Medical image fusion in 3-D by the multiresolution directional-oriented Hermite transform

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Abstract

In this paper, a new fusion algorithm for three-dimensional multimodal medical images (volumes) based on Hermite transform is proposed. This algorithm assumes registered volumes so the problem focuses on the scheme of pattern extraction at voxel level and the decision rule based on the linear algebra in order to get a new volume with the most important features of the original sources. The choice of Hermite transform as a model for image analysis lies in the fact that it uses functions that have been proposed to model the profiles of the receptive fields, which are present in the human visual system.

Keywords: Volumes fusion, 3D medical images, Hermite transform, linear algebra, muliresolution

1. Introduction

Medical images can be acquisitioned by different techniques (modalities). Several of them are actually three–dimensional data, and frequently they need be linked so that the information can be complemented and integrated, emphasizing the important structures. Because of this, there is the need for fusion of medical images, which can be defined as the combination of images of different modalities in one image with as much information, in order to display together and integrated all the information (anatomical

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and functional) to simplify their interpretation. Since the images used in this study are three-dimensional, the concept is extended to the volumes fusion.

Fusion techniques can be divided into spatial domain and transform domain techniques [1]. In the first case, the input images are fused into spatial domain, the fusion process deals with the original voxel values. In contrast, in the transform domain techniques it is possible to use a framework where the salient features of the images are clearer than in the spatial domain.

In the literature some methods of medical image fusion have been reported using a transformation to perform data fusion, some of these transformations are the discrete wavelet transform (DWT) [2], the contourlet transform [3], the curvelet transform [4], and the Hermite transform [5]. Of all these methods, the wavelet transform has been the most used technique for the fusion process, however, this technique has certain problems in the analysis of signals from two or more dimensions, an example of this is the points of discontinuity that can not always be detected, and another drawback is its limitation to capture directional information. The contourlet and the curvelet transforms have shown better results than the wavelet transform due to multi-directional analysis, but they require an extensive orientation search at each level of the decomposition. Because of this, the Hermite transform provides significant advantages to the process of image fusion, first this model of representation includes some properties of human visual system such as the local orientation analysis and the Gaussian derivative model of primary vision, it also allows multiresolution analysis so it is possible to describe the salient structures of an image with an excellent approximation in a small number of coefficients. The latter has the additional advantage of reducing noise without introducing artifacts.

In this work, the input volumes are assumed to have negligible registration problems, thus the volumes can be considered registered. The proposed scheme fuses volumes at the voxel-level using a multiresolution directional-oriented Hermite transform of the source images by means of a decision map. The results indicate that our method best characterized important structures of the volumes and consequently allowed to obtain perceptually better volumes.

The rest of the paper is organized as follows. Section 2 presents the basic concepts of Hermite Transform. Section 3 describes the proposed image fusion algorithm. Section 4 focuses on experiments, evaluation criteria and analysis of results. Finally conclusions are introduced in section 5.

2. The Hermite Transform (HT)

The Hermite transform (HT) [6][7] is a special case of polynomial transform, which is a technique of local decomposition of signals and can be regarded as an image description model. The process of this technique involves two steps. In a first step, the input image $L(x,y)$ is windowed with a local function $w(x,y)$ at several equidistant positions in order to achieve a complete description of the image. In the second step the local information of each analysis window is expanded in terms of a family of orthogonal polynomials. The polynomials $G_{m,n-m}(x,y)$ used to approximate the windowed information are determined entirely by the window function in such a way the orthogonality condition is satisfied.

The polynomial transform is called Hermite transform if the windows used are Gaussian functions. The Gaussian window is isotropic (rotationally invariant), separable in Cartesian coordinates and their derivatives mimic some processes at the retinal or visual cortex of the human visual system [8]. In a Gaussian window function, the associated orthogonal polynomials are the Hermite polynomials, which are defined as

$$G_{n-m,m}(x,y) = \frac{1}{\sqrt{2^n (n-m)!m!}} H_{n-m}\left(\frac{x}{\sigma}\right) H_m\left(\frac{y}{\sigma}\right) \tag{1}$$

where $H_i\left(\frac{x}{\sigma}\right)$ denotes the *ith* Hermite polynomial orthogonal to the Gaussian window with standard deviation σ.

