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REGULAR PAPER

Discrete wavelet transform based principal component averaging fusion for medical images

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ABSTRACT

Image fusion schemes play a vital role in medical image analysis and treatment planning. In this paper, a novel principal component averaging fusion based on discrete wavelet transform is proposed for fusion of CT-MRI and MRI images. Even though multiscale fusion methods result in effective integration of image details; Pixel level fusion methods based on principal component analysis (PCA) schemes do not loose popularity because of conceptual simplicity. Conventional principal components analysis fusion evaluates principal components based on eigen values of the source images. Using discrete wavelet transform (DWT), source images are decomposed into multiscale inputs and the principal components are evaluated for multiscale coefficients. Average of principal components of all these relevant decomposed elements will constitute weights for fusion rule. This method incorporates the advantage of wavelet transform into PCA fusion in the form of eigen values of multiscale representations. Performance of the proposed method is experimented on CT-MRI and MRI medical images. Analysis of qualitative and quantitative metrics clearly demonstrates that this method exhibits superior results than many other well known fusion schemes.

1. Introduction

The main objective of pixel level fusion methods is to have faithful integration of image details from two or more source images into a single image without any image distortion and loss of image details. According to fusion of information at different stages, image fusion algorithms are classified into pixel level fusion, feature level fusion and decision level fusion [1]. Pixel level fusion schemes fuse raw source information into a composite image [2] and preserve more source image details. Features such as region or edges are used to fuse source images in feature level fusion schemes. This scheme provides robustness to mis-registration and noise [3]. Image descriptors are combined directly in application dependent decision level fusion schemes [4,5].

In literature, many transform domain fusion schemes have been suggested. Among all these schemes, transform domain methods, particularly multiscale pyramid transform methods [6–8], stationary wavelet transform (SWT) [9,10], discrete wavelet transform (DWT) [11,12], dual tree complex wavelet transform (DTCWT) [13,14] and non subsampled contourlet transform (NSCT) [15] are able to provide successful image fusion results. SWT and DWT fail to provide directional information but DTCWT and NSCT exhibits directionality and shift invariance property [14,15].

PCA provides a linear weighted fusion algorithm in spatial domain. PCA fusion fuses source images using principal components evaluated from eigen values, thus importance can be given to image details of the source images based on co-variance properties. Highest two principal components that represent variance of the pixels [16] contribute to the weights for the fusion rule in PCA scheme. PCA fusion is a linear weighted fusion scheme [17] that often leads to effective fusion of image details and edge information by proper evaluation of weights. In local principal component averaging fusion (LPCAv) [18], weights for the PCA fusion are evaluated by splitting the source images into number of small blocks. Then Principal components are determined from the covariance matrix of relevant blocks of source images. Average of the principal components of all the blocks constitutes the weights for the fusion rule. In Fuzzy C-Means clustering principal component averaging fusion (FCMPCAv) [19], weights are decided by segmenting source images into number of clusters. Covariance of relevant clusters of source images helps to evaluate principal components and hence weights for the fusion rule. In this paper, this concept is extended to

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the coefficients of DWT transform hence named as discrete wavelet transform principal component averaging fusion (DWTPCAv). Thus principal components of all these multiscale representations of source images are used to constitute the weights for the fusion rule. Performance evaluation of DWTPCAv is carried out by evaluating non-reference qualitative and quantitative metrics such as Average quality index (AQI), Average mutual information (AMI), Average peak signal to noise ratio (APSNR) and Hossny, Nahavandi-Creighton metric (Q_{HNC}).

The content of this paper is organized as follows. Section 2 elaborately presents the DWTPCAv with its block diagram, PCA, LPCAv and FCMPCAv. Section 3 consists of metrics for performance evaluation, configuration for simulation, results and discussion. Conclusion is given in Section 4.

2. Discrete wavelet transform based principal component averaging fusion

Analysing the conventional PCA fusion clearly reveals that the weights for the fusion rule are derived from the principal components of source images. The principal components are evaluated based on the covariance and mean of the entire image that can be called as global variance and global mean. By considering global mean to derive the covariance matrix, due importance is not given to the local covariance and local mean from local regions. It can be interpreted that local variations of gray values of the source images are suppressed by the global variations.

To incorporate the contribution of local covariance and local mean into the principal component analysis fusion, a novel concept in the form of principal component averaging is suggested in LPCAv fusion. This method is based on covariance of local regions of source images. Source images are split into small blocks and the principal components are evaluated for corresponding blocks of source images. For each pair of blocks, principal components m_1 & m_2 are evaluated. Average of m_1s and m_2s are calculated to have weights for the fusion rule. FCMPCAv fusion uses principal component analysis on segmented regions of source images. Fuzzy C-Means clustering is adopted to cluster the source images into number of clusters. Principal components are evaluated for the relevant clusters of the source images. Again weights for the fusion rule are determined by average of m_1s and m_2s.

