A MEDICAL IMAGE FUSION METHOD FOR WEB DISTRIBUTED APPLICATIONS

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Abstract: Medical images acquired with different medical modalities contain important diagnostic information. The combination of complementary data from these images can lead to more important information for diagnosis process. The fusion process allows combination of salient feature of these images. In this paper we present a method for medical image fusion, based on discrete wavelet transform. This method is implemented in a web distributed application, using Java technology. The web dedicated application allows physicians to realize a fusion from a remote place. We have also calculated some quantitative parameters for fusion process evaluation.

Key words: image fusion, wavelet transform, distributed application, multi-resolution decomposition.

I. INTRODUCTION

In recent years, medical imaging became very useful for assisted diagnosis process. There are many medical modalities that give important information about different diseases. These equipments are accompanied by software applications which offer image processing facilities. Many of these modalities offer complementary information. For example, CT provides best information about denser tissue and MRI offers better information on soft tissue, [3]. These complementarities have led to idea that the combining images acquired with different medical devices, will generate an image that can offer more information than each other separate. In this way, the result image can be very useful in the diagnosis process, and that's why the image fusion has become an important research field.

Not all hospitals or medical offices have software applications for image fusion, so a remote access to such an application can be useful for physicians which want to use this method in the assisted diagnosis process. The fusion process can be a part of such a distributed application that runs in a medical center and specialists situated at distance can access this application by Internet. They could load the images in the application and the result image will be displayed with a web browser.

There are some important requirements for the image fusion process, [5]:

- The fused image should preserve all relevant information from the input images
- The image fusion should not introduce artifacts which can lead to a wrong diagnosis

Many image fusion methods have been introduced in the literatures including simple pixel-by-pixel averaging using SNR (Signal to Noise Ratio), wavelet transform methods, Laplacian pyramid method and conditional probability network.

In recent years, researchers developed different medical applications including image fusion techniques and some of them have been upgraded to commercial software applications, such as HermesJade software package, offered by Hermes Medical Solutions, implemented in Java, [14]. Another solution for medical image fusion is implemented by MadenaSoftware[13], for MacOS-X operating system. None of these offer information about the implemented fusion methods. Metapix solution [12] is implemented in Matlab, and provides methods for pixel-level image fusion of spatially registered grayscale images. All these applications offer local solutions for the image fusion.

II. DISCRETE WAVELET TRANSFORM IN IMAGE FUSION PROCESS

The fusion techniques can be classified in two main categories: for spatial domain and for transform domain. In spatial domain, fusion is realized using local characteristics. If $g(\cdot)$ represents the „fusion rule" the technique can be defined in this way:

$$I_f(x,y) = g(I_1(x,y),\ldots,I_T(x,y)) \tag{1}$$

where $I_f(x,y)$ is the fused image and $I_1(x,y),\ldots,I_T(x,y)$ are the input images.

The reason of passing to the transform domain is the fact that salience caracteristics of the image are observed more easier than in spatial domain, and this is important to recognize informational underlayer of the image for fusing them comparing with the independent „combination" of the pixels. Fusion based on transforms has some advantages over other simple methods, like:

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energy compaction, larger SNR, reduced features, etc. The transform coefficients are representative for image pixels.

The most transforms used in images proccesings split the image in important local components and transform method become very important. Considering transform operator $\Im(\cdot)$ and fusion rule $g(\cdot)$, the fusion techique may be expressed as:

$$I_f(x,y) = \Im^{-1}\{g(\Im\{I_1(x,y)\},...,\Im\{I_T(x,y)\})\} \quad (2)$$

The operator $g(\cdot)$ describes the information included from many input images. This operation reprezents the fusion rule.

The researchers developed many algorithms for image fusion, such as [8]:
- image pyramid approaches: Laplacian pyramid, Gaussian Pyramid, ratio of low pass pyramid, contrast pyramid, Filter-Subtract-decimate (FSD) Pyramid, Morphological Pyramid, Gradient Pyramid
- wavelet based methods
- Total Probability Density Fusion
- Biologically-Inspired Fusion

Later improvements have been obtained in image fusion process with introduction of multi-resolution analysis (MRA), by employing several decomposition schemes, specially based on discrete wavelet transform, uniform rational banks, and Laplacian pyramids.