The inverse 3D discrete HT is defined as

$$\begin{aligned} L(x,y,z) = \sum_{n=0}^{\infty}\sum_{m=0}^{n}\sum_{l=0}^{m}\sum_{(p,q,r)\in S} & L_{l,m-l,n-m}(p,q,r)\, P_l(x-p) \\ & \cdot P_{m-l}(y-q)\, P_{n-m}(z-r) \end{aligned} \tag{2}$$

where P_l, P_{m-l} and P_{n-m} are the synthesis filters for x, y and z directions respectively, and the Hermite coefficients $L_{l,m-l,n-m}$ are obtained by convolving the original signals $L(x,y,z)$ with the filters $D_l(x)\, D_{m-l}(y)\, D_{n-m}(z)$ followed by subsampling on a sampling lattice S. Fourier transforms of the filters can be expressed in spherical coordinates $\omega_x = \omega \cos\theta \cos\phi$, $\omega_y = \omega sen\theta \cos\phi$ y $\omega_z = \omega sen\phi$ as

$$d_l(\omega_x)\, d_{m-l}(\omega_y)\, d_{n-m}(\omega_z) = g_{l,m-l}(\theta)\, g_{m,n-m}(\phi)\, d_n(\omega) \tag{3}$$

where $d_n(\omega)$is the Fourier transform of the Hermite filter 1D $D_n(r)$, with r the polar coordinate and the function g is expresses the directional selectivity of the filter and is defined as

$$g_{m,n-m}(\theta) = \sqrt{\frac{n!}{m!\,(n-m)!}} \cos^m \theta sen^{n-m}\theta \tag{4}$$

The best fit of the original signal $L(x, y, z)$ by a 1D pattern K [6]

$$K\left((xcos\theta + ysin\phi)\, cos\theta + zsin\phi\right) \tag{5}$$

is found by maximizing the directional energy

$$\sum_{n=0}^{\infty} K^2_{n,\theta,\phi} = \sum_{n=0}^{\infty} \left[\sum_{m=0}^{n} \sum_{l=0}^{m} g_{l,m-l}(\theta) \cdot g_{m,n-m}(\phi) \cdot L_{l,m-l,n-m} \right] \tag{6}$$

over all (θ, ϕ).

Therefore, the best 1D approximation of the 3D Hermite coefficients is given by

$$\widehat{L}_{l,m-l,n-m} = K_{n,\theta,\phi} g_{l,m-l}(\theta)\, g_{m,n-m}(\phi) \tag{7}$$

for $n = 0, \ldots, \infty$, $m = 0..n$ and $l = 0, \ldots, m$ with (θ, ϕ) as optimal angles, where $\widehat{L}_{l,m-l,n-m}$ are the steered Hermite coefficients.

The HT has the advantage of high-energy compaction by adaptively steering the HT [9]. The steering property of the Hermite filters explains itself because they are products of polynomials with a radially symmetric window function. The $N + 1$ Hermite filters of Nth-order form a steerable basis for each individual Nth-order filter. Because of this property, the Hermite filters at each position in the image adapt to the local orientation content. Fig. 1 shows the HT and the steered HT over a volume. For the directional Hermite decomposition, first, a HT was applied and then the coefficients were rotated toward the estimated local orientation, according to a criterion of maximum oriented energy at each window position. This implies that these filters can indicate the direction of one-dimensional pattern independently of its internal structure.

A multiresolution decomposition using the HT can be obtained through a pyramid scheme [10]. In each layer the zero order coefficients are transformed to obtain -in a lower layer- a scaled version of the above. Once the coefficients of Hermite decomposition of each level are obtained, the coefficients can be projected to one dimension by its local orientation of maximum energy. In this way we obtain the multiresolution 3D directional-oriented HT, which provides information about the location and orientation of the structure of the image at different scales.

