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ORIGINAL RESEARCH ARTICLE

Analysis for the integration of images obtained by computed tomography and magnetic resonance imaging

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ABSTRACT

The integration of medical images is the process of registering and fusing them to obtain a greater amount of diagnostic information. In this work an analysis is performed for the integration of images obtained through computed axial tomography and magnetic resonance imaging, for which a tool was developed in the Matlab program, where the registration is implemented through equivalent features; in addition, the pairs of images are compared by several fusion rules, with a view to identify the best algorithm in which the resulting fused image contains the most information from the original representations.

Keywords: Medical Image Integration; Matlab Software; Image Registration; Image Fusion; Computed Tomography; Magnetic Resonance Imaging

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1. Introduction

Medical imaging has become a fundamental tool in today's clinical practice because of its ability to detect diseases earlier than ever before[1]. With the development of new methods in medical imaging diagnosis, the need arose to combine all available image data sets in a spatially correct manner.

Sometimes the information provided by different imaging techniques or medical modalities may be confusing or inconclusive. For these cases, image integration methods can produce very interesting clinical results, especially in some specific areas such as the interpretation of functional images, neurosurgery, radiotherapy, among others[2,3].

In the case of radiotherapy, before applying it, its planning is carried out, in which the aim is to direct the radiation to an exact part of the body where the cancer or tumor is located, in order to reduce its incidence to the nearby healthy parts, so in this process it is necessary to have as much imaging information about the patient as possible.

While computed tomography (CT) is the primary modality for most image-based radiotherapeutic planning, other modalities, such as magnetic resonance imaging (MRI), provide important data that can improve overall patient care and management[4]. The integration of images produced with CT and MRI is very useful, because it allows taking advantage of the best of both modalities: CT provides rigorous geometric accuracy requirements and MRI provides optimal tissue differentiation [5-8].

2. Characteristics of the image integration process

The image integration process consists of 2 steps or stages: an initial stage, where the alignment of the images is performed, known as registration, and a second stage where the result of the integration is visualized, known as fusion[9].

When listing the capabilities of a recording algorithm, the terms intramodality and intermodality are used, depending on whether they are applied to studies of the same or different types, as well as intrasubject and intersubject, depending on whether they come from the same or different patients. There are many criteria by which the different image registries can be classified, but they are usually classified according to their nature[10].

- Equivalent features methods: where the procedures based on aligning equivalent points in each of the images to be registered are grouped. From their coordinates that represent the same position in the patient, the rigid transformation that will register the 2 studies can be calculated.
- Methods based on segmented image structures: these algorithms use the edges or surfaces that are most distinguishable in medical images, from which they are extracted automatically or semi-automatically. If equivalent structures are segmented in several images, the registration between them can be calculated by matching these surfaces.
- Volumetric methods: the basis of these methods is the assumption that some kind of arithmetic combination of the voxels of the images can provide a measure of the resemblance between them, which will reach an optimal value when the images are aligned.

Image fusion is a digital technique that aims to visually improve a representation and thus enhance its use in various applications[11]. The term fusion refers to the combination of information from 2 or more data sets related to the same scene, coming from different sources, in order to obtain a new set that provides better knowledge or information than those provided by the 2 primitive data sets separately[12].

When merging, you can work on 3 different levels of abstraction:

- Pixel level (high)
- Characteristic level (medium)
- Decision level (low)

Pixel-level algorithms can work in both the wavelet and spatial domains, although in medical imaging scenarios it is very useful to work with representations defined in the wavelet domain[13].

2.1 Wavelet fusion

This method consists of decomposing the images with a wavelet transform, and as a result obtaining submatrices of coefficients that refer to the approximate image and those of vertical, horizontal and diagonal details, and then combining the coefficients of the images. For this purpose, the relationship between the pixel sizes of the original or input representations is considered.

This combination of coefficients can be done in 2 ways[14]:

(1) Replacing the wavelet detail coefficients of the first input image with the corresponding coefficients of the second image.