Wavelets are used for time frequency localization, and perform multi-scale and multi-resolution operations. Discrete wavelet transform (DWT), transforms a discrete time signal to a discrete wavelet representation. It converts an input series x0, x1, .., xm, into one high-pass wavelet coefficient series and one low-pass wavelet coefficient series (of length n/2 each) given by the (3) formulas, [1].

In practice, such a transformation will be applied recursively on the low-pass series until the desired number of iterations is reached.

$$H_i = \sum_{m=0}^{k-1} x_{2i-m} \cdot s_m(z)$$
$$L_i = \sum_{m=0}^{k-1} x_{2i-m} \cdot t_m(z) \quad (3)$$

where sm(z) and tm(z) are called wavelet filters, k is the length of the filter, and i=0, ..., [n/2]-1.

Image multi-resolution analysis was introduced by Mallat in the decimated case (critically sub-sampled), [9]. The main difference between the decimated and undecimated fusion algorithm is the presence or absence of subsampling when the wavelet decomposition is performed.

The DWT has been extensively employed for remote sensing data fusion. Couples of sub-bands of corresponding frequency content are merged together. The fused image is synthesized by taking the inverse transform. In literature are proposed fusion schemes based on 'a trous' wavelet algorithm and Laplacian pyramids (LP).

Image fusion is implemented by two-dimensional discrete wavelet transform.

The resolution of an image, which is a measure of amount of detail information in the image, is changed by filtering operations of wavelet transform and the scale is changed by sampling. The DWT analyses the image at different frequency bands with different resolutions by decomposing the image into coarse approximation (LL) and detail coefficients (HL, LH and HH), like in Figure 1.

The transform is applied on the previously registered images. This operation generates coefficients for images. A fusion rule has to be established and applied on these coefficients. The fused image is obtained using inverse transform.

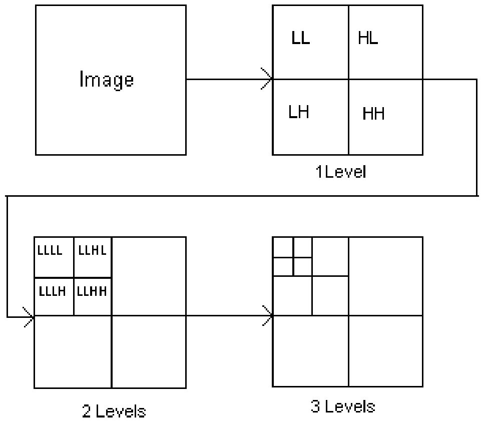


Figure 1. Image decomposition scheme using 2D DWT

III. IMAGE FUSION RULES

For every fusion process, a fusion rule has to be used, as can be seen in relation (2). There are some basis rules that are describesd in literature:

1. *At pixels level* : information fusion is realized pixel by pixel in the initial or transformed domain. Every (x,y) pixel of the source image T is combined using different methods for obtaining the corespondent pixel in fused image I_T. There are some basis transform schemes, briefly presented below:
- Fusion by averaging: this method realizes the averaging of corresponding coefficients of every image

$$\Im\{I_f(x,y)\} = \frac{1}{T}\sum_{i=1}^{T}\Im\{I_i(x,y)\} \quad (4)$$

- Fusion by absolut maximum: this method selects maximum absolute value between the corresponding coefficients from every image

$$\Im\{I_f(x,y)\} = \operatorname{sgn}(\Im\{I_f(x,y)\})\max_i|\Im\{I_i(x,y)\}| \quad (5)$$

- Fusion by noise rejection: the fusion and noise

rejection processes are realised simultaneously by using a comparison threshold for transform coefficients.
- High/low fusion: the combination of high level frequency parts of some images with low level frequency parts of other images.

2. *At region level*: for a more efficient exploitation of the image structure, these schemes group the image pixels to obtain continuous regions, for example objects, and impose different fusion rules for every region. For the fusion process, the priority is calculated based on wavelet coefficients energy, variance or entropy, to impose the contribution of every region in fusion process together with other experimental methods. A decision map of coefficients is realized and fused image is built based on it.

Fusion rules determine how the source transforms will be combined. There are two basic steps for determining the rules:
– compute salience measures corresponding to the individual source transforms
– decide how to combine the coefficients after comparing the salience measures.

Figure 2 presents a general fusion process using multi-level image decomposition, [6].

