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IMPROVING THE ACCURACY OF THE PET/MRI TRIDIMENSIONAL MULTIMODAL RIGID IMAGE REGISTRATION BASED ON THE FATEMD

The subject matter *of the article is the improvement in the accuracy of multimodal image registration between PET and MRI images in the medical field. The focus of the article pertains to the importance of these images in diagnosis, interpretation, and surgical intervention.* ***This study increased*** *the accuracy of PET/MRI multimodal image registration achieved through a new approach based on the multi-resolution image decomposition. The tasks to be solved are: The study proposes a new method, the fast and adaptive three-dimensional mode decomposition (FATEMD), to generate multi-resolution components for accurate registration.* ***The method used****: The study uses the FATEMD approach, which estimates the transformation parameters of the registration from the PET image and the residue of the second level of the MRI image that is obtained after the extraction of the first two tridimensional intrinsic mode functions (TIMFs). The following* ***results*** *were obtained: The proposed method of multimodal registration between PET and MRI images involves the use of the fast and adaptive three-dimensional mode decomposition (FATEMD) approach. This approach was tested on 25 pairs of images from the Vanderbilt database and was found to have improved accuracy compared to the usual method, as shown through comparative studies using measures of mutual information, normalized mutual information, and entropy correlation coefficient.* ***Conclusion****. The main objective achieved in the study was to enhance the accuracy of PET/MRI multimodal image registration through the application of the FATEMD decomposition method. This approach is novel compared to traditional methods as it involves estimating the transformation parameters from the PET image and the second level residue of the MRI image, resulting in more precise outcomes as opposed to using just the PET and MRI images alone. The integration of multiple imaging techniques, such as PET and MRI, provides healthcare professionals with a more comprehensive view of a patient's anatomy and physiology, leading to enhanced diagnosis and treatment planning.*

Keywords: *Rigid Registration; Multimodal Registration; FATEMD; TIMF; Mutual Information; anatomical information; PET; MRI.*

List of abbreviations

PET – Positron Emission Tomography;
MRI – Magnetic Resonance Imaging;
CT – Computerized Tomography;
IMF – Intrinsic Mode Function;
BIMF – Bidimensional Intrinsic Mode Function;
TIMF – Tridimensional Intrinsic Mode Function;
RES – Residue;
EMD – Empirical Mode decomposition;
BEMD – Bidimensional Empirical Mode decomposition;
FABEMD – Fast and Adaptive Empirical Mode decomposition;
FATEMD – Fast and Adaptive Tridimensional Empirical Mode decomposition;
RIRE – Retrospective Image Registration Evaluation;
MI – Mutual Information;
NMI – Normalized Mutual Information;
ECC – entropy correlation coefficient.

1. Introduction

Image registration aims at finding the optimal transformation that aligns two or more images taken by one or more modalities and obtained at different times or from different viewpoints. It plays a crucial role in many applications such as satellite imagery [1], robotics [2], stereoscopy [3], motion estimation [4], and especially medical imaging. In this latter context, the registration finds a fertile field of its application and represents a crucial step in many situations such as the fusion of data coming from different modalities [5], remote sensing images [6, 7], medical images [8], and radiotherapy [9], etc.

Medical imaging involves two complementary aspects: the first is related to the structure and anatomy of the imaged organs, while the second provides crucial information about their function and metabolism. The fusion of these two aspects into a single image is highly useful in diagnosing and interpreting diseases [10-12].

However, the success of image fusion depends on accurate multimodal registration, which can be challenging when fusing images with significant differences. For example, PET/MRI image registration can be difficult as PET images reflect functional activity, while MRI images show organ structure. Despite the potential benefits of combining these two types of images, the low resolution of PET images and the high resolution of MRI images can lead to unreliable results. In addition to the resolution differences, patient motion can impact the success of combining PET and MRI images. PET images are acquired over a longer time frame than MRI images, and even small movements during the PET scan can result in misregistration between the two modalities. This misalignment can make it challenging to accurately combine the functional and anatomical information from both image types. Therefore, more precise multimodal registration methods are crucial for successful image fusion. To address this challenge, we propose an approach that aligns PET and MRI images by preserving the general shape of the target organ while eliminating the details contained in the MRI image, thus increasing the degree of similarity between the two images.

Our proposed method is based on estimating the transformation parameters for image registration using the PET image and the residue of the second level of the MRI image. By extracting the first two temporally invariant mode functions (TIMFs), we eliminate the details that could affect the registration accuracy. The first TIMFs contain high frequencies, while the residue contains low frequencies in the form of homogeneous areas representing the general shape of the imaged organ. Since the images being aligned represent the same organ, our approach increases the similarity between the images, ultimately improving the accuracy of registration.

The rest of the paper is organized as follows: the Sect. 2 describes the FATEMD and the multimodal image registration. The Sect. 3 presents the proposed approach, the Sect. 4 shows some experimental results; finally, the Sect. 5 concludes the paper.