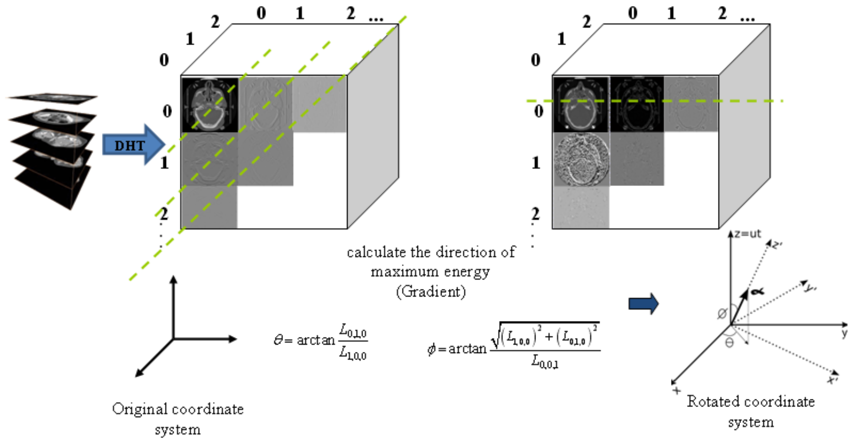

Figure 1: The Discrete Hermite Transform (DHT) 3D and the Steered Hermite Transform over a volume

3. Proposed fusion algorithm

The general framework for the proposed algorithm includes the following stages. First a multiresolution HT of the input volumes is applied. Then, for each level of decomposition, the orientation of maximum energy is detected to rotate the coefficients, so the first order rotated coefficient has most edge information. Afterwards, taking this rotated coefficient of each volume we apply a linear dependence test. The result of this test is then used as a decision map to select the coefficients of the fused volume in the multiresolution HT domain of the input volumes. The approximation coefficients in the case of HT are the zero order coefficients, which, in this case, just are averaged to generate the zero order coefficient of the fused volume. Finally the fused volume is obtained by applying the inverse multiresolution HT where fused coefficients in each level can retrieve zero order coefficients of the higher level. Fig. 2 shows a simplified representation of this method.

The linear dependence test evaluates the voxels inside a cube of $w_s \times w_s \times w_s$, if those voxels are linearly independent, then there is no relevant feature in the cube. However, if the voxels are linearly dependent, it indicates the existence of a pattern. The fusion rule selects the coefficient with the highest dependency value. A higher value will represent a stronger pattern. A simple and rigorous test for determining the linear dependence or independence of vectors is the Wronskian determinant [11][12]. The dependency of the window centered at a voxel (i, j, k) is described in

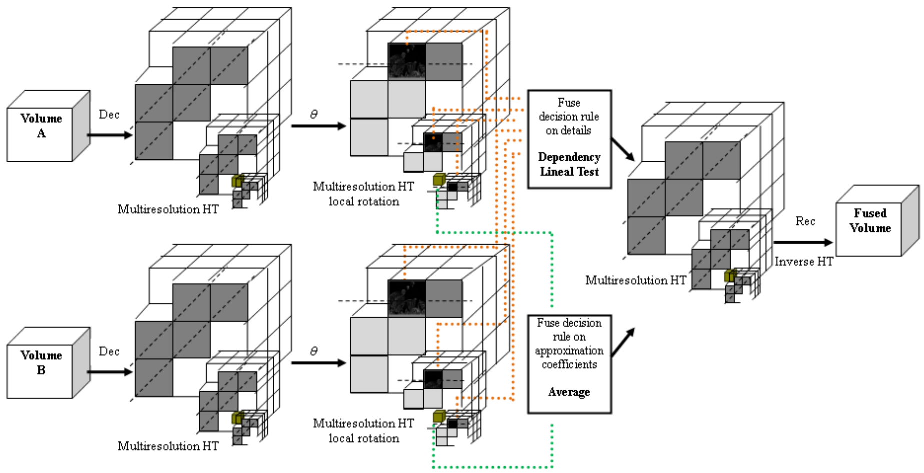

Figure 2: Fusion scheme with Multiresolution Directional-oriented Hermite Transform