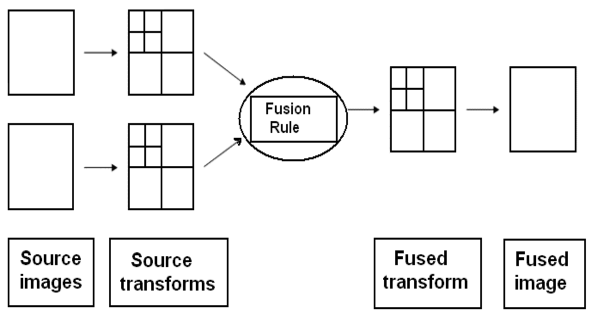


Figure 2. General fusion process

There are different fusion schemes that are implemented using DWT, such as:
- *maximum selection* (MS): this scheme chooses the coefficients with the maximum magnitude from every subband
- *weighted average* (WA): This scheme developed by Burt and Kolczynski uses a normalized correlation between the two images subbands over a small local area. The resultant coefficient for reconstruction is calculated from this measure using a weighted average of the two images coefficients
- *window based verification (WBV) scheme*: This scheme creates a binary decision map to choose between each pair of coefficients using a majority filter, [4].

IV. MEDICAL IMAGE REGISTRATION

Before fusion process there is a very important step which must be realized, namely image registration. Multi-modality registration means the matching of the same scene acquired from different sensors. According to the matching features, the medical image registration process can be divided into three main categories: point-based, surface-based, and volume-based methods, [7].

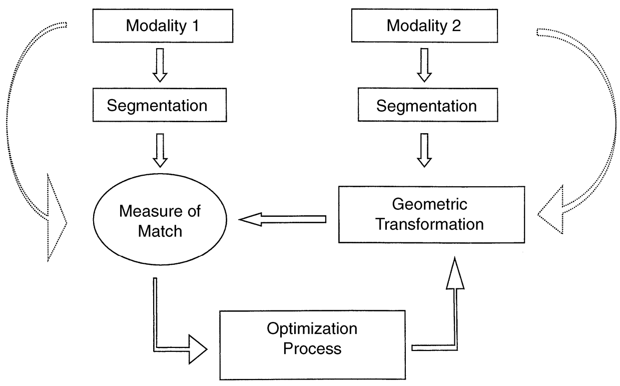


Figure 3 . Generic scheme for image registration

A generic registration scheme consists in selecting image characteristics to be used in registration process, defining the measure of matching which quantify the spatial similarity between reference and transformed image, and applying an optimizing technique for determining the independent parameters of the transformation model.

In the registration process it is necessary to establish and selecting the matching features to be used. A geometric transformation is applied on an image and the result is used for computing the measure of match between this image and the other one, as shown in Figure 3.

The most representative transformations include the affine, the bilinear, the rigid, and the projective transformations, [7]. The computed measure of match can be used to improve the accuracy of the algorithm. Several match measures have been employed, depending on the application as well as the implementation of the transform. Correlation methods are suitable for both 2-D and 3-D image intra-modality registration. The mutual information (MI) criterion is also employed for registering multimodal medical images.

For a point-based registration one solution for retrieving the matching features is to determine the centers of gravity of the two images. In this case, the geometric transformation consists in a simple translation of an image over the other one.

V. FUSION METHOD EVALUATION

For image fusion performance evaluation have been proposed various methods. The fused image should contain the important information from all of the input images. The notion of 'important information' depends on the application.

We calculated two parameters which can evaluate the fusion performance: fusion factor (FF) and fusion symmetry (FS). Mutual information is the amount of information that one image contains about another. Considering 2 input images A, B and a fused image F, we can calculate the amount of information that F contains about A and B, according to the relations, [11]:

$$MI_{FA}(f,a)=\sum_{f,a} p_{FA}(f,a)\cdot\log\frac{p_{FA}(f,a)}{p_F(f)\cdot p_A(a)} \tag{6}$$

$$MI_{FB}(f,b)=\sum_{f,b} p_{FB}(f,b)\cdot \log \frac{p_{FB}(f,b)}{p_F(f)\cdot p_B(b)} \tag{7}$$

where:

$$p_B(b)=\sum_a p_{AB}(a,b)$$
$$p_A(a)=\sum_b p_{AB}(a,b) \tag{8}$$
$$p_{AB}(a,b)=\frac{h(a,b)}{\sum_{a,b} h(a,b)}$$