2. Materials and methods

2.1. Fast and Adaptive Tridimensional Empirical Mode decomposition: FATEMD

Huang et al. [13] introduced an EMD that can decompose any signal into a set of components, referred to as Intrinsic Mode Functions (IMFs), with varying frequencies ranging from high to low. Nunes et al. [14, 15] extended the EMD to two dimensions by proposing the BEMD (Bidimensional Empirical Mode Decomposition), which has significant characteristics for developing new approaches in image processing and multi-scale analysis. This method has been widely used in various applications, such as signal and image processing [16], image fusion [17], cancer analysis [18], and satellite imagery [19].

However, the extensive execution time required for BEMD poses a significant challenge for its real-time application. To address this issue, Bhuiyan et al. [20] developed a new approach for two-dimensional empirical mode decomposition, known as FABEMD (Fast and Adaptive Bidimensional Empirical Mode Decomposition). This method replaces the interpolation function with a filtering technique that involves a smoothing operation, leading to improved BEMD performance in terms of both execution time and decomposition quality. FABEMD has been adopted in several applications, including image fusion [21], image registration [22, 23], video processing [24], and neural style transfer [25]. To process volumetric images commonly used in medical imaging, we propose a three-dimensional extension of FABEMD, called FATEMD [26], which can decompose a volume image into a set of components ranging from high to low frequencies.

The FATEMD algorithmic steps can be summarized as follows:

1) set $\mathrm{i} = 1,\ \mathrm{R_i(m,n,p)} = \mathrm{V(m,n,p)}$;

2) generate the maps of the maxima and minima denoted $\mathrm{Map_{max}(m,n,p)}$ and $\mathrm{Map_{min}(m,n,p)}$ by browsing $\mathrm{R_i(m,n,p)}$ by a cube sized $3 \times 3 \times 3$. In this method a maximum (resp. minimum) must be grater strictly (resp. lower strictly) than its neighborhoods contained in the browsing cube;

3) calculate the size of the cube which will serve to create the envelopes of the extrema and their smoothness;

4) create the envelopes of maxima and minima denoted $\mathrm{Env_{max}(m,n,p)}$ and $\mathrm{Env_{min}(m,n,p)}$;

5) smoothing the envelopes of maxima and minima denoted $\mathrm{Env_{max-S}(m,n,p)}$ and $\mathrm{Env_{min-S}(m,n,p)}$;

6) calculate the mean envelope:
$\mathrm{Env_A(m,n,p)} = \frac{\mathrm{Env_{max-S}(m,n,p)} + \mathrm{Env_{min-S}(m,n,p)}}{2}$;

7) Calculate the $\mathrm{i^{th}}$ TIMF:
$\mathrm{TIMF_i(m,n,p)} = \mathrm{R_i(m,n,p)} - \mathrm{Env_A(m,n,p)}$;

8) Calculate:
$\mathrm{R_{i+1}(m,n,p)} = \mathrm{R_i(m,n,p)} - \mathrm{TIMF_i(m,n,p)}$;

9) If $\mathrm{R_{i+1}(m,n,p)}$ contains more than two extrema then

Go to the step 2) with $\mathrm{i} = \mathrm{i} + 1$

Else

The decomposition is complete.

At the end of the decomposition the volume V can be reconstructed from the K TIMFs and the residue as follows:

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$$V(m,n,p) = \sum_{i=1}^{K} TIMF_i(m,n,p) + R_{K+1}(m,n,p).$$

The Figure 1 illustrates the result of the FATEMD decomposition of an MRI volume image.

