

COLORECTAL MRI IMAGE REGISTRATION USING PHASE MUTUAL INFORMATION FROM NON-PARAMETRIC PROBABILITY DENSITY FUNCTION ESTIMATOR

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ABSTRACT

We propose a nonrigid registration algorithm and apply it to align pre- and post-chemotherapy colorectal MRI images. The algorithm combines feature-based and intensity-based image registration methods. We use local phase, as computed by monogenic signal, as the feature descriptor, and as the similarity measure in the registration algorithm, phase mutual information, which is estimated using NP windows, a non-parametric probability density function (PDF) estimator. Local deformations are modeled using the polyaffine transformation, which guarantees a smooth and invertible warping toward high image resolution. The algorithm is implemented in an adaptive manner, which makes the registration efficient and reliable. We show encouraging preliminary results and will include a performance evaluation on five of cases in the final paper.

Index Terms— Colorectal Image, Nonrigid Registration, Local Phase, Mutual Information, Polyaffine Transformation.

1. INTRODUCTION

Colorectal cancer is the third most common form of cancer in the developed world and causes over 400,000 deaths each year worldwide. MRI is the primary imaging modality for the detection and diagnosis of colorectal cancer. Currently, about 65% of patients are given courses of chemoradiotherapy (CRT) in order to downstage the tumour prior to the decision of whether or not to proceed to surgery. More precisely, following CRT, a second set of MRI scans is performed to inform the questions: did the tumour respond to CRT? If so, what is the new TNM staging for the tumour? However, due to the dramatic anatomical changes in the shape and appearance of the tumour following CRT, it is often difficult for clinicians to answer these questions. This paper presents an algorithm for deformable image registration, which we apply to pre- and post-CRT colorectal MRI images.

A number of methods in the literature have been devised for mutual information-based nonrigid registration [1]. However, as reported by Bond and Brady [2], the key problem in applying these intensity-based methods to colorectal images is that the algorithms analyze entropy at a single scale

and equate signal complexity with ‘interesting features’. As a result, the algorithms tend to concentrate upon points that are locally complex (high entropy) instead of those that are of the most clinical interest, which are often least varying, most bland regions of the image, such as the mesorectum and colorectum. They then developed a graphical representation of anatomical knowledge relevant for colorectal cancer and a model of how that anatomy will be changed after CRT, both of which can be incorporated to guide those intensity-based algorithms. The resulting registrations were found to be more accurate on average, and, more importantly more reliable, in the sense that they were far less likely to converge to local minima.

Inspired by their work, we propose a nonrigid registration algorithm for the pre- and post-CRT colorectal MRI images that combines feature-based and intensity-based image registration methods. Given a set of interesting points (either provided by the graphical representation of anatomical knowledge [2] or identified by calculating the local mis-match measure to particular image regions [3]), the local phase is used as the image descriptor, and phase mutual information, as estimated using the non-parametric probability density function (PDF) estimator, NP windows, is used as the similarity measure to capture the feature relationship. We use the polyaffine transformation, a diffeomorphic transformation, which mixes several local displacements via an ordinary differential equation (ODE), to model local deformations. The registration proceeds in an adaptive manner to reduce computation time and converge to the final registration. In the following section, we present the various detail of our method: image local phase, phase mutual information as estimated by NP windows, the polyaffine transformation and the registration algorithm.

2. METHOD

2.1. Local Phase

Intensity is used as the image descriptor for most image registration methods. Recently, local phase has been proposed as an image descriptor that better describes image structure than signal magnitude. Some authors have argued that local

phase is a good representation for multimodal image registration [4, 3].

Local phase can be efficiently estimated using the monogenic signal [5]. The basic idea is to construct a pair of vector valued filters that are both odd and distributed with isotropic energy in the frequency domain. Let I be the image, then in the space domain, local phase ϕ can be calculated using the vector valued filters of h_1 and h_2 and the bandpass filtered image $g = f * I$ (where f is the bandpass filter) as:

$$\phi(x, y) = \tan^{-1} \left(\frac{g}{\sqrt{(h_1 \otimes g)^2 + (h_2 \otimes g)^2}} \right) \quad (1)$$

The local phase is normally interpreted as a qualitative description of a detected feature, such as the edge or ridge in a signal.