- $p_A(a)$, $p_B(a)$ and $p_F(f)$ are the probability density functions of the individual images, [9].
- $p_{FA}(f,a)$ and $p_{FB}(f,b)$ are the joint probability density functions
- $p_{AB}(a,b)$ is the joint distribution
- $h(a,b)$ is the joint histogram

An image fusion performance measure can be defined as:

$$MI_F^{AB}=MI_{FA}(f,a)+MI_{FB}(f,b) \tag{9}$$

This relation indicates that this method reflects the total amount of mutual information that the fused image F contains about A and B. This measure represents the Fusion Factor FF. The bigger the FF, the better the fusion process performs.

Another calculated measure is Fusion Symmetry (FS), which denotes the symmetry of the fusion process related to two input images.

$$FS=abs\left(\frac{MI_{FA}(f,a)}{MI_{FA}(f,a)+MI_{FB}(f,b)}-0.5\right) \tag{10}$$

A small value for this parameter indicates a good quality for the fusion process.

VI. DEDICATED APPLICATION FOR IMAGE FUSION USING DISCRETE WAVELET TRANSFORM

We have implemented a distributed web application for image fusion using an orthogonal Haar DWT. We used Java technology and an advanced framework, named Stripes, to organize the application according to MVC architecture.

The user has to have an account to access this application. After authentication, he can upload two images and apply a fusion method for them. The result is shown in the browser.

The input images to be fused are decomposed by forward wavelet transformation. Each image is decomposed into the same levels using a periodic discrete wavelet transform. The wavelet transform decomposes each image into low- and high-frequency sub-band images.

The multi-level decomposition of the image realizes the processing of the image first on horizontal, then on vertical direction. At horizontal processing the pixels placed in the left vertical half of the result image are obtained by summing the two adjacent pixels from that row in source image, and the pixels of the right half are obtained by difference between the same pixels from source image. The process is similar for vertical processing.

The next step after decomposition of source images is the application of the fusion rule.

In our application we used the fusion rule proposed by Burt si Kolczynski (B&K). Their fusion scheme introduces two new measures: *match* – which determines the similarity degree of 2 image zones and *salience* – which represents the pertinent information (variance or energy), [2].

$$s_i^{(k)}(n\mid g)=\sum_{\Delta n\in W^{(k)}}\left|u_i^{(k)}(n+\Delta n\mid g)\right|^2$$

$$m_{AB}^{(k)}(n\mid g)=\frac{2\sum_{\Delta n\in W^{(k)}} u_A^{(k)}(n+\Delta n\mid g)\cdot u_B^{(k)}(n+\Delta n\mid g)}{s_A^{(k)}(n\mid g)+s_B^{(k)}(n\mid g)} \tag{11}$$

$$f^{(k)}(n\mid g)=\alpha_A(n\mid g)\cdot u_A^{(k)}(n\mid g)+[1-\alpha_A(n\mid g)]\cdot u_B^{(k)}(n\mid g)$$

$$\alpha_A(n\mid g)=\begin{cases}1\\0\\ \frac{1}{2}+\frac{1}{2}\cdot\left(\frac{1-m_{AB}^{(k)}(n\mid g)}{1-\tau}\right)\\ \frac{1}{2}-\frac{1}{2}\cdot\left(\frac{1-m_{AB}^{(k)}(n\mid g)}{1-\tau}\right)\end{cases}, for \begin{cases}m_{AB}^{(k)}(n\mid g)\le\tau\\ m_{AB}^{(k)}(n\mid g)\le\tau\\ m_{AB}^{(k)}(n\mid g)>\tau\\ m_{AB}^{(k)}(n\mid g)>\tau\end{cases}, and \begin{cases}s_A^{(k)}(n\mid g)>s_B^{(k)}(n\mid g)\\ s_A^{(k)}(n\mid g)\le s_B^{(k)}(n\mid g)\\ s_A^{(k)}(n\mid g)>s_B^{(k)}(n\mid g)\\ s_A^{(k)}(n\mid g)\le s_B^{(k)}(n\mid g)\end{cases}$$

where:

S_i- energy of image i at level k
m_{AB} – the matching measure (correlation)
τ – the threshold
α – the weighted factor
f – the fusion rule

In our method the following parameters are computed:

- energy of each image: we have used a sliding window of 2x2 pixels
- the correlation factor between images
- the weighted factor α; for every pixel in approximation image, we weigted with α the corresponding pixels in the details images, using the third formula of the relations (11).
- for approximation coefficients we used the maximum selection rule, because on the used images we obtained the best visual results with this method.