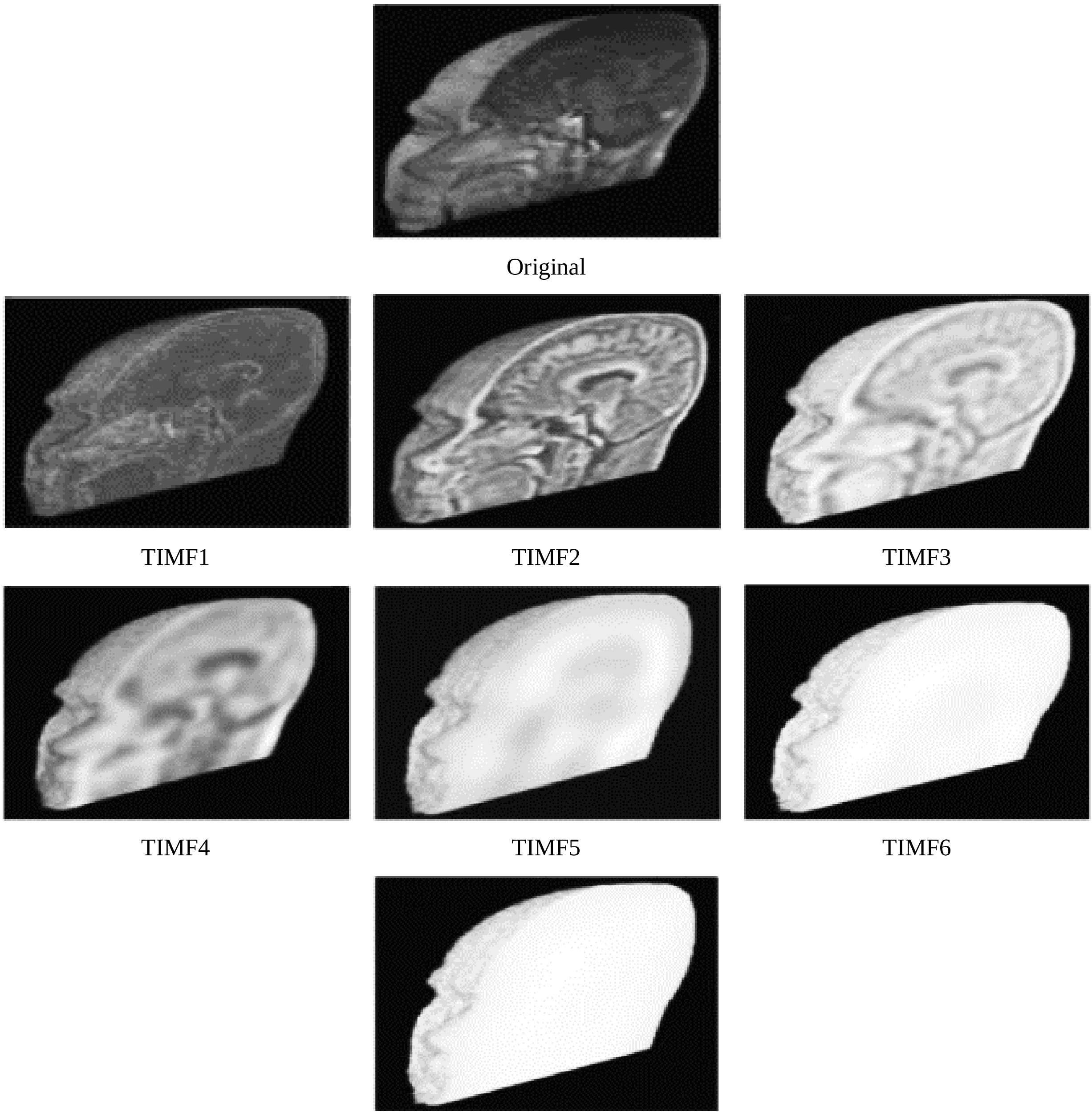
2.2 Multimodal image registration

2.2.1. Introduction

For Generally, the registration can be formulated as follows:

$$\hat{T} = \arg\max_{T \in \Gamma} S(I, J, T).$$

The image registration finds the optimal transformation T , which belongs to the space of transformations Γ , which aligns the source and the target images (respectively denoted I and J) while optimizing a similarity function, denoted S (depending on S, You need either to maximize or minimize S). This function measures the degree of similarity between the pair of the images I and J.



Original TIMF1 TIMF2 TIMF3 TIMF4 TIMF5 TIMF6 Residu

Fig. 1. Result of FATEMD decomposition of a volumetric MRI image

There are several approaches to multimodal image registration, including those based on neural networks [27, 28]. While monomodal registration [29] involves registering images acquired by the same modality, multimodal registration [30, 31] requires the alignment of images acquired by different modalities and can be more complex. Multimodal registration is crucial for data fusion and can also be useful in aligning preoperative and intra-operative images.

Depending on the primitives used during the registration process, we can distinguish between two approaches: geometric and iconic [32]. The geometric approach requires a segmentation step which cannot be guaranteed for all types of images. This approach is not suitable for multimodal registration, unlike the iconic approach, which uses natively the information on the intensities of voxels or pixels in the images without prior pretreatment. It can be used in the monomodal and multimodal cases.

In this paper, we consider the iconic multimodal registration concerning the alignment of the PET / MRI representing the human brain.

2.2.2. Similarity measure

The similarity measure represents an important issue and an axial step in the process of multimodal registration. It allows measuring and quantifying the degree of similarity between the pair of images to be registered. All similarity measures assume that there exists a relationship between the intensities of the involved images. Indeed, this relationship can be explained by the fact that the intensities of the two images represent the same physical structures.

In the context of multimodal registration, mutual information is treated as the most robust similarity measure. This measure was proposed independently by Viola et al. [33] and Colignon et al. [34]. Mutual information provides a measure of the amount of common information between the two images, considering pixel distributions rather than individual values. Mutual information-based medical image registration has been widely used and has been successful in several approaches [34 - 37].

The mutual information of two images I and J can be defined as follows:

$$\mathrm{IM}(\mathrm{I},\mathrm{J}) = \mathrm{H}(\mathrm{I}) + \mathrm{H}(\mathrm{J}) - \mathrm{H}(\mathrm{I},\mathrm{J}),$$

where $\mathrm{H}(\mathrm{I})$ and $\mathrm{H}(\mathrm{J})$ represent, respectively, the entropy of the image I and J, and $\mathrm{H}(\mathrm{I},\mathrm{J})$ is the joint entropy. The marginal entropies $\mathrm{H}(\mathrm{I})$ and $\mathrm{H}(\mathrm{J})$ measure the complexity of the images I and J; while the joint entropy $\mathrm{H}(\mathrm{I},\mathrm{J})$ measures the amount of information that the images I and J provide simultaneously.

