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Intensity-based image registration using scatter search

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ABSTRACT

Objective: We present a novel intensity-based algorithm for medical image registration (IR).
Methods and materials: The IR problem is formulated as a continuous optimization task, and our work focuses on the development of the optimization component. Our method is designed over an advanced scatter search template, and it uses a combination of restart and dynamic boundary mechanisms integrated within a multi-resolution strategy.
Results: The experimental validation is performed over two datasets of human brain magnetic resonance imaging. The algorithm is evaluated in both a stand-alone registration application and an atlas-based segmentation process targeted to the deep brain structures, considering a total of 16 and 18 scenarios, respectively. Five established IR techniques, both feature- and intensity-based, are considered for comparison purposes, and ground-truth data is used to quantitatively assess the quality of the results. Our approach ranked first in both studies and it is able to outperform all competitors in 12 of 16 registration scenarios and in 14 of 18 registration-based segmentation tasks. A statistical analysis confirms with high confidence ($p < 0.014$) the accuracy and applicability of our method.
Conclusions: With a proper, problem-specific design, scatter search is able to provide a robust, global optimization. The accuracy and reliability of the registration process are superior to those of classic gradient-based techniques.

1. Introduction

In its most general formulation, image registration (IR) [1] is the task of aligning two or more images in order to establish a spatial correspondence of their common content. Such images usually have the same or a similar subject but have been acquired under different conditions, such as time and viewpoint, or by multiple sensors. In medical image analysis, IR is a key technology that allows to "fuse" visual information from different sources [2]. Applications include combining images of the same subject from different modalities, aligning temporal sequences of images to compensate for motion between scans, image guidance during interventions and aligning images from multiple subjects in cohort studies. The remarkable developments in medical imaging technology over the last decades determine a constant demand for better image processing and analysis techniques. Dealing with novel, more diverse, and increasingly accurate sources of imaging data is the main challenge in IR and it explains why it is still a very active research field.

The alignment between two images is specified as a spatial transformation, mapping the content of one image to the corresponding area of the other. A popular strategy among IR methods is to perform the alignment by considering only salient and distinctive parts of the image, such as lines, corners and contours, called *features*. This strategy has the advantage of greatly reducing the complexity of the problem, but relies on the ability to detect the features correctly. However, this approach is limited to the cases in which features alone are able to characterize the image content. IR methods following this approach are called *feature-based* [2,1], while the term *intensity-based* (or voxel-based) names the methods in which the whole image data is used.

Regardless of this division, the core of every IR technique is an *optimization process* that explores the space of geometrical transformations. Two strategies are available. In *parameters*-based approaches the search is directly performed in the space of the

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transformation parameters. Hence, a solution is a vector of values for the parameters of the registration transformation. In *matching-based* approaches, features are matched through a search in the space of feature correspondences; once a suitable matching has been found, the transformation parameters are derived accordingly by numerical methods. In both cases the search is guided by a *similarity metric*, a function that measures the degree of resemblance between the input images. This can be done either by comparing the whole images or just their corresponding features. Traditional parameters-based methods use classic gradient-based optimization algorithms, while matching-based methods use matching algorithms like iterative closest point (ICP) [3].

Many features of IR problems, such as noise, discretization and differences in the order of magnitude of the transformation parameters still pose a challenge to traditional optimization methods. A number of alternative approaches are based on *metaheuristics* [4], which have proven their ability to deal with complex real-world problems in a large number of fields, including computer vision and image processing. In particular, metaheuristic-based registration approaches have demonstrated to be a promising solution to overcome the drawbacks of traditional optimization algorithms [5,6]. Scatter search (SS) [7–9] is a prominent example of such techniques. It has already been applied to image registration problems as optimizer of feature-based approaches. In IR, SS has been successful both when used to find matchings among features [10] as well as in searching for the transformation parameters directly [11].

In this work, SS is used as base for a novel intensity-based IR method. The algorithm is specifically designed to take advantage of the characteristics of the IR process to improve the optimization. To evaluate its effectiveness, our method is compared with an heterogeneous group of competitors in two experimental studies involving simulated and real medical images. A thorough analysis of the results is performed, and their significance is assessed by means of different statistical tests.

The paper is structured as follows. In Section 2, we review the image registration problem and present several techniques to solve it. Section 3 introduces the basics of SS and the design of our IR method. In Section 4, we present the experimental studies along with the analysis of their results. Finally, conclusions are provided in Section 5.