The fused image is obtained by applying inverse discrete wavelet transform over the result matrix.

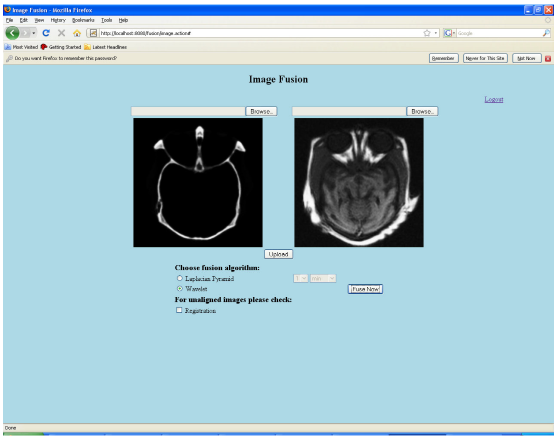


Figure 4. Choosing the fusion method for the selected images

Figure 4 presents the interface for choosing the fusion method for the selected images. If the images are not registered, the user has to select the registration check box. Figure 5 presents the results obtained using DWT for two registered images, using the fusion rule described above.

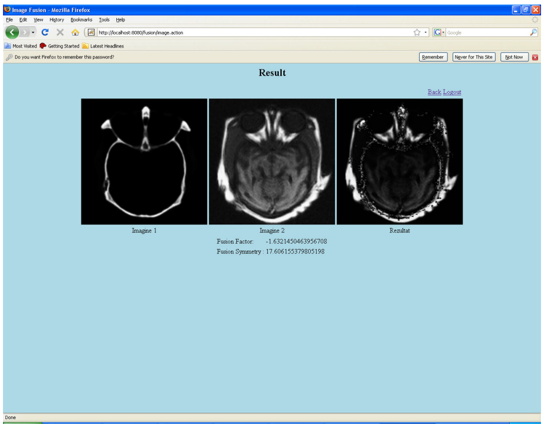


Figure 5. The result of the fusion between CT and MRI registered images

Because in most cases medical images are not registered, we implemented a registration method which can be applied before the fusion process.

This method uses a point-based algorithm which determines the centers of gravity for the images and then tries to maximize the mutual information, [10].

The images centers of gravity are computed on using the following steps:

```
Input imageA;
cog_x=0; cog_y=0; total=0;
For i=1 To height Do
        For j=1 To width Do
            I=(R_i,j+G_i,j+B_i,j)/3;
            cog_x = cog_x + (I*i);
            cog_y = cog_y + (I*j);
            total = total + I;
        EndFor
EndFor
cog_x=cog_x/total;
cog_y=cog_y/total;
Output cog_x, cog_y.
```

where:

- height, width – the image dimensions
- $R_{i,j}$, $G_{i,j}$, $B_{i,j}$ - color components fom RGB space for the pixel with (i,j) coordinates
- cog_x, cog_y – the center of gravity coordinates
- total - the value used to normalise the center of gravity coordinate

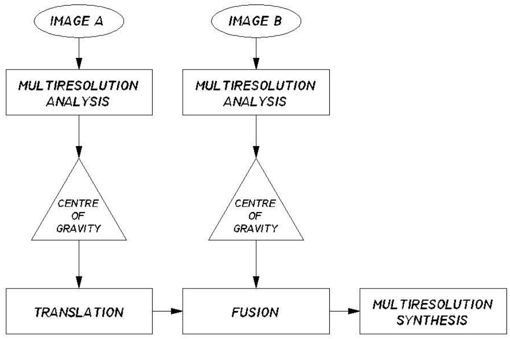
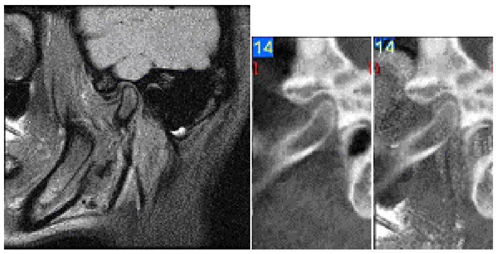


Figure 6. The implemented image registration scheme

An image is translated over the other one to matching their centers of gravity and then the fusion rule is applied. Figure 6 describes this method.



a) b) c)

Figure 7. The fusion result between a MRI image and a CT image registered with the presented method

Figure 7 presents the result of fusion (7.c) between a MRI image (7.a) and a CT image (7.b), which represents a TMA (temporomandibular articulation). These images are registered with the method presented in Figure 6.