(2) Adding the wavelet detail coefficients of the first input image to the corresponding coefficients of the second image.

In the substitution method, the wavelet planes corresponding to the second input image are eliminated and replaced by the planes corresponding to the first one. However, in the addition method all spatial information of the second image is preserved.

Thus, the great advantage of the addition method is that the detail information from both sensors is taken into account and used; therefore, it is proposed as the way to select the coefficients.

2.2 Similarity measures

In image integration, the accuracy of the results depends very much on the similarity measure used. These measures can be calculated on complete images or blocks of them.

Broadly speaking, there are 2 types of similarity measures: those based on geometric methods, which use the extraction of different characteristics, and those based on the level of intensity; the latter are also divided into 2 types: averages and statistics.

2.3 Implementation of the tool for image integration study

To carry out the study of the integration of images produced with CT and IMR, a tool was developed in Matlab, taking advantage of the methods and facilities provided by this development environment. **Figure 1** shows the main interface of the tool.

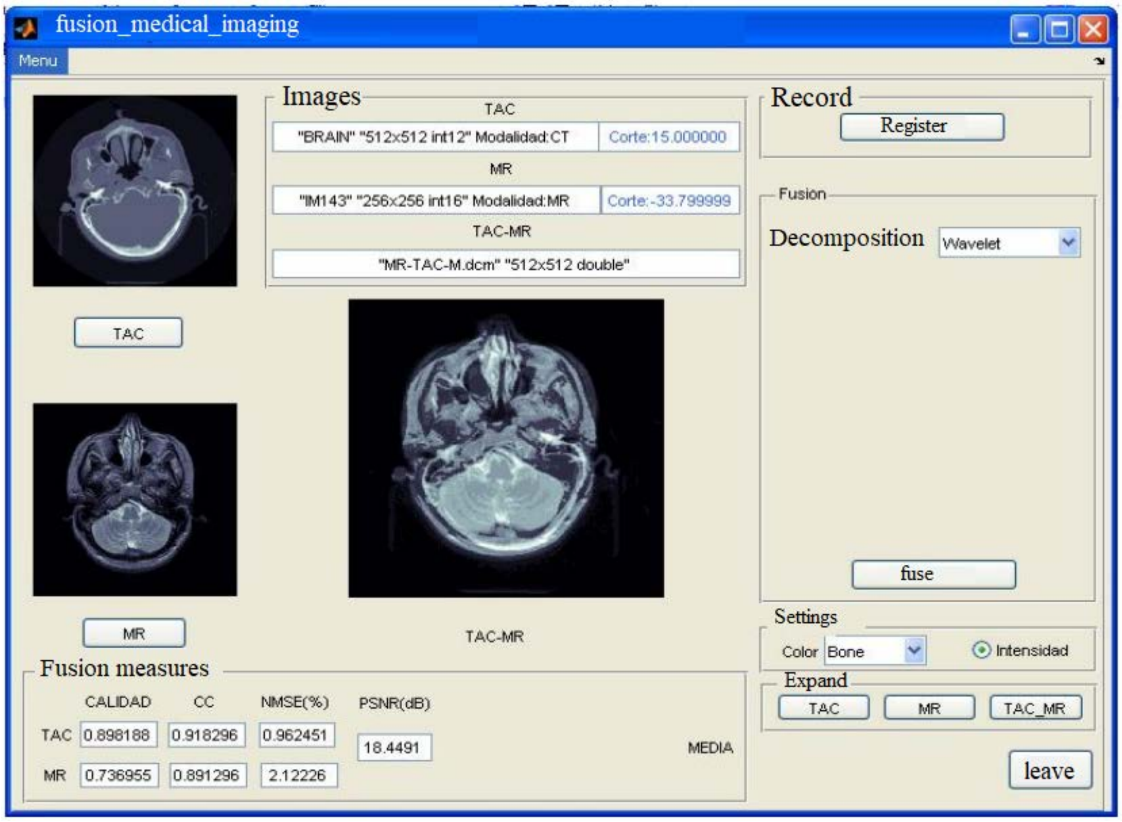

Figure 1. Main view of the tool.