2.2.3. Transformation model

We are interested in the registration of brain images, which explains the use of the model of the rigid transformations.

The model describing the rigid transformation is defined by the following formula:

$$\mathrm{P_C} = \mathrm{R} * \mathrm{P_S} + \mathrm{T},$$

where R and T represent respectively the rotation and translation matrix, $\mathrm{P_C}$ is the target image and $\mathrm{P_S}$ is the source image.

2.2.4. Optimization model

Optimization plays a critical role in the registration process, as its objective is to determine the optimal value of the similarity function [38-41]. In our study, we utilized Powell's method [42] as the optimization algorithm, which has the advantage of not requiring the derivation of the similarity function. Its principle is to transform a multidimensional optimization problem into a series of one-dimensional optimizations, one for each parameter of the function to be optimized. However, it does not provide a guarantee of convergence to the global optimum. In such situations, the only solution is a close and reasonable initialization to the desired optimum.

3. Proposed approach

The proposed method takes advantage of the fact that the two images being registered depict the same organ. It increases the similarity between the MRI and PET images by reducing the level of detail in the MRI image using the FATEMD decomposition. Specifically, the approach estimates the registration transformation parameters based on the PET image and the second-level residue generated by FATEMD from the MRI image, after extracting the first two TIMFs. This approach is motivated by the potential adverse effects of the high-frequency information contained in the first TIMFs on registration accuracy, while the residue provides a representation of the organ's overall shape (brain) through its homogeneous regions. By improving the similarity between the images, the proposed method enhances the accuracy of multimodal image registration.

The formulation of the PET / MRI registration process using the proposed approach can be expressed as follows:

$$\hat{\mathrm{T}} = \arg\max_{\mathrm{T}\in\Gamma} \mathrm{S}(\mathrm{TEP},\mathrm{RES},\mathrm{T}),$$

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where the RES is the second level residue resulting from the FATEMD decomposition of the MRI image and can be calculated as follows:

$$\mathrm{RES} = \mathrm{MRI} - \sum_{i=1}^{2} \mathrm{TIMF}_i.$$

The flowchart illustrated in Figure 2 shows the steps followed during the registration process based on the proposed approach.

After decomposing the MRI image on two TIMFs and a residue, we estimate the transformation parameters of the registration by maximizing the mutual information between the generated residue and the PET image. First, we initialize the transformation of the MRI residue image, then we maximize the mutual information between the MRI residue and the transformed PET image using Powell's algorithm as an optimization method, and finally the optimal transformation parameters are applied to the original MRI image.

4. Experimental results and comparative study

In this section, we illustrate some experimental results accompanied by a comparative study between the medical image registration based on the proposed approach and the usual one that concerns the registration of the images without using the FATEMD decomposition. We use Java as a programming language; the experiments are performed under a PC having the following characteristics: 4 Cores at 2.4 GHz processor with 8G RAM. The used images in the tests were obtained from the Vanderbilt database, also called Retrospective Image Registration Evaluation (RIRE) project [43] which is considered as one of the most common databases used in the brain image registration providing a set of a brain volumes coming from different modalities (CT, MRI and PET) and concerning a set of patients.

We refer to the usual approach as the one that directly estimates the registration transformation parameters from the original PET and MRI images. In contrast, the proposed approach estimates these parameters from the PET image and the second level residue obtained from the FATEMD decomposition of the MRI image.

