Biomedical Signal Processing and Control 27 (2016) 103–111

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Medical image fusion using discrete fractional wavelet transform

Xiaojun Xu [a,b,*], Youren Wang [a], Shuai Chen [b]

[a] Nanjing University of Aeronautics and Astronautics, College of Automation Engineering, Nanjing 210016, Jiangsu, China
[b] Huainan Normal University, College of Mechanical and Electrical Engineering, Huainan 232001, Anhui, China

ARTICLE INFO

Article history:
Received 30 July 2015
Received in revised form
24 December 2015
Accepted 16 February 2016

Keywords:
Medical image fusion
Fractional wavelet transform
Wavelet
Multiresolution analysis

ABSTRACT

A multimodal medical image fusion method based on discrete fractional wavelet (DFRWT) is presented in this paper. With a change in p order in domain (0,1], source medical images are decomposed by DFRWT in different p order. The sparsity character of the mode coefficients in subband images changes. According to the method, to enhance the correlation between subband coefficients, the non-sparsity character of the mode coefficients in low p order should be utilized. The coefficients of the all subbands are fused using the weighted regional variance rule. Finally, inverse DFRWT is applied to obtain a fused image. Subjective and objective analyses of the results and comparisons with other multiresolution domain techniques show the effectiveness of the proposed scheme in fusing multimodal medical images.

© 2016 Published by Elsevier Ltd.

1. Introduction

Medical images in different modality display different characteristic information of human viscera and diseased tissue. Anatomical images, such as computerized tomography (CT) and magnetic resonance imaging (MRI), provide high-resolution human anatomical information but do not reflect the function of organ metabolic information. Functional medical images such as positron emission tomography (PET) provide functional information on organ metabolism and blood flow but do not provide the focus positional information because these images are of low spatial resolution [1,2]. Therefore, studying how complementary information from different modalities can be combined to obtain more useful information through image fusion has important significance for clinical use.

Image fusion can be performed in three different levels [3,4], i.e., from low to high: pixel level, feature level, and decision level. Pixel-level image fusion is the primary method, and its special features are its large amount of information and high precision. At present, pixel-level image fusion is the main method in medical fusion research [5]. In the past decades, people have proposed many pixel-level approaches, such as intensity–hue–saturation (IHS) [6], principal component analysis (PCA) [7], and multiresolution-analysis-based methods [8]. Among these methods, the most widely used methods are multiresolution analysis (MRA) techniques such as Laplacian pyramid (LP) and discrete wavelet transform (DWT) [9–11] because of the influence of spectral degradation in IHS and PCA. In the LP method, each pyramid level generates only one bandpass image, and the method fails to introduce any spatial orientation selectivity in the decomposition process and, hence, often causes blocking effects. The DWT has good time–frequency localization characteristics and multiresolution characteristic, and it can offer the information in horizontal, vertical, and diagonal directions and low-pass components. However, the result of the DWT fusion method has a pseudo-Gibbs effect because of the *down-sampling* process at each DWT decomposition stage. To overcome the limitations of the lack directionality of the DWT methods, curvelets are considered an effective model in capturing curvilinear properties [12], such as lines and edges. Contourlet transform is derived from the anisotropic scaling relations of curvelet transform, which, in a certain sense, is a form of application of the curvelet transform [13]. The contourlet transform can provide a multiscale and directional decomposition of images, which is more suitable for catching complex contours, edges, and textures. Because of the down-sampling process in the coefficient decomposition step, the contourlet and, curvelet transforms are shift variant, and the image fusion quality is affected by it. The nonsubsampled contourlet transform (NSCT) [14,15] is a shift-invariant version of the contourlet transform, which uses nonsubsampled pyramids (NSPs) and nonsubsampled directional filter banks (NSDFBs) to decompose source images in a multidirectional way, and provides

* Corresponding author at: Nanjing University of Aeronautics and Astronautics, College of Automation Engineering, Nanjing 210016, Jiangsu, China. Tel.: +86 15855435368.
E-mail address: hfxjxu@163.com (X. Xu).

http://dx.doi.org/10.1016/j.bspc.2016.02.008
1746-8094/© 2016 Published by Elsevier Ltd.

an effective way to obtain a more accurate analysis of multimodality images. Because transform coefficients of the NSCT in each subband are same as the original image size, its redundancy results in increase in computational complexity and longer fusion time.