In equation 1, the quadrature bandpass filter is used to improve the spatial localization and the local phase is estimated in a small spatial span and over a narrow range of frequencies. One should be careful to choose a zero mean bandpass filter for an affine (or deformable) registration as some bandpass filters are not affine invariant, which make it difficult to accurately predict the effect of an increment to the affine transformation so as to bring about a desired change in phase. We propose to use the Mellor-Brady filter (a scale invariant filter) [4] to estimate the local phase, which reduce this problem significantly. Figure 1 shows the phase estimated from a colorectal MR image. Note that because of the invariance to image contrast, the local phase image has largely corrected the bias magnetic field in the colorectal MR image.

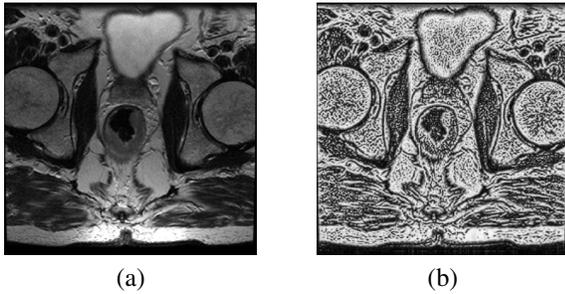


Fig. 1. Example of local phase representation of an image. (a): a pre-CRT colorectal image. (b): the local phase image presentation using the Mellor-Brady Filter at finest scale.

2.2. Phase Mutual Information from NP windows

It is now straightforward to extend the intensity based mutual information to one based on phase [4]:

$$MI(\phi_I, \phi_J) = \sum \mathcal{P}(\phi_I, \phi_J) \ln \left(\frac{\mathcal{P}(\phi_I, \phi_J)}{\mathcal{P}(\phi_I)\mathcal{P}(\phi_J)} \right) \quad (2)$$

where $\mathcal{P}(\phi_I, \phi_J)$ is the phase joint probability and $\mathcal{P}(\phi_I)$, $\mathcal{P}(\phi_J)$ is the individual phase probability. Replacing the

intensity-based mutual information with the local phase, one can detect a meaningful structural relationship between the local shapes of an image pair.

Recently Kadir and Brady[6] proposed, and Joshi[7] further developed, a method to estimate the PDF of a discrete signal using a continuous representation. The method is based on the observation that a critically sampled or oversampled discrete signal can be reconstructed to the original continuous signal if an appropriate interpolation procedure is employed. Additional information, modelled in the interpolation method, helps to improve PDF estimation. Dowson *et al.* [8] have extended this method to calculate joint PDFs for a pair of images. We now briefly describe their method.

Consider a pair of 2-dimensional (2D) images. Let Y_1 and Y_2 denote the intensity variables (or phase variables as in our method) for the two images. Continuous random variables X_1 and X_2 denote positional variables in 2D. We divide the image into several piecewise sections. The intensity variables Y_1 and Y_2 are deterministically related to the positional variables by half-bilinear interpolation over a piecewise section, obtained by joining the centres of three neighbouring pixels. Next, it is assumed that the positional variables are uniformly distributed over this piecewise half bilinear region i.e. $f_{X_1, X_2}(x_1, x_2) = 1$ for $0 \leq x_1, x_2 \leq 1$, and $x_1 + x_2 \leq 1$, where $f(\cdot)$ denotes a PDF. Hence the following equations can be written:

$$y_1(x_1, x_2) = a_1x_1 + b_1x_2 + c_1 \quad y_2(x_1, x_2) = a_2x_1 + b_2x_2 + c_2 \quad (3)$$

$$x_2(y_1, y_2) = \frac{b_1y_2 - b_2y_1 + c_1b_2 - b_1c_2}{b_1a_2 - a_1b_2} \quad (4)$$

$$x_1(y_1, y_2) = \frac{a_1y_2 - a_2y_1 + c_1a_2 - a_1c_2}{a_1b_2 - b_1a_2} \quad (5)$$