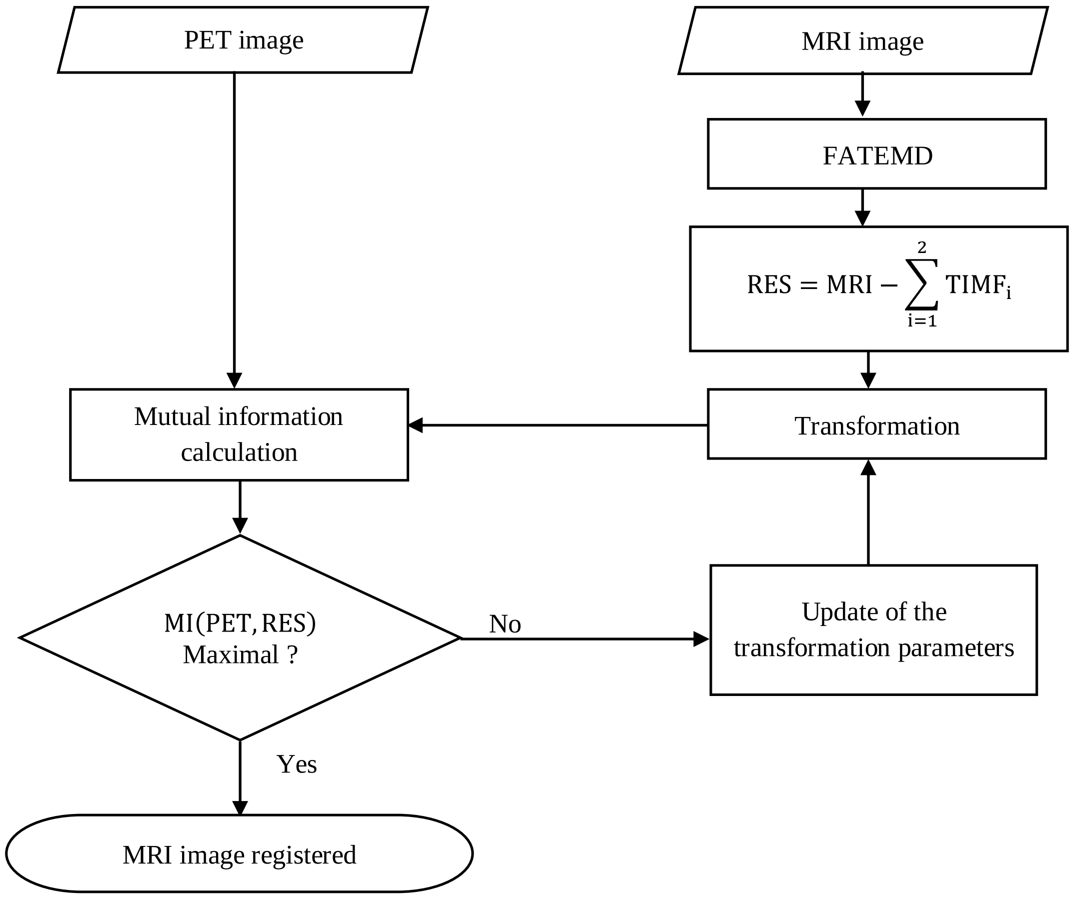


Fig. 2. Flowchart of the registration process based on the proposed approach

To objectively and precisely compare the accuracy of the proposed approach and the usual one, we conducted simulation tests as follows: starting with a perfectly aligned (golden standard transformation) image, we applied a random transformation to the target image and then estimated the optimal transformation parameters to align the involved images. Finally, we calculated the registration error between the estimated and perfect parameters.

A series of tests were conducted to evaluate the accuracy of the proposed approach and the usual approach for intra-subject multimodal registration, using 25 pairs of PET and MRI images. Three similarity measures, namely mutual information, normalized mutual information, and entropy correlation coefficient, were used to compare the results. The comparison was performed globally on intra-subject images representing the same patient, and the results are shown in Figure 3. According to the comparison results, the proposed approach outperforms the usual one in terms of accuracy using all three similarity measures.

Based on the comparison results shown in Figure 3, we find that the proposed approach provides more accurate results compared with the usual one using the three similarity measures.

To provide examples of the registration process, we present two illustrations based on the usual approach and the proposed one. In these examples, we first maximize the mutual information between the PET and MRI images using the Powell algorithm, and then maximize it between the PET image and the second level residue generated from the FATEMD decomposition of the MRI image.

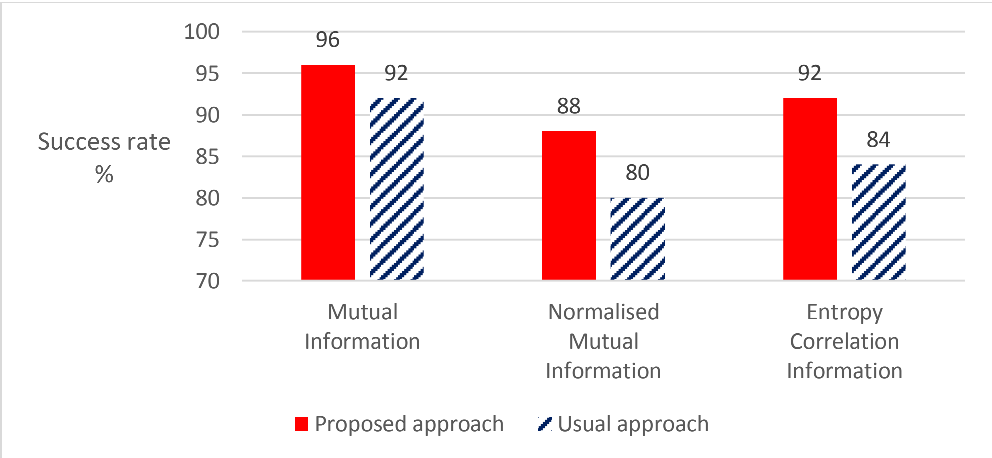
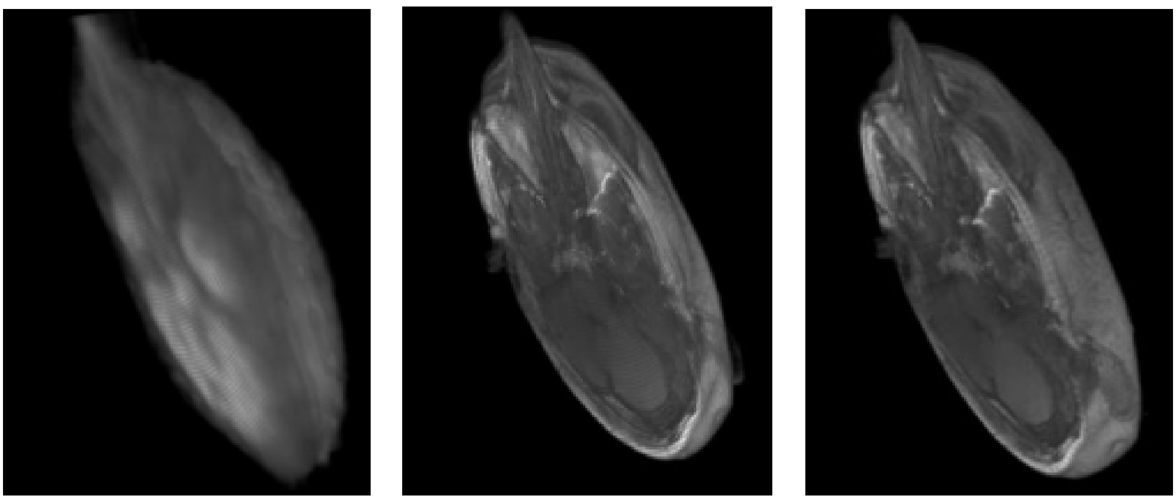