The register implemented is by equivalent characteristics. For this purpose, this work relies on the use of the Matlab functions *cpselect* and *imtransform*. The first one allows to select the points that correspond in both images, and then use the second one to apply the geometric transformation that results from matching the points selected by the user with the first one. **Figure 2** shows the selection of the corresponding points between the images.

In the development of the image integration tool, the following fusion rules belonging to the family, based on the combination of coefficients, were implemented:

- Arithmetic mean
- Gaussian weighted average
- Laplacian weighted average
- Multiresolution image averaging

Having referred to the above, and working in the Matlab environment, the previous steps that have been carried out in all cases for a correct implementation of the chosen mechanism are explained.

The first step was to read the input images and then convert their coefficients to the required data type, and normalize the entire matrix by setting all values to positive and delimiting them between 0 and 255.

The next step was to check the size of the images. If they did not match, we increased the size of the smaller one by interpolating by a factor L. We also forced the matrices to be square if they were not.

Once these previous steps were completed, the matrices of the images were available and were processed with the appropriate size and in the desired range of values. The images were then decomposed using the light wavelet transform to obtain from each of them the submatrices of approximation and horizontal, vertical and diagonal details.

After all the above was executed, the fusion algorithms could be applied. Finally, from the variable containing the matrix resulting from the operations performed by the fusion mechanism, a new image was generated, which constitutes the final resulting image.