$$D_A(i,j,k) = \sum_{m=i-w_s}^{i+w_s} \sum_{n=j-w_s}^{j+w_s} \sum_{o=k-w_s}^{k+w_s} L_A^2(m,n,o) - L_A(m,n,o) \qquad (8)$$

where $L_A(m,n,o)$ is the first order steered Hermite coefficient of the source volume A with spatial position (m,n,o). The fusion rule is expressed in (9). The coefficient of the fused HT is selected as the one with largest value of the dependency measure.

$$L_F(i,j,k) = \begin{cases} L_A(i,j,k) & si \;\; D_A(i,j,k) \geq D_B(i,j,k) \\ L_B(i,j,k) & si \;\; D_A(i,j,k) < D_B(i,j,k) \end{cases} \qquad (9)$$

We apply this rule to all detail coefficients and average the zero order Hermite coefficients as (10).

$$L_{000_F}(i,j,k) = \frac{1}{2}\left[L_{000_A}(i,j,k) + L_{000_B}(i,j,k)\right] \qquad (10)$$

4. Experiments and results

Fig. 3 and Fig. 4 show the results for a slice in two fusion experiments using computed tomography (CT), magnetic resonance imaging (MRI) and positron emission tomography (PET). In all of them we used the linear dependence test with a window size of 3×3. The transforms have two decomposition levels; the wavelet transform used was db4 and for the HT we used a Gaussian window with spread $\sigma = \sqrt{2}$, a subsampling factor $T = 2$ between each pyramidal level. From these figures, we can notice that the image fusion method based on the HT preserved better the spatial resolution and information content of both images.

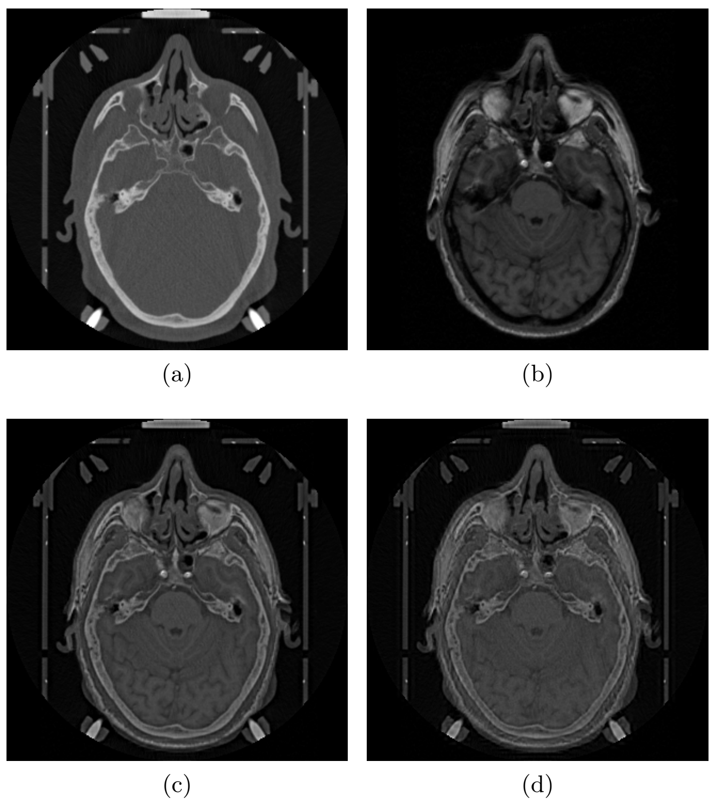

Figure 3: Results of image fusion in medical images, using the dependency test rule and different analyze techniques. (a) CT (b) MR, c) by HT, d) by wavelet transform

