ARTICLE IN PRESS

Signal Processing: Image Communication xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Signal Processing: Image Communication

journal homepage: www.elsevier.com/locate/image

Fast medical image registration using bidirectional empirical mode decomposition

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ARTICLE INFO

Keywords:
Medical image registration
Fast method
Mutual information maximization
Bidirectional empirical mode decomposition

ABSTRACT

This paper focuses on an acceleration of the mutual information maximization method for medical image registration. Our approach is based on fast adaptive bidirectional empirical mode decomposition (FABEMD). The registration is performed for the informative intrinsic image modes. It aims to reduce the computational complexity of the mutual entropy maximization algorithm by extracting only essential data. Optimization process consists of several steps: image structural reduction using FABEMD, sequential parameters search, image downsampling, and, finally, multilevel parametric space search. We compare our approach to standard mutual information maximization method (MMI) and analyze results for multimodal medical images. Experiments show that proposed method produces consistent results very close to MMI, while reducing the registration time by 200 time on average.

1. Introduction

Biomedical image processing and automated analysis has gained a great interest amongst researchers in the past two decades. The interest stems primarily from the vast variety of applications in health care. Among the problems associated with the automated analysis are image segmentation and registration. In this work, we focus on image registration limited to the class of biomedical images.

Image registration is a crucial step for image analysis because valuable information is conveyed in more than one image. Images received at different times, from various viewpoints, or by different sensors can be juxtaposed and appear to be complementary. Therefore, accurate integration (or fusion) of the useful information from two or more images is very important. In our case, we attempt to recover the parameters of an isotropic affine transformation (shift, rotation and scaling) between two input images, since this kind of transformation is the most common in biomedical imaging.

There are two major groups of algorithms for solving this kind of image registration problems [1]: intensity-based and keypoint-based. The most popular intensity-based methods include Fourier-Mellin (log-polar Fourier) transform phase correlation [2], image moment analysis [3], and mutual information maximization [4] (with different variations [5]). Keypoint-based methods are classified according to the used feature point extraction technique, feature descriptor, and feature point matching algorithm. Intensity-based methods are known [6] for either being slow or producing very inaccurate results. On the other hand, keypoint-based methods tend to be much faster than intensity-based methods, but usually show some instability [1].

The peculiarity of medical image registration task is that the images are sometimes represented by different imaging modalities, such as computed tomography (CT), magnetic resonance (MRI), and positron emission tomography (PET). Keypoint-based methods usually have troubles with different imaging modalities, while intensity-bas-ed methods work fine with multimodal medical images [4].

One of the most common intensity-based methods is the maximization of mutual information (MMI) method. We have chosen MMI method as a base for our image registration technique because it is robust to different environmental variations. It is widely used for medical image registration and works fine for different imaging modalities including CT, MRI and PET images [4].

It is important to reduce the computational complexity of image registration methods for biomedical images because the registration procedures are time consuming. Previous researchers attempted to reduce the computational complexity of some accurate time-proven intensity-based methods, e.g. [7]. In that work, the authors introduced a novel acceleration technique for MMI method. Authors used fast approximate empirical mode decomposition to extract the most representative low-frequency components of the input images. The suggested method allowed to effectively reduce the quantity of components' histogram bins used to compute mutual information. The authors were able to increase registration speed up to the factor of 5.

We proposed further improvements for the existing acceleration

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http://dx.doi.org/10.1016/j.image.2017.04.003
Received 30 January 2016; Received in revised form 14 January 2017; Accepted 4 April 2017

scheme, such as adaptive input image downsampling and multilevel parametric space search [8]. In this work we further enhance [8], adding new algorithms for initial estimate and search of scale. We explain all steps of image registration technique and test our method on the set of medical images from the Retrospective Registration Evaluation Project [9]. The developed method shows correct results not only for unimodal case but also for the multimodal image registration.