In recent years, a novel time–frequency analysis theory, namely fractional wavelet transform (FRWT) [16,17], has been proposed, and the fractional wavelet transform has extended the analysis method of wavelet transform from the time–frequency domain to time–fractional-frequency domain. The time–frequency analysis theory can characterize signal features in time and fractional-frequency domain [18]. The FRWT is more flexible for image processing and provides a new approach to image fusion because of fractional frequency, which is a new concept.

To solve the aforementioned problems, we present a new multimodal medical image fusion method using discrete fractional wavelet (DFRWT), which is based on a multiresolution principle in low p order [19,20]. The DFRWT performs multilevel fusion over two sets of multimodal medical images using a self-*adaptive weighted* scheme. The proposed fusion method is compared with other multiresolution methods such as LP, DWT, curvelet and contourlet transforms, and NSCT. The superiority of the proposed fusion method is validated through subjective vision and objective fusion metrics for medical image fusion.

The rest of this paper is organized as follows. In the next section, we explain the concept of the FRWT and how the DFRWT is realized. Section 2 provides the analysis of the histogram distribution form and sparsity of subband mode coefficients in different p orders under a 2-D DFRWT. Section 3 describes an image fusion algorithm based on the DFRWT. Section 4 gives the experimental results and evaluates the performance of various methods. Conclusions are summarized at the end of this paper.

2. Preliminaries

2.1. Definition of the fractional wavelet transform

The FRWT was first introduced by Shijun in 2012 as a generalization of the wavelet transform. The FRWT was derived from fractional convolution [16,17,21]. The pth-order continuous FRWT can be defined as

$$W_{p,x}(\alpha, a, b) = \int_{-\infty}^{+\infty} f(t)\bar{\psi}_{p;a,b}(t)\mathrm{d}t = \int_{-\infty}^{+\infty} f(t)\cdot e^{i\frac{t^2-b^2}{2}\cot\alpha}\frac{1}{\sqrt{a}}\bar{\psi}\left(\frac{t-b}{a}\right)\mathrm{d}t. \quad (1)$$

here $\psi_{p;a,b}(t) = \frac{1}{\sqrt{a}}e^{-i\frac{t^2-b^2}{2}\cot\alpha}\psi\left(\frac{t-b}{a}\right) = e^{-i\frac{t^2-b^2}{2}\cot\alpha}\psi_{a,b}(t)$ is the kernel of the fractional wavelet. In $\alpha = p\pi/2$, p denotes the order of the fractional Fourier transform (FRFT), and α indicates the rotation angle of the transformed signal for the FRFT. For $p \in (0, 1]$, kernel $\psi_{a,b}(t)$ is a continuous affine transformation of mother wavelet $\psi(t)$, where a is called the scaling parameter and b is a translation parameter, which determines the time location of the wavelet. Note that when $p = 1$, the FRWT coincides with the WT. In literature [16,17] each fractional wavelet component is essentially a differently scaled bandpass filter in the fractional Fourier domain. The analysis of the signal equivalent to multiresolution analysis (MRA) process in the time–fractional domain plane and a novel signal processing tool has time–fractional frequency domain localization characteristics.