Fig. 3. A comparison result between the usual approach and the proposed one based on the mutual information, the normalized mutual information and the entropy correlation coefficient



Source image (PET) Target image (MRI T1) Registered image

Fig. 4. Registration result based on the usual approach

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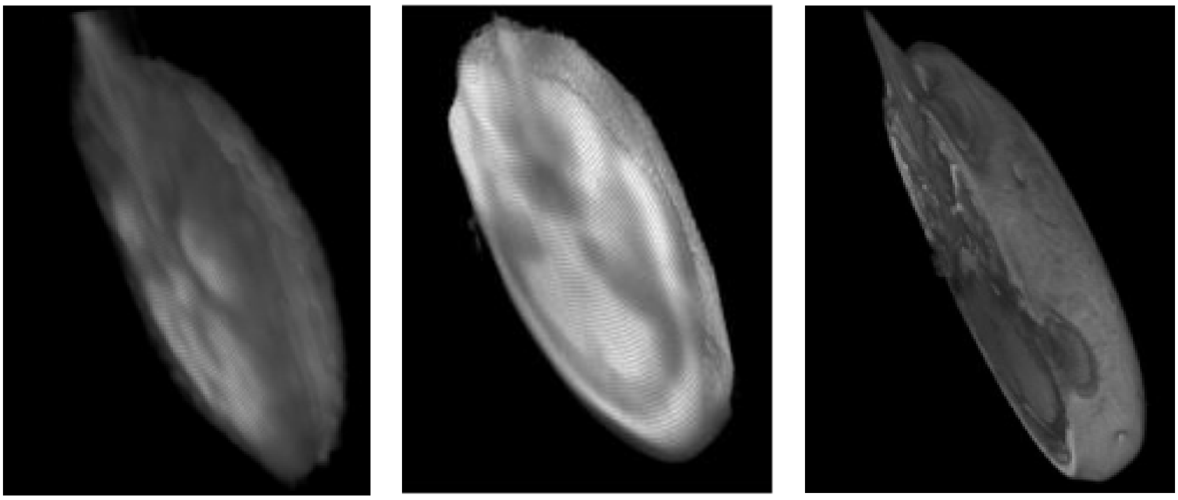


Source image (PET) Second level residue of the MRI image Registered image

Fig. 5. Registration result based on the proposed approach

Table 1

Parameter transformation found by both approaches

	Translation (Voxel)			Rotation (°)		
	Δx	Δy	Δz	(OX)	(OY)	(OZ)
Usual approach	-13	-2	5	-3	3	-11
Proposed approach	-11	-9	7	-6	17	-9

Table 2

Parameter transformation found by both approaches

	Translation (Voxel)			Rotation (°)		
	Δx	Δy	Δz	(OX)	(OY)	(OZ)
Usual approach	-3	-4	-4	-2	6	3
Proposed approach	-3	-6	-7	-6	13	5

Figure 4 displays the results of registering PET and MRI images using the usual approach, while Figure 5 illustrates the results obtained using the proposed approach. Table 1 presents the optimal transformation parameters obtained from both methods. Note that the ideal transformation parameters for this case involve a translation of $(\Delta x = 11,\ \Delta y = 9, \Delta z = -6)$ and a rotation of $(Ox = 6^{\circ},\ Oy = -17^{\circ}, Oz = 9^{\circ})$. Comparing the values of the golden standard transformation with those in Table 1 reveals that the proposed approach accurately estimated the perfect parameters with a very narrow margin of error. In contrast, the usual approach underestimated these parameters. Moreover, the registration results depicted in Figures 4 and 5 support this conclusion, indicating that the proposed approach (Figure 5) is more accurate than the usual one (Figure 4).