Figure 8 presents the result of fusion between the same images. These images are registered with a method based on user interaction, in a Java stand-alone application. The user establishes in every image a point where the images have to overlap. The smallest image is translated over the bigger one to realize the matching of those points. The result is obtained using the maximum selection rule for fusion.

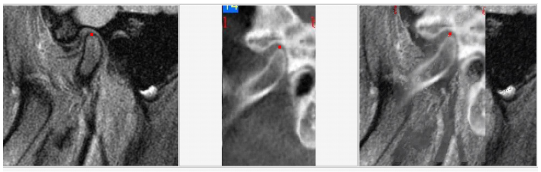
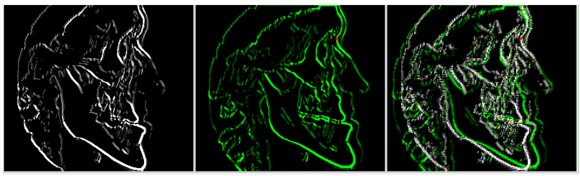


Figure 8. The fusion result between a MRI image and a CT image registered using user interaction

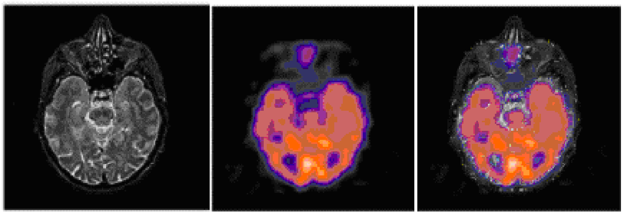
The same registering method was applied for images presented in Figure 9. This figure shows the fusion result between two images acquired with the same equipment pre (9.a) and post (9.b) surgery. We applied a contour detection technique before registering and fusion processes. The fused image (9.c) shows the differences between these two images. This fusion may be useful for quantify de correction degree of the facial disharmony.



a) b) c)

Figure 9. The fusion result of two images acquired at different moments in time

The Figure 10 presents the fusion result between a MRI image (10.a) and a SPECT image (10.b) from the head. In this case we have also used the maximum selection rule.



a) b) c)

Figure 10. Fusion between MRI and SPECT images from the head

We tested the proposed fusion method on some radiological images, with the following fusion rules: maximum selection (max-abs), choose-max and the rule proposed by Burt and Kolczynski (B&K). We calculated the fusion factor and the fusion symmetry on each case. The results are presented in Table 1.

Table 1. Results obtained for fusion factor and fusion symmetry for different radiological images

Image type	Fusion rule	FF	FS
MRI – CT head	Max-abs	4.006	0.250
	Choose-max	1.96	0.92
	B&K	2.90	0.23
MRI – CT ATM, unregistered	Max-abs	0.600	0.012
	Choose-max	0.512	0.011
	B&K	0.544	0.029
MRI – SPECT head	Max-abs	0.586	0.149
	Choose-max	0.525	0.034
	B&K	0.486	0.122

As the FF indicated how much information is extracted from the source images, we can say that the maximum selection rule offers the best results for the tested images.

VII. CONCLUSIONS AND FUTURE WORK

The medical image fusion is a very important technique and there is a real interest in this kind of applications. There are many methods for realizing this purpose and they have to be studied to choose the better one to a dedicated domain.

Our application is intended to be useful for physicians who need to fusion multi-modality images for support in diagnosis. The physicians can have access to this application from remote locations, if they have Internet connection and an account. In this way they can do image fusion from their medical office or from home.

The used fusion performance parameters offer a quantitative evaluation of the process. The results have to be validated by physicians, because different fusion rules can relieve different image characteristics.

The registration method needs to be optimized for better results and we want to implement such an optimization scheme in the future. We also want to integrate other techniques for fusion and registration and testing them for different types of complementary medical images.

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