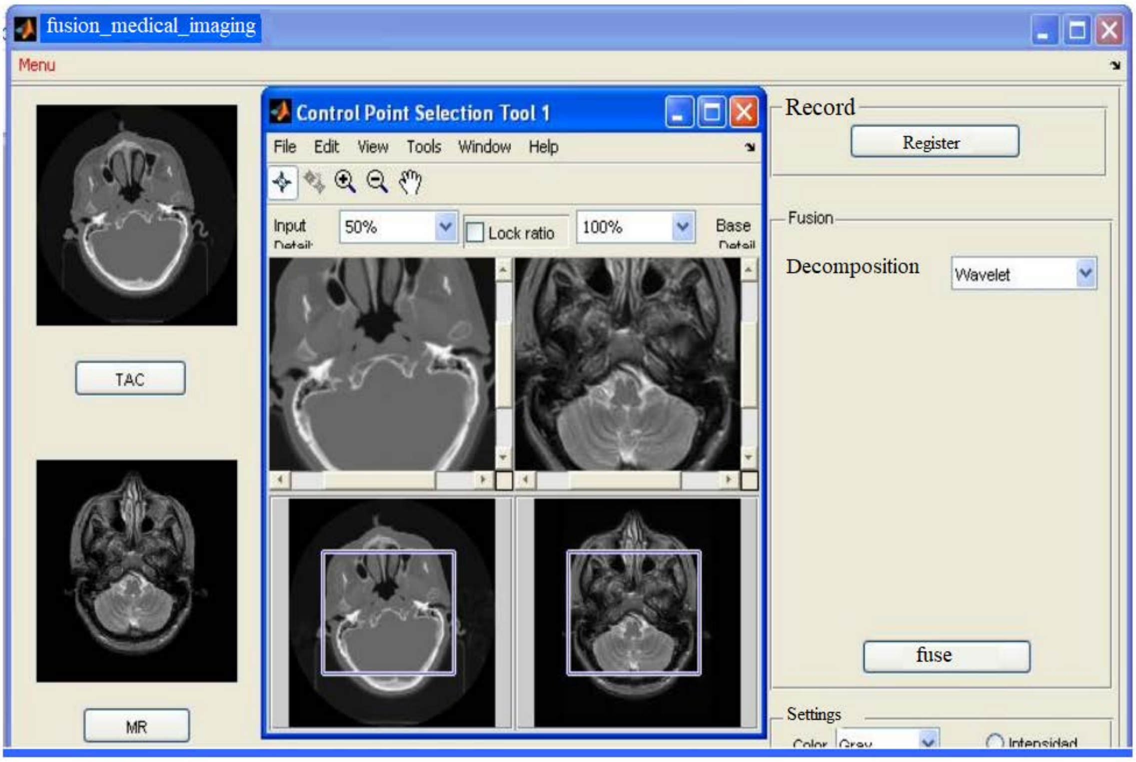

Figure 2. View of the selection of the corresponding points between images.

2.4 Merger rules implemented

The following is a brief description of the fusion rules or algorithms of the coefficient combination family. These algorithms in turn can be classified as: in the spatial domain and over wavelet domains.

2.4.1 Arithmetic mean

The fusion rule based on the arithmetic mean can be implemented both in the spatial domain, in which the image is not decomposed and the mean is calculated directly on the gray levels, averaging the coefficients of the images in corresponding positions, and in the wavelet domain, in which case we proceed in the same way in the arithmetic mean as in the spatial domain, except that the mean is calculated once the decomposition of the images has been performed, averaging the approximation and detail submatrices of each one.

2.4.2 Gaussian weighted average

This fusion mechanism is defined in the wavelet domain and calculates the arithmetic mean of the approximation submatrices, while for the detail submatrices it performs a weighting by means of a Gaussian weight matrix or mask W, prior to averaging.

With that matrix W, the windows of size S surrounding the coefficient (m,n) of interest in each of the detail sub-matrices are weighted and averaged, leaving a single matrix of size S, whose coefficients are divided by the sum of all those of the Gaussian matrix, and the resulting coefficients are summed to obtain a single coefficient that will be the one occupying the position (m,n) in the merged image.

2.4.3 Laplacian weighted average

This algorithm is also defined in the wavelet domain and calculates the arithmetic mean of the approximation submatrices, while for the detail submatrices it performs a weighting by means of a Laplacian weight matrix or mask L, prior to averaging. This weight matrix will have a size of 3×3, and is characterized by giving a much higher weighting to the central pixel of the window, while the sum of all the coefficients of this mask adds up to zero. It acts as a high pass filter.

The sum of the coefficients of the matrix obtained after weighting and averaging will be the coefficient that will be at position (m,n) in the final merged image.

2.4.4 Arithmetic mean of multiresolution images

This algorithm is another one that is also defined in the wavelet domain and calculates the arithmetic mean between the approximation submatrix obtained by decomposing one of the images and the original matrix of the other image in the spatial domain. The only drawback found for this implementation is that one of the matrices to be merged is formed by wavelet coefficients, while the coefficients of the other are directly the intensity levels in the grayscale; then their ranges of values differ. For this, it has been necessary to "force" that the ranges of values of the coefficients are similar.

2.5 Obtaining similarity measures

In order to be able to compare and evaluate the different fusion algorithms in a quantitative way, a series of similarity measures are calculated which, based on different evaluations, are intended to show which fusion techniques offer the best results with respect to others.

The numerical measures implemented are:

- Quality: this measure refers in this case to the quality of the spatial resolution of the images. The range of possible values it can take is from 0 to 1. The closer to 1 the better the results.
- Correlation coefficient (CC): is a statistical measure that quantifies the relationship between 2 signals, and indicates the similarity at the structural level between the reference image and the fused one. The closer to 1, the better the results.
- Normalized mean squared error (NMSE): quantifies the difference between the desired or expected signal and the obtained one. From the expression of the mean square error. It is normalized and expressed as a percentage. The lower the value, the better.
- Signal-to-noise ratio (PNSR): defines the relationship between the maximum energy of a signal and the noise that affects its correct representation. Its unit of measurement is the decibel, and the higher the value, the better.