To establish a relationship between the FRWT and the MRA, literature [17] has given the definition of the MRA concept of the FRWT. The series of approximation subspace sequences $\left\{V_j^\alpha\right\}$ is composed of fractional scale function $\phi_{p;j,k}(t)$, namely,

$$V_j^\alpha = \text{span}\left\{\phi_{p;j,k}(t)\,\middle|\,\phi_{p;j,k}(t) = e^{-i\left((t^2/2)-(1/2)(k2^j)^2\right)\cot\alpha} \times \phi_{j,k}(t), j, k \in z\right\}$$
$$\text{and}\quad V_j^\alpha \subset V_{j-1}^\alpha. \quad (2)$$

The series of subspace sequences $\left\{W_j^\alpha\right\}$ is composed of fractional wavelet function $\psi_{p;j,k}(t)$, namely,

$$W_j^\alpha = \text{span}\left\{\psi_{p;j,k}(t)\,\middle|\,\psi_{p;j,k}(t) = e^{-i\left((t^2/2)-(1/2)(k2^j)^2\right)\cot\alpha} \times \psi_{j,k}(t), j, k \in z\right\}, \quad (3)$$

where W_j^α is the orthogonal complement of V_j^α in V_{j-1}^α.

Literature [19] analyzed conditions of the construction orthonormal basis of fractional wavelet in time and fractional domains and gave a new transitive relation on adjacent scales space function $\phi_{p;j,k}(t)$, $\psi_{p;j,k}(t)$, $\psi_{p;j-1,k}(t)$. If function spaces V_j^α, W_j^α, and V_{j-1}^α meet the conditions of orthogonality discussed in literature [16], then direct sum decomposition $L^2(R) = \oplus_{j\in z}W_j^\alpha$ can be obtained from $V_{j-1}^\alpha = W_j^\alpha \oplus V_j^\alpha$.

2.2. Algorithm of the discrete fractional wavelet transform

Specific derivation of the implementation procedure on the DFRWT coefficient decomposition and reconstruction was *proposed in* literature [19]. Fig. 1 shows the flowchart of the coefficient decomposition of one layer of the DFRWT. Discrete sequences $\left\{c'^j_n\right\}$ are the j-th layer coefficients in the decomposition of a continuous function $f(t)$ of base $\left\{\phi_{p;j,k}(t)\right\}$ in V_j^α. Discrete sequences $\left\{c'^{j+1}_k\right\}$ and $\left\{d'^{j+1}_k\right\}$ are the $(j+1)$-th layer coefficients in the decomposition of a continuous function $f(t)$ of base $\left\{\phi_{p;j+1,k}(t)\right\}$ in V_{j+1}^α and $\left\{\psi_{p;j+1,k}(t)\right\}$ in W_{j+1}^α, respectively. First, $\left\{c'^j_n\right\}$ is multiplied with discrete chirp signal sequences, i.e., $c^j_n = c'^j_n \times e^{i(1/2)\left(n\times 2^j\right)^2\cot\alpha}$. Then a DWT is performed on the discrete sequences of $\left\{c^j_n\right\}$ to obtain coefficients $\left\{c^{j+1}_k\right\}$ and $\left\{d^{j+1}_k\right\}$ in the wavelet domain. Finally, $\left\{c^{j+1}_k\right\}$ and $\left\{d^{j+1}_k\right\}$ are multiplied with discrete sequences $e^{-i(1/2)\left((2k)\times 2^j\right)^2\cot\alpha}$ to obtain the results of approximate coefficients $\left\{c'^{j+1}_k\right\}$ and detail coefficient $\left\{d'^{j+1}_k\right\}$ in the fractional wavelet domain in the $(j+1)$-th layer. The obtained values are complex. The decomposition into approximations and

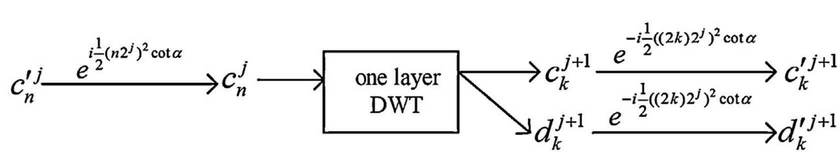

Fig. 1. The flow chart of coefficient decomposition of one layer DFRWT.

Download English Version:

https://daneshyari.com/en/article/6951239

Download Persian Version:

https://daneshyari.com/article/6951239

Daneshyari.com