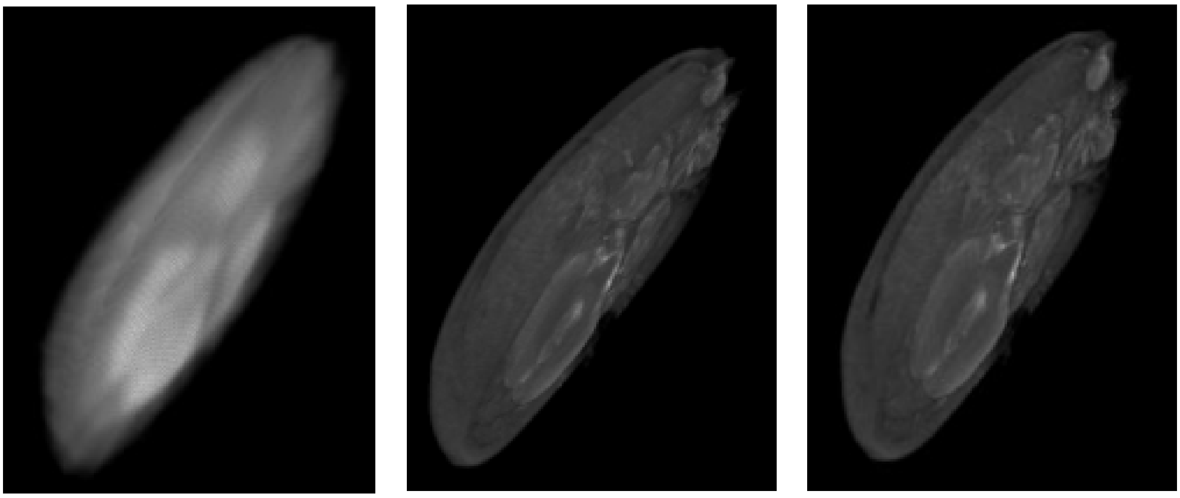
The second example illustrates the result of the iconic registration of a PET and an MRI-T2 images.

This second experiment aimed to further support the findings of the first one. Figure 6 shows the results of the registration of PET and MRI images using the usual approach, while Figure 7 illustrates the outcomes obtained using the proposed approach. Table 2 provides the optimal transformation parameters obtained from both methods. It is important to note that the optimal transformation parameters for this case involve a translation of $(\Delta x = 3,\ \Delta y = 6, \Delta z = 7)$ and a rotation of $(Ox = 6^{\circ},\ Oy = -12^{\circ}, Oz = -5^{\circ})$. Comparing the values of the optimal transformation with those in Table 2, it is evident that the proposed approach accurately estimated the ideal parameters with a very narrow margin of error, whereas the usual approach underestimated these parameters. Furthermore, the registration results shown in Figures 4 and 5 reinforce this conclusion, indicating that the proposed approach (Figure 7) is more accurate than the usual approach (Figure 6).

In addition to describing the experimental procedure for both approaches as described earlier, we also analyzed the execution time of the registration process. The execution time analysis for registering 3D multimodal images of 25 pairs of MRI and PET images using mutual information as the metric is presented in this section. The results are summarized in Table 3, which shows the average execution time of 25 tests, excluding the time required for image decomposition, which was measured to be 2 minutes and 46 seconds on average.

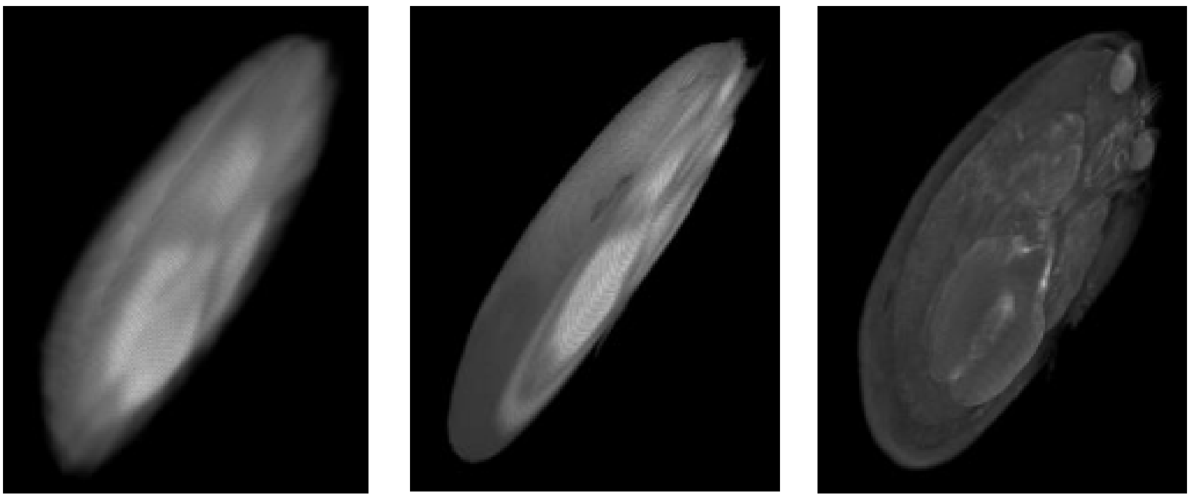
It is important to note that each image pair was tested 20 times, and the average execution time for each pair was calculated. Additionally, we repeated the experiments to account for the initialization of Powell's optimization method, which can make it challenging to obtain accurate execution time measurements.

