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Medical Image Fusion using Hybrid DCT-DWT based Approach

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Abstract – **During a clinical study or diagnosis, many sources of information are available to the clinician: different imaging modalities, and different tools to better study the structure or pathology. The clinician must synthesize these different pieces of information in order to perform accurate and reliable diagnosis and / or treatment. However, this synthesis can be long, tedious and remains highly dependent on the operator who takes care of it.**

In this context, image fusion appears as a new tool to help diagnosis; making the task easier for the doctor by providing a simpler fusion tool than mental fusion. As part of this work, the paper presents a comparative study of fusion techniques, the first one based on the discrete wavelet transform (DWT) and the second one based on discrete cosine transform (DCT) and the third one that is new based on the hybridization of DCT and DWT.

Keywords – **CT, DCT, DWT, MRI, PET, SPECT TEMP.**

I. INTRODUCTION

Image fusion has become a commonly used term in medical diagnosis and treatment. [1] The term is used when multiple images of the patient are recorded and overlaid or fused to provide additional information. Fused images can be created from multiple images of the same imaging modality, [2] or by combining information from multiple modalities, [3] such as magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), and single photon emission computed tomography (SPECT). In radiology and radiation oncology, these images serve different purposes. For example, CT images are most often used to determine differences in tissue density while MRI images are typically used to diagnose brain tumors.

Medical imaging is a set of techniques for visualizing a part of the human body or organ and to preserve an image. It aims to help in the diagnosis, to guide a therapeutic gesture, such as a puncture, or to follow the results of a treatment in the medium term.

Medicine and surgery continue to evolve, this is even truer for ten years with the irruption of the machine in the diagnosis. While the doctor remains reader and referee, but it is the computer that reveals the anatomy. Many images and information can now be accessed through medical imaging.

The next evolution may well be the fusion of information that can be provided by different medical imaging techniques. We would thus have the information of several analyzes in one image. The idea of combining the different images of the same object or scene appeared interesting and useful.

In the medical field, there are a large number of imaging modalities (conventional x-ray, X-ray, ultrasound, magnetic resonance imaging (MRI), positron emission tomography (PET), single photon emission computed tomography, (TEMP), etc.), Each acquisition modality has different characteristics, and serves to highlight particular tissue properties. The exams are complementary, but also redundant in some cases. The doctor then makes a diagnosis by simultaneously or alternatively viewing the images, and by synthesizing the different types of information.

This is the purpose of this research work, we are interested in the fusion of medical images. According to Bloch, "information fusion involves combining information from multiple sources to improve decision-making" [4]. We want to fuse the information that we will provide an MRI (magnetic resonance image), and a PET (positron emission tomography).

To realize this study, it will first be necessary to recalibrate the images which will not have the same

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sizes and resolutions because they come from different sources, this in order to be able to superpose them, and will present two methods for fused medical images, the first based on the discrete wavelet transform (DWT), the second on the discrete cosine transform (DCT) and hybrid of DWT and DCT methods.

II. Proposed Method

A. Proposed Wavelet based Fusion Algorithm

The diagram in Figure 1 shows the concept of wavelet fusion process. The image fusion by this method is carried out respecting the following steps [5]:

- Specification of the histogram of the spatial high resolution image to that of the multispectral images.
- Decompose the panchromatic image into an approximation image and three wavelet coefficients.
- Replace each approximation of the panchromatic image by the multispectral image.
- The inverse wavelet transform makes it possible to synthesize multispectral images with high spatial resolution.

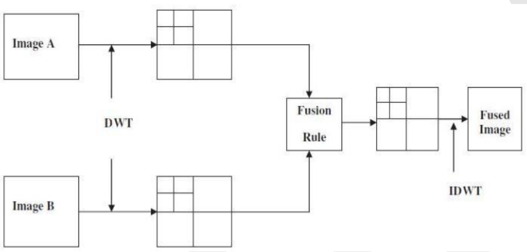

Figure 1: DWT fusion process [5]

The exploitation of the transform in IHS and the multi-resolution analysis associated with the wavelet makes it possible to give a new method of fusion of images. This method consists of combining the two tools.

In the context of frame theory, I. Daubechies proposed a discretization of scale and translation factors such as:

$$a_m = a_0^m, m \in Z \text{ and } a_0 > 1 \quad (1)$$

$$b_n = nb_0 a_0^m, n \in Z \text{ and } b_0 > 0 \quad (2)$$

Then the wavelet family is of the form:

$$\psi_{m,n}(x) = a_0^{-\frac{m}{2}} \psi(a_0^{-m}x - nb_0) \quad (3)$$

Such discretization allows the family, at each scale a_m, to cover all the signal support without too much redundancy, each wavelet being essentially concentrated on the $[a_0^m nb_0, a_0^m(n+1)b_0]$ interval.

