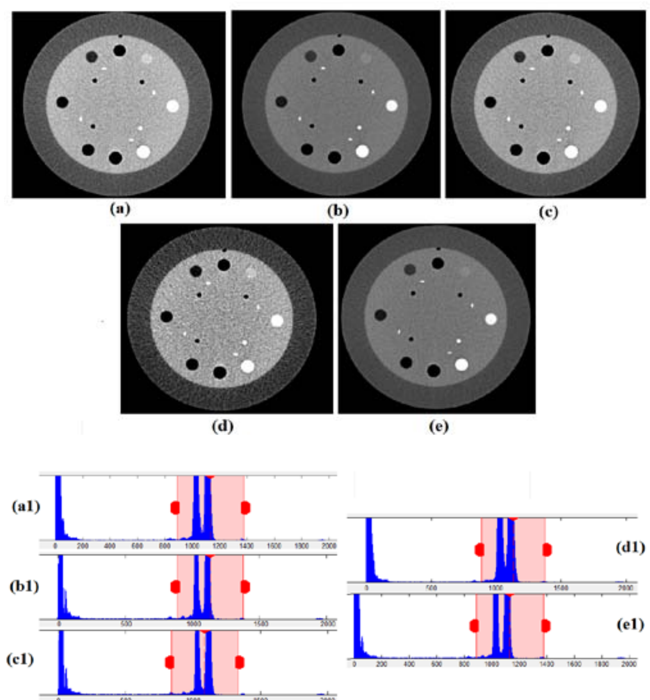


Figure2. Comparison of performance of different fusion algorithms in case of medium and low dose phantom images (512×512) (a) and (a1) Fusion result and contrast map of DTCWT fusion (b) and (b1) Fusion result and contrast map of Proposed method (c) and (c1) Sparse fusion result and contrast map respectively (d) and (d1) Low dose (e) and (e1) High dose image and its contrast plot.

Figure.3 shows the results of fusion for the case of low dose and medium dose images of phantom. On visual analysis, proposed method seems to perform better than the existing fusion methods especially for the low-contrast aspects of the phantom i.e. the circular structures which appear to be very clear in proposed method. Result of the proposed method contains sharp edges. Visually, sparse fusion result and proposed methods result are better than DTCWT fusion result. Usual fusion algorithms combine complementary details from source images. The proposed algorithm simultaneously denoises the source images

Source Images	Methodology	PSNR (db)	Correlation	SSIM	MI	RMSE
Figure 2	DTCWT	33.0941	0.998	0.999	1.0188	0.0400
	Sparse Fusion	33.9437	0.999	0.999	1.0275	0.04100
	Proposed	34.4349	0.999	1	1.13	0.0380
Figure 3	DTCWT	36.9855	0.998	.999	1.1444	.0447
	Sparse Fusion	37.2351	0.998	1	1.1895	0.0303
	Proposed	38.3179	0.999	1	1.2038	.0285

TABLE 1. PERFORMANCE OF FUSION METHODS BY THE QUALITY EVALUATION METRICS

in sparse domain since the dictionary is trained using high dose image. Hence fusing low dose and medium dose images suppresses the noise and enhance the
Informative details for precise diagnosis. Moreover proposed methodology outperforms other methods in terms of quantitative metrics. Contrast plot of the proposed method seems to be very similar to that of reference image. Contrast plot of sparse fusion seems almost similar to reference but slightly dense near 0. Contrast map of DTCWT is disappointing.

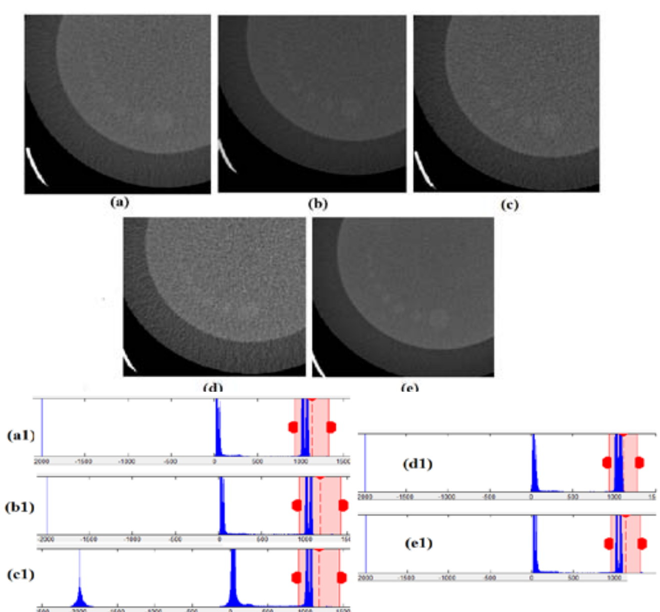


Figure3. Comparison of performance of different fusion algorithms in case of medium and low dose dicom abdomen images (512×512) (a) and (a1) Fusion result and contrast map of DTCWT fusion (b) and (b1) Fusion result and contrast map of Proposed method (c) and (c1) Sparse fusion result and contrast map respectively (d) and (d1) Low dose (e) and (e1) High dose image and its contrast plot.

V. CONCLUSION

Multi dosage image fusion may play a future role in clinical diagnosis. In this paper an innovative multi dosage image fusion is proposed for fusing low dose CT images using initial fused image and strong focused image. Unlike the traditional fusion algorithms, our method removes noise that hides the critical details as well and thereby enhancing the quality of low dose CT images. The results of the proposed method outperform DTCWT fusion and Sparse fusion in terms of qualitative and quantitative measurements. This algorithm is constructed with the assumption that the source images are registered. It can also be extended in the future to fuse multi dosage non registered images as well.

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