The mutual information (MI) has been proposed as a performance measurement of image fusion in absence of ground truth [19]. The amount of information correspondent to image A contain in the fused image is determined as follows

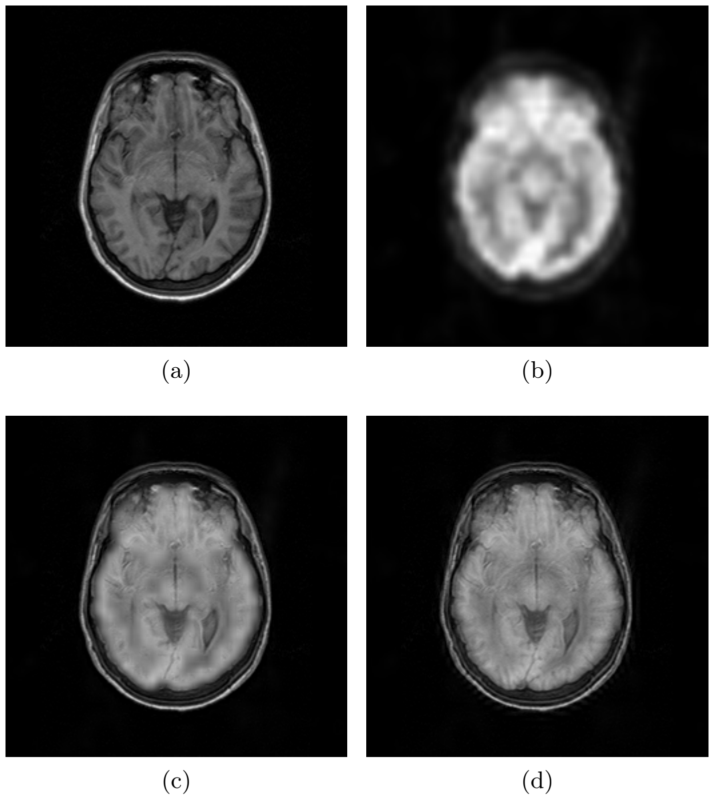

Figure 4: Results of image fusion in medical images, using the dependency test rule and different analyze techniques. (a) MR (b) PET, c) by HT, d) by wavelet transform

$$MI_{FA}\left(I_F, I_A\right) = \sum P_{FA}\left(I_F, I_A\right) \log \left[\frac{P_{FA}\left(I_F, I_A\right)}{P_F\left(I_F\right) P_A\left(I_A\right)} \right] \tag{11}$$

Then, mutual information is calculated by

$$MI_F^{AB} = MI_{FA}\left(I_F, I_A\right) + MI_{FB}\left(I_F, I_B\right) \tag{12}$$

At first glance, the results obtained in Fig. 3 and Fig. 4 were very similar, thought quantitatively it is possible to verify the performance of the proposed algorithm. Tab. 1 shows the performance using the MI.

Table 1: Performance measurement of Fig. 3 and Fig. 4 applying the fusion rule based on linear dependency with different methods

Data	Fusion Method	MI_{FA}	MI_{FB}	MI_F^{AB}
CT/MR	Hermite Transform	1.9378	1.2987	3.2366
	Wavelet Transform	1.8213	1.2022	3.0235
MR/PET	Hermite Transform	1.6170	1.7661	3.3832
	Wavelet Transform	1.6260	1.7435	3.3695

5. Conclusions

We have presented a multiresolution tridimensional fusion method based on the directional-oriented HT using a linear dependency test as fusion rule. We have experimented with this method for multi-modal volumes and we have obtained a good performance. Both subjective and objective results show that the proposed scheme outperforms other methods based on the wavelet transform.

The HT has proved to be an efficient model for the representation of signals because derivatives of Gaussian are the basis functions of this transform, which optimally detect, represent and reconstruct perceptually relevant image patterns, such as edges and lines.

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