On the other hand, the transform will no longer be invariant in translation as the continuous transform, because of the dependence of the parameters. To express the coefficients of the discrete wavelet transform, we note them by:

$$d_n^m = \langle \psi_{m,n}, f \rangle = a_0^{-\frac{m}{2}} \int \overline{\psi}\,(a_0^{-m}x - nb_0) f(x) dx \quad (4)$$

We show in the specialized literature [5] that if the $\{\psi_{m,n},\ m,n \in Z\}$ family is a frame, then we will have:

$$\frac{b_0 Log(a_0)}{\pi} A \le \int_{-\infty}^{+\infty} \frac{|\Psi(\omega)|^2}{|\omega|} d\omega \le \frac{b_0 Log(a_0)}{\pi} B \quad (5)$$

Where A and B are two positive constants of a given frame.

This expression simply shows us that the admissibility condition is verified and the wavelet $\psi_{m,n}$ is analyzing. In this case, the construction of numerically stable algorithms for reconstructing the signal from its wavelet coefficients d_n^m is possible:

$$f(x) = \frac{2}{A+B} \sum_{m,n} \langle \psi_{m,n} m f(x) \rangle \, \psi_{m,n} + R \quad (6)$$

With, $\|R\| \le O\left(\frac{B}{A} - 1\right) \|f(x)\|$, it expresses an error term.

If the base is orthonormed then the term R will be zero. However, it is best to minimize the redundancy of this representation. In this case, we choose values of $a_0 = 2$, $b_0 = 1$ for which the wavelets ψ_{a_0,b_0} constitute an orthonormal basis. We conclude that orthonormality is a necessary condition for the transition from the continuous wavelet transform to the discrete wavelet transform [5].

The principle of image fusion by this combination is discussed in the following section.

B. Evaluation Criteria

The process of evaluating the fusion is performed from the standpoint of spatial content and spectral content.

1) Visual Assessment Criterion

Visual analysis is necessary to verify the quality of the images obtained by the fusion, indeed, although the human visual system differs from one individual to another but we can see the injection of the structures by an increased clarity of the image. image, and preservation of the spectral information by the colored composition.

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2) *Statistical Evaluation Criterion*

Several statistical parameters are used for quantitative analysis. For our study we use the following parameters: information entropy, spatial frequency, correlation coefficient, standard deviation and mutual information.

a) Information Entropy (IE)

Information Entropy is a criterion that measures the degree of information in the image, the larger the IE, the more the diffuse image of information [6].

$$IE = -\sum_{i=0}^{L-1} P_f(i) \log_2 P_f(i) \tag{7}$$

Where, P_f is the ratio of the number of pixels with the value of gray level to i on the total number of pixels.

b) Correlation Coefficient (CC)

It describes the degree of correlation between two images. The closer the CC is to 1, the higher the degree of correlation. For two images A and B, with x_{ij} and x'_{ij} the pixel values respectively, and $\mu(A)$, $\mu(b)$ the corresponding average values [6].

$$CC = \frac{\sum_{j=1}^{N}\sum_{i=1}^{M}(x_{i,j}-\mu(A))(x'_{i,j}-\mu(B))}{\sqrt{\sum_{j=1}^{N}\sum_{i=1}^{M}(x_{i,j}-\mu(A))^2 (x'_{i,j}-\mu(B))^2}} \tag{8}$$

c) *Spatial Frequency (SF)*

It measures the total activity and level of clarity of an image, a large value means that the fusion result is good [6].

$$SF = \sqrt{RF^2 + CF^2} \tag{9}$$

Where,

$$RF = \sqrt{\left(\frac{1}{M(N-1)}\right)\sum_{i=0}^{M-1}\sum_{j=0}^{N-2}\{F(i,j+a) - F(i,j)\}^2}$$

And

$$CF = \sqrt{\left(\frac{1}{N(M-1)}\right)\sum_{i=0}^{M-2}\sum_{j=0}^{N-1}\{F(i+1,j) - F(i,j)\}^2}$$

d) Standard Deviation (STD)

Standard deviation is the square root of the variance. The variance of an image reflects the degree of dispersion between the grayscale values and the average grayscale value, the larger the STD, the greater the dispersion.

$$STD = \sqrt{\frac{\sum_{i=0}^{N-1}\sum_{j=0}^{M-1} F(i,j)}{NM}} \tag{10}$$

e) *Mutual Information (MI)*

Compare between the source image and the fused image, the smaller the value, the less the relationship between the two images.

$$MI = \sum_{af} P_{AF}(a,f) \log \frac{P_{AF}(a,f)}{P_A(a)P_F(f)} \tag{11}$$

Where, $P_{AF}(a,f)$ is the joint histogram of the fused image F and the source image A.