The results illustrated in Table 3 show that our approach is almost three times faster than the usual approach for image registration, which is an advantage for some applications where time is an important factor. However, if we consider the image decomposition time, the usual approach may prove to be faster.



Source image (PET) | Target image (MRI T2) | Registered image

Fig. 6. Registration result based on the usual approach



Source image (PET) | Second level residue of the MRI image | Registered image

Fig. 7. Registration result based on the proposed approach

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Table 3
Average Execution Time for 3D Multimodal Image Registration using Mutual Information Metric

Approaches	Average Execution Time (in seconds)
Proposed approach	7.12
Usual approach	24.03

However, it is important to emphasize, that precision is paramount in the field of medical imaging, as every error can have serious consequences for patients. Thus, even though our approach takes a little more time, it offers better precision for 3D multimodal image registration, which is essential in this delicate field.

Conclusion

In this work, we presented a new medical image registration approach aiming to improve the accuracy of the PET/MRI multimodal iconic registration while exploiting the FATEMD decomposition. The proposed approach was compared to the usual method using the Vanderbilt database of brain images and evaluated through simulation tests on 25 pairs of PET and MRI images. The results showed that the proposed approach, which uses the PET image and the second level residue of the MRI image for estimating the transformation parameters, was more accurate than the usual method that uses only the original PET and MRI images.

This work opens up new avenues for future research and development in this field. One potential area for further improvement is to explore the use of other decomposition techniques along with the FATEMD decomposition to enhance the accuracy of the registration process. Another possibility could be to evaluate the proposed approach on larger datasets to validate its robustness and generalizability. Overall, this work highlights the importance of using advanced image processing techniques in the field of medical imaging, and we believe that the proposed approach can make a significant impact in the diagnosis and treatment of various diseases.

Contribution of authors: Creation of a dataset from the Vanderbilt database, implementation of the algorithm, analysis of literature, and writing of the paper, including the definition of the problem – **Abderazzak Taime**; Development of evaluation and results analysis strategy to ensure the effectiveness of the experimental studies – **Aziz Khamjane**; establishment and justification of the study's objectives and purpose, research methodology and presentation of results. Revision of the document – **Jamal Riffi** and **Hamid Tairi**.

All the authors have read and agreed the published version of the manuscript.

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ПІДВИЩЕННЯ ТОЧНОСТІ РЕЄСТРАЦІЇ ТРИВИМІРНОГО МУЛЬТИМОДАЛЬНОГО ЗОБРАЖЕННЯ PET/MRI НА ОСНОВІ FATEMD

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Предметом статті є підвищення точності мультимодальної реєстрації зображень між PET та MRI зображеннями в медичній галузі. Основна увага статті зосереджена на значенні цих зображень для інтерпретації, діагностики та хірургічного втручання. Метою цієї роботи є підвищення точності мультимодальної реєстрації зображень PET/MRI, що досягається за допомогою нового підходу, заснованого на декомпозиції зображень із різною роздільною здатністю. Завдання, які потрібно вирішити: дослідження пропонує новий метод, швидку та адаптивну тривимірну модову декомпозицію (FATEMD), для створення компонентів із різною роздільною здатністю для точної реєстрації. Використаний метод: у дослідженні використовується підхід FATEMD, який оцінює параметри трансформації реєстрації з PET-зображення та залишку другого рівня зображення MRI, отриманого після вилучення перших двох тривимірних функцій внутрішнього режиму (TIMFs). Були отримані наступні результати: запропонований метод мультимодальної реєстрації між зображеннями PET та MRI передбачає використання підходу швидкої та адаптивної тривимірної декомпозиції мод (FATEMD). Цей підхід було перевірено на 25 парах зображень із бази даних Вандербільта та було встановлено, що він має підвищену точність порівняно з традиційним методом, як показали порівняльні дослідження з використанням показників взаємної інформації, нормалізованої взаємної інформації та коефіцієнта ентропійної кореляції. Висновок: основна мета дослідження полягає в тому, щоб підвищити точність мультимодальної реєстрації зображень PET/MRI шляхом застосування методу декомпозиції FATEMD. Цей підхід є новим порівняно з традиційними методами, оскільки передбачає оцінку параметрів трансформації на основі PET-зображення та залишку другого рівня зображення MRI, що дає більш точні результати на відміну від використання лише зо-

бражень PET та MRI. Інтеграція багатьох методів візуалізації, таких як PET та MRI, надає медичним працівникам більш повне уявлення про анатомію та фізіологію пацієнта, що веде до покращеної діагностики та планування лікування.

Ключові слова: мультимодальна реєстрація; FATEMD; TIMF; взаємна інформація; анатомічні відомості; PET; MRI.

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