3. Analysis of results

When talking about image fusion using wavelet algorithms in the context of medical imaging, it is not interesting to go beyond the first level of wavelet decomposition, since the results worsen significantly as one goes to the next level. In this study we have reached the third level of decomposition, although only at the first level have, we obtained useful results for a diagnostic examination.

The table shows a comparison between the fusion rules and the similarity measures implemented, in the integration of an image produced by CT and MRI. The results of this study led to the following conclusions:

- Calculating the arithmetic mean over wavelet coefficients does not provide any advantage over the average calculated in the spatial domain directly over the gray intensity levels.
- The Gaussian weighted average is calculated by weighting with a Gaussian weight window, which gives way to low frequencies and results in a visually "smoothed" image, so to speak. It is the algorithm that seems to offer the least level of detail, although the numerical results have been quite good for all 3 types of fusion.
- The Laplacian weighted mean gives very poor results; in fact, they are the worst of the group by far. This is because the Laplacian weight matrix acts as a high-pass filter, preserving the high frequencies, which are nothing more than abrupt changes in intensity levels, thus causing the edges of the image to be enhanced. For other fields of image processing, it may be of great use, but certainly not for a medical image fusion study.
- Calculating the mean between the approximation matrix in the wavelet domain of one of the images together with the original matrix of the other image in the spatial domain, gives worse values than calculating the arithmetic mean with the 2 images in the same domain.
- The Gaussian weighted mean gives very similar values to the arithmetic mean, and is very

insensitive to changes in window size. If anything, the values are somewhat better for the smaller window. The mean in multiresolution images worsens the data for the last 2.

- The similarity measures offer better results when comparing the image fused with the CT with respect to the magnetic resonance.

Table 1. Comparison between merger rules and similarity measures

Fusion rule	Quality		CC		NMSE (%)		PNSR
	TAC	MR	TAC	MR	TAC	MR	(dB)
Arithmetic mean in the spatial domain	0.898188	0.736955	0.918296	0.891296	0.962451	2.12226	18.4491
Arithmetic mean in the wavelet domain	0.898188	0.736955	0.918296	0.891296	0.962451	2.12226	18.4491
Weighted average Gaussian window: 3	0.895649	0.729278	0.918282	0.891299	0.986279	2.20609	18.3119
Weighted average Gaussian window: 5	0.892254	0.71856	0.918063	0.891115	1.004335	2.31117	18.1714
Weighted average Gaussian window: 11	0.896736	0.731159	0.917612	0.890525	0.962368	2.16662	18.4044
Gaussian weighted average window: 21	0.89626	0.732077	0.917368	0.890235	0.976799	2.16915	18.3695
Laplacian weighted average	0.511876	0.377916	0.902037	0.874698	10.1409	14.1194	9.22054
Arithmetic mean of multiresolution images	0.842843	0.625043	0.925931	0.878429	1.71326	3.85103	15.903

The list of algorithms for an RMI-CT fusion was ordered from the best to the worst in results, as follows:

- Arithmetic mean (spatial and wavelet)
- Gaussian weighted average (window size 11)
- Media in multiresolution images.
- Laplacian weighted average.

4. Conclusions

The integration of medical images is an extremely useful process with multiple clinical applications. However, there are still technical aspects to be solved for its daily use to become a reality. The difficulty in identifying common points in the studies leads to recommend the use of external markers, which must be optimized so that interference with the image and their availability and ease of use are acceptable. Ideally, they can be dispensed with in the future, so that registration is performed automatically and with minimal operator intervention, provided that the registration performed is completely reliable. Coordination between the different specialists involved must also be improved, where it is essential to install image networks that speed up the transmission of studies to the place where the integration takes place.

With this work, an analysis of methods for registering and fusing images obtained with CT and IMR was carried out, and the importance of image integration in the medical context is highlighted. In addition, the best fusion method was determined in a group of four, without downplaying the importance of any of them, since there is no single method that is the best in general.

Conflict of interest

The authors declare that they have no conflict of interest.

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