C. Discrete Cosine Transform

The discrete cosine transform (DCT) helps separate the image into parts (or spectral sub-bands) of differing importance (with respect to the image's visual quality). The DCT is similar to the discrete Fourier transform: it transforms a signal or image from the spatial domain to the frequency domain (Figure 2).

A discrete cosine transform (DCT) expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies. DCTs are important to numerous applications in science and engineering, from lossy compression of audio (e.g. MP3) and images (e.g. JPEG) (where small high-frequency components can be discarded), to spectral for the numerical solution of partial differential equations [7]. The use of cosine rather than sine functions is critical in these applications: for compression, it turns out that cosine functions are much more efficient (as described below, fewer are needed to approximate a typical signal), whereas for differential equations the cosines express a particular choice of boundary conditions.

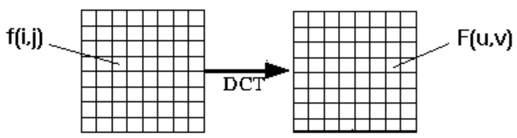

Figure 2: Transformation of function into DCT [7]

In particular, a DCT is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using only real numbers. DCTs are equivalent to DFTs of roughly twice the length, operating on real data with even symmetry (since the Fourier transform of a real and even function is real and even), where in some variants the input and/or output data are shifted by half a sample. There are eight standard DCT variants, of which four are common.

The most common variant of discrete cosine transform is the type-II DCT, which is often called simply "the DCT"; its inverse, the type-III DCT, is correspondingly often called simply "the inverse DCT" or "the IDCT". Two related transforms are the discrete sine transforms (DST), which is equivalent to a DFT of real and odd functions, and the modified discrete cosine transforms (MDCT), which is based on a DCT of overlapping data.

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The two-dimensional DCT of an M×N matrix A is defined as follows:

$$B_{pq} = \alpha_p \alpha_q \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{mn} \cos\frac{\pi(2m+1)p}{2M} \cos\frac{\pi(2n+1)q}{2N} \quad (12)$$

Where, $\begin{matrix} 0 \le p \le M-1 \\ 0 \le q \le N-1' \end{matrix}$

$$\alpha_p = \begin{cases} \frac{1}{\sqrt{M}}, & p = 0 \\ \sqrt{\frac{2}{M}}, & 1 \le p \le M-1 \end{cases}$$

$$\alpha_q = \begin{cases} \frac{1}{\sqrt{N}}, & q = 0 \\ \sqrt{2/N}, & 1 \le q \le N-1 \end{cases}$$

The values B_{pq} are called the DCT coefficients of A. The DCT is an invertible transform, and its inverse is given by:

$$A_{mn} = \sum_{p=0}^{M-1} \sum_{q=0}^{N-1} \alpha_p \alpha_q B_{pq} \cos\frac{\pi(2m+1)p}{2M} \cos\frac{\pi(2n+1)q}{2N} \quad (13)$$

Where, $\begin{matrix} 0 \le m \le M-1 \\ 0 \le n \le N-1 \end{matrix}$ and,

$$\alpha_p = \begin{cases} \frac{1}{\sqrt{M}}, & p = 0 \\ \sqrt{\frac{2}{M}}, & 1 \le p \le M-1 \end{cases}$$

$$\alpha_q = \begin{cases} \frac{1}{\sqrt{N}}, & q = 0 \\ \sqrt{2/N}, & 1 \le q \le N-1 \end{cases}$$

The inverse DCT equation can be interpreted as meaning that any M×N matrix A can be written as a sum of MN functions of the form:

$$\alpha_p \alpha_q \cos\frac{\pi(2m+1)p}{2M} \cos\frac{\pi(2n+1)q}{2N} \quad (14)$$

Where, $\begin{matrix} 0 \le p \le M-1 \\ 0 \le q \le N-1 \end{matrix}$

III. Simulation And Results

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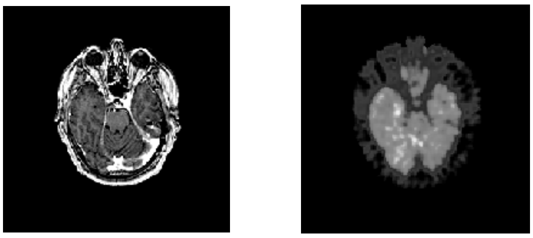
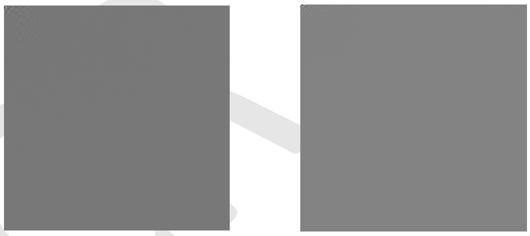
A. Simulation Results for DCT