2. Previous approaches and methods

2.1. Fast adaptive bidirectional empirical mode decomposition

Fast adaptive bidirectional empirical mode decomposition [10] was designed as an alternative way to decompose an image into a set of intrinsic modes of different scale. While straightforward implementation of Huang's EMD algorithm [11] in case of bidimensionality requires enormous amount of time to process an image, FABEMD sacrifices some mathematical rigorousness, e.g. the obtained modes do not conform the constraints imposed on them by Huang, for a significant performance gain. Still, FABEMD shares some ideas with the original EMD. The outline of used decomposition algorithm [8] is as follows:

1. Set the initial window size w to 3.
2. Given an input grayscale image I, find strict local extrema of the image in a window of size w. Points p of local maximum should satisfy

$$I(p) > I(q),\ \forall\ q \in W_w(p), \tag{1}$$

where $W_w(p)$ denotes a window of size w centered at p. Points p of the local minimum should satisfy

$$I(p) < I(q),\ \forall\ q \in W_w(p). \tag{2}$$

3. For each local maximum determine the smallest Chebyshev distance to another local maximum and denote it by $d_{\max}$. For each local minimum determine the smallest Chebyshev distance to another local minimum and denote it by $d_{\min}$. Calculate the overall scale $d = \min(d_{\max}, d_{\min})$.
4. Update the current window size $w = 2\lceil\frac{d}{2}\rceil + 1$. This step ensures that we operate with windows of increasing odd sizes.
5. Calculate upper U and lower L envelopes using the corresponding rank filters of size w:

$$U(p) = \max_{q \in W_w(p)} I(q),\ L(p) = \min_{q \in W_w(p)} I(q). \tag{3}$$

6. Calculate mean envelope R by averaging the upper and the lower envelopes with the subsequent smoothing using a box filter of size w:

$$R(p) = \frac{1}{w^2} \sum_{q \in W_w(p)} \frac{U(q) + L(q)}{2}. \tag{4}$$

7. Decompose I into the sum of $M = I - R$ (high-frequency intrinsic mode) and R (low-frequency residue).
8. Apply steps 2–7 to R instead of I to refine the decomposition. Stop when R is no longer decomposable (contains either less than 2 maxima or less than 2 minima).

Fig. 1 shows an example of the FABEMD of an MRI image. In [7] was noticed that in practice the window size w exhibits an instant increase during the decomposition procedure, as demonstrated in Table 1. We use this fact to determine the most representative mode M_k. We define it as the last mode with the least relative detail loss:

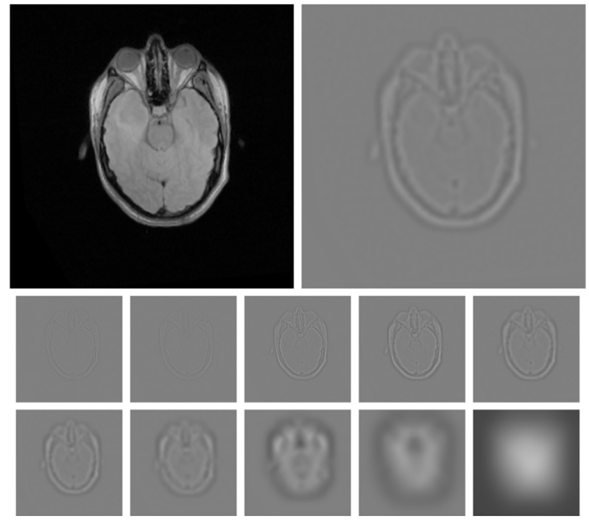
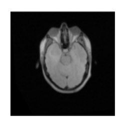
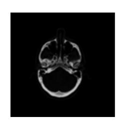
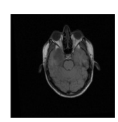
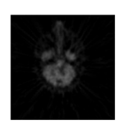


Fig. 1. An example of the FABEMD of an MRI image. The input image (*top left*), the most representative mode (*top right*), intrinsic modes (*bottom*).

Table 1
Window sizes of intrinsic modes obtained via FABEMD. The most representative (using formula 5) modes are highlighted.

Image	Description	IMF 1	2	3	4	5	6	7	8	9
	512 × 512 mri	2	3	4	6	8	12	18	44	85
	512 × 512 ct	2	3	4	6	9	18	27	36	114
	256 × 256 mri	2	3	4	5	7	10	18	45	–
	128 × 128 pet	2	3	4	5	9	12	39	–	–

$$k \to \max: \frac{w_k}{w_{k-1}} \leq \frac{w_i}{w_{i-1}},\ \forall\ i. \tag{5}$$

Such definition provides an intuitive and a quite stable way for adaptive extraction of a midrange component from an input image suitable for subsequent analysis. An example of the most representative mode is given in Fig. 1.

The selected mode can be interpreted as the last mode before loss of the important ridge information. This loss is detected by a jump in the window size caused by disappearing of a ridge in the image.

2.2. Mutual information and histogram sparsification

The idea behind the mutual information maximization method is simple: one should maximize the mutual information functional for two images I and J by adjusting the parameters of the transform between