2. Image registration

A typical IR problem involves two images, conventionally called *model* (I_M) and *scene* (I_S), with different roles in the registration process. The model is the reference (or target) image, while the scene is the image that is transformed to reach the geometry of the other. The registration aims to find a geometric transformation f that aligns the scene to the model; in other words, f is such that the model I_M and the transformed scene $f(I_S)$ are as similar as possible.

Several components characterize an IR method. First we have the *transformation model*, that determines which kind of transformation can be used to align the images. This choice depends entirely on the concrete application; very simple models such as translation transform can be enough in certain contexts such as remote sensing [12]. At the other end of the spectrum there are *non-rigid* (also called elastic) transformations, such as B-spline and thin-plate splines transformations, able to represent local deformations (warpings) using hundreds or even thousands of parameters. Other common choices include rigid transform, which allows translation and rotation, similarity transform, which also admits scaling, and affine transformation, which can also represent shearing. These are examples of global transformations having respectively 6, 7 and 12 degrees of freedom for 3D images.

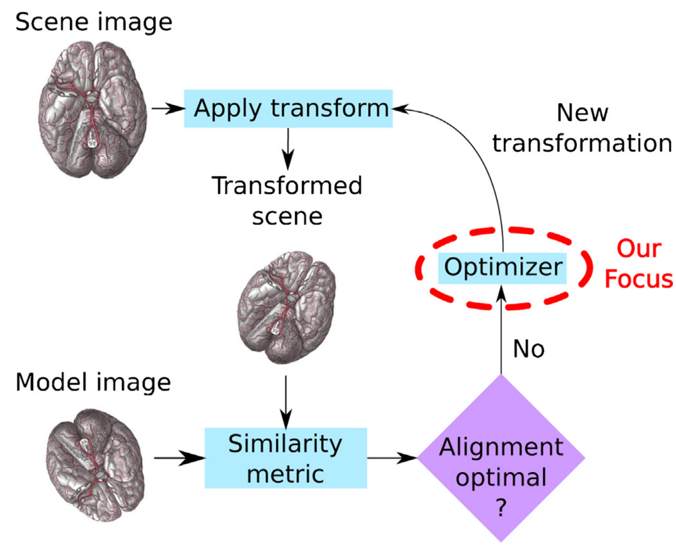

Fig. 1. The interactions among the components of a registration technique.

The second component of any IR method is the *similarity metric*, a function $F(I_1, I_2)$ that measures the degree of resemblance between two images. As the final performance of any IR method depends on the accurate estimation of the alignment of the images, this is a crucial IR component [13]. The quality of a transformation f is obtained by computing the similarity metric over the model I_M and the transformed scene $f(I_S)$. The actual evaluation mechanism depends on the nature of the registration approach. In feature-based methods the similarity metric usually measures the distance between corresponding features [14]. For instance, the alignment can be evaluated using mean square error (MSE) between the points of the model and those of the transformed scene. If the model has r feature points, each point x_i is assigned to the closest point in the transformed scene c_i, and the MSE is given by:

$$\mathrm{MSE} = \frac{1}{r}\sum_{i=1}^{r}\|x_i - c_i\|^2$$

In intensity-based approaches, instead, the resemblance of the intensity values in the two images are considered. Sum of squared differences (SSD), normalized correlation (NC) and mutual information (MI) [15,16] are typically used. The subject of the images and their acquisition technique determine the kind of the relationship between the intensity distributions, which in turn decides what similarity metrics are appropriate. For instance, when two images have been acquired using different sensors, a scenario called *multimodal* registration, the relationship between the intensity values in the images can be strongly non-linear. While NC can handle a linear relationship, metrics based on information theory, such as MI, are better suited for this scenario. MI is defined as

$$\mathrm{MI} = \sum_{s\in L_S, m\in L_M} p(m,s,f)\log_2\frac{p(m,s,f)}{p_M(m)\ \ p_S(s,f)}$$

where L_M and L_S are sets of regularly spaced intensity bins centers, p is the discrete joint probability and p_M, p_S are the marginal discrete probabilities of the model and scene images.

The third main component of an IR method is the *optimizer*. It is responsible for finding the best transformation, in terms of similarity metric, among the transformations in our transformation model. Fig. 1 shows the flow chart of the whole registration process.

Each optimizer has a different search strategy, which depends also on the nature of the algorithm. One approach is to perform the search directly in the space of the transformation parameters.