(a) MRI image (b) PET image

Figure 3: Input images



(a) MRI image DCT coefficient (b) PET image DCT coefficient

Figure 4: DCT coefficients of images

Figure 5: Fused DCT coefficient

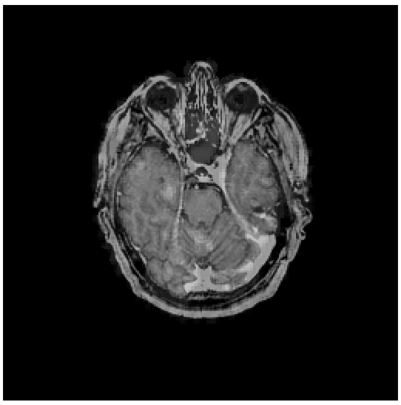


Figure 6: Fused image by DCT

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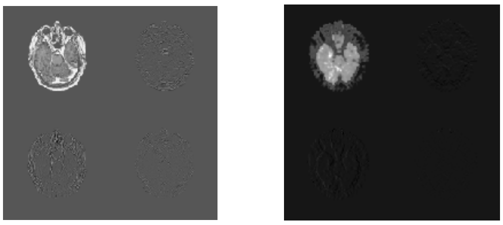
B. Simulation Results for DWT



(a) MRI image DWT coefficient (b) PET image DWT coefficient
Figure 7: DWT coefficients of images

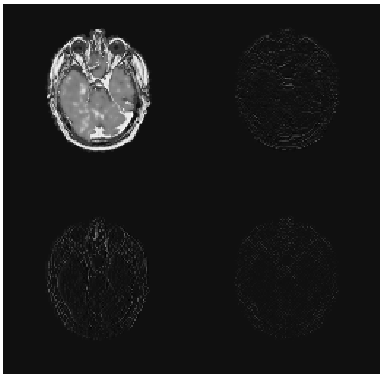


Figure 8: Fused DWT coefficient

Figure 9: Fused image by DWT

C. 5.3 Simulation Results for DCT-DWT

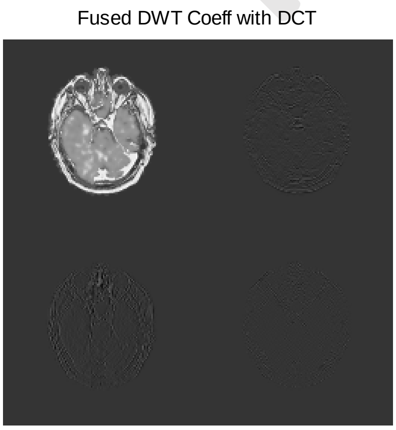


Figure 10: Fused DWT coefficients with DCT

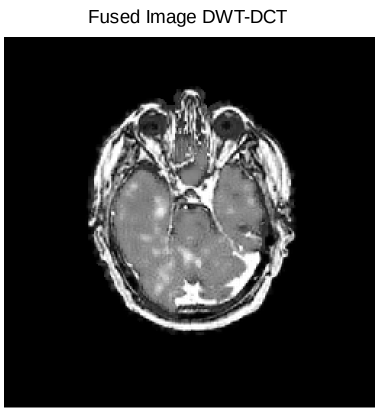


Figure 11: Fused image by DCT- DWT

Table 1: Result comparison

Entropy of Fused Image by DCT	2.9449766
Entropy of Fused Image by DCT	3.0993554
Entropy of Fused Image by DWT-DCT	3.1398059

IV. Conclusion

In this paper, we presented and compared methods of fusion of medical images and more specifically couples to MRI and PET images by exploiting the wavelet transform, the discrete cosine transform, and a hybrid DCT-DWT based approach.

It was found that the proposed hybrid approach outperforms other approaches on the basis of entropy.

As perspectives for future work, this work can be extended by merging images of other modalities of medical imaging (CT + SPECT, CT + MRI or even CT + MRI + SPECT), and 3D medical images, apply on the fusion of images of other methods and other geometric wavelets such as Triangulation wavelets, the Ridgelet transform or the Beamlet transform, as well as the use of so-called high-level methods.

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