Multiscale transform methods first decompose source images into multiscale representations with different orientations and resolutions. Wavelet based methods are used to visualize image information in different scales and resolutions of source images. Principal component averaging is experimented on multiscale representations of source images derived from DWT. Source images are decomposed into low-low (LL), low-high (LH), high-low (HL) and high-high (HH) elements, where LL is approximate coefficients and remaining three are detailed coefficients. LL coefficients of both source images are taken as input matrices for principal component analysis. Hence highest principal components are given as m_1 and m_2 of LL coefficients. Similarly LH, HL and HH coefficients are processed to evaluate the principal components. This is illustrated in Figs. 1 and 2.

Let x_i^1 and x_i^2 are the approximate coefficients of two source images expressed as column vectors; where the elements of x_i^1 are from source image IM1 and the elements of x_i^2 are from source image IM2.

$$X_i^1 = \mathrm{LL}_n^1 = \begin{bmatrix} x_1^1 \\ x_2^1 \\ \vdots \\ x_k^1 \end{bmatrix} \quad \text{and} \quad x_i^2 = \mathrm{LL}_n^2 = \begin{bmatrix} x_1^2 \\ x_2^2 \\ \vdots \\ x_k^2 \end{bmatrix}; \tag{1}$$

where $i = 1, 2, 3, \ldots, k$; k is number of approximate coefficients; n is level of decompositions in DWT.

Covariance between two vectors is

$$\mathrm{Cov}(x_i^1, x_i^2) = E[(x_i^1 - \mu_{x_i}^1)(x_i^2 - \mu_{x_i}^2)] \tag{2}$$

Mean of all pixels is

$$\mu_{x_i}^1 = \left(\frac{1}{k}\right)\sum x_i^1 \quad \text{and} \quad \mu_{x_i}^2 = \left(\frac{1}{k}\right)\sum x_i^2 \tag{3}$$

Diagonal matrix D of eigen values and a matrix V of corresponding eigenvectors are computed.

The normalized components m_1 and m_2 are computed from V based on the following conditions

If $D(1, 1) > D(2, 2)$

$$m_1(\mathrm{LL}_n^{1,2}) = \frac{V(1,1)}{V(1,1)+V(2,1)} \quad ; m_2(\mathrm{LL}_n^{1,2}) = \frac{V(2,1)}{V(1,1)+V(2,1)} \tag{4}$$

Else

$$m_1(\mathrm{LL}_n^{1,2}) = \frac{V(1,2)}{V(1,2)+V(2,2)} \quad ; m_2(\mathrm{LL}_n^{1,2}) = \frac{V(2,2)}{V(1,2)+V(2,2)} \tag{5}$$

Similarly m_1 and m_2 for the detailed coefficients are also evaluated. Mean of all these m_1 and m_2 constitute weights for fusion rule and given by

$$m_{1(\mathrm{av})} = \frac{m_1(\mathrm{LL}_n^{1,2}) + m_1(\mathrm{LH}_n^{1,2}) + m_1(\mathrm{HL}_n^{1,2}) + m_1(\mathrm{HH}_n^{1,2})}{N};$$
$$m_{2(\mathrm{av})} = \frac{m_2(\mathrm{LL}_n^{1,2}) + m_2(\mathrm{LH}_n^{1,2}) + m_2(\mathrm{HL}_n^{1,2}) + m_2(\mathrm{HH}_n^{1,2})}{N};$$
$$\text{for} \quad n = 1, \quad N = 4; \quad n = 2, \quad N = 7 \tag{6}$$

and the fused image is given by

$$z = m_{1(\mathrm{av})} * \mathrm{IM1} + m_{2(\mathrm{av})} * \mathrm{IM2} \tag{7}$$

Algorithm

1. Evaluate DWT of source images IM1, IM2 with one or two decomposition levels and db3 wavelets
2. Apply principal component analysis for approximate and detailed coefficients of source images.
3. Find out principal components for corresponding coefficients of source images as stated above.
4. Evaluate average of m_1s and m_2s as given in Eq. (6)
5. Apply PCA fusion to source images using average of principal components as given in Eq. (7)
6. Evaluate performance metrics for the proposed and existing algorithms as stated in Section 3.

3. Simulation and analysis

To validate the proposed fusion model, two sets of perfectly registered CT-MRI images and three sets of MRI images are experimented on a set of fusion algorithms. All the images shown in Figs. 3 and 4 are of size 256 × 256 and rendered from whole brain atlas database that gives free access of images for educational and research purpose. CT images depict higher tissue density and bone structures. On contrary, MRI describes parenchyma of object of interest. Thus fusion of CT-MRI images will yield a composite image with both the contents. Fusion of MRI proton density and T2 weighted images contribute complementary image details to the fusion result.