The joint PDF f_{Y_1, Y_2} can be calculated by using the transformation formula for functions of random variables. In particular,

$$f_{Y_1, Y_2}(y_1, y_2) = f_{X_1, X_2}(x_1, x_2) |J| \quad (6)$$

where x_1 and x_2 are given by Eqns. 4 and 5, and $|J|$ is the Jacobian and is equal to $|1/(a_1b_2 - b_1a_2)|$ in this case. Therefore,

$$f_{Y_1, Y_2}(y_1, y_2) = \frac{2}{|a_1b_2 - b_1a_2|} \quad (7)$$

The joint PDF has constant value inside the region defined by the constraints on the spatial variables. Depending upon the particular values of the coefficients (a_1, b_1, c_1) and (a_2, b_2, c_2) , these constraints produce variety of regions in the joint PDF domain, including triangles, lines, and points. This is further described in Fig. 2. The joint PDF obtained over each triplet of pixels is added and normalised to get the joint PDF of the given pair of images. The marginal PDFs f_{Y_1} and f_{Y_2} can be obtained by integrating over the appropriate variables. As shown in Fig.2 and compared with the intensity marginal PDFs, the phase one is relatively flat and

contains limited information. However, this property leads to a simplified joint histogram, which is useful for nonrigid registration.

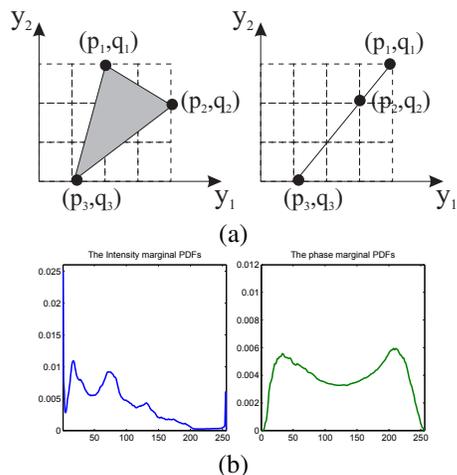


Fig. 2. (a): Various regions induced by constraints on the spatial variables in Eqns. 4 and 5. Shape of these regions depends upon particular values of the coefficients. Consider a triplet of intensity values (p_1, p_2, p_3) in the first image and corresponding intensity values (q_1, q_2, q_3) in the second image. Let (a_1, b_1, c_1) and (a_2, b_2, c_2) be the corresponding coefficients in the half bilinear interpolation equations. Then the left subfigure shows the triangular region induced by the intensity values when $a_1 b_2 - b_1 a_2 \neq 0$. The right subfigure shows the linear region when $a_1 b_2 - b_1 a_2 = 0$ but not all of the individual coefficient values zero. The third possible case induces a point when a_i 's and b_i 's are zero. This case is not shown here. (b): The intensity (left) and phase (right) marginal PDFs of a colorectal MRI image.

2.3. Polyaffine Transformation

We assume that the deformation between the pre- and post-CRT colorectal images is composed of a locally affine transformation. The polyaffine framework is used to obtain a globally non-rigid transformation to model the deformation that presents several local behaviours [9]. The idea behind the polyaffine transformation is to weight the sum of local displacements according to a weight function for each arbitrary image region:

$$\mathbf{D}_{spatial}(x, y) = \frac{\sum_i w_i(x, y) \mathbf{D}_i(x, y)}{\sum_i w_i(x, y)} \quad (8)$$

where w denotes the weight function for image region i within an image and \mathbf{D} denotes the local displacement in each image region. The weight function is modeled by a Gaussian function which acts as a pre-defined shape for each region and

models its influence in the image space. The local displacement modeled by an affine transformation is obtained via an ODE to guarantee invertibility, since all the transformations induced by the ODE are reversible. Therefore it can avoid the ‘folding’ effect that a traditional spline-based transformation tends to produce at the high image resolution. A local mismatch measure that assesses both local phase mutual information and local phase entropy is used to automatically identify those regions of the image which seem to be maximally misaligned [10, 3]. In order to remove superfluous degrees of freedom and avoid the regular grid of control points that increases the computation, the control point of a polyaffine transformation is placed at the centre of a maximally misaligned region.

2.4. The Algorithm

A multi-scale framework is implemented to make the registration faster and to increase the likelihood of finding the global optimum in terms of phase mutual information by tuning the polyaffine parameter space. Specifically, the source (pre-CRT) and the floating (post-CRT) images are first decomposed into the phase representation. From the coarse scale to the finest scale, the polyaffine affine transformation parameters (rotation, scaling, shearing and translation) are found by maximizing the phase mutual information at the coarser scale. The optimized polyaffine transformation matrix from the finest scale is then applied to warp the floating image in spatial space. The algorithm can be easily extended to an adaptive one. This can be achieved by calculating the local mis-match measure using phase mutual information before proceeding to next scale. If the global phase mutual information tends to increase but does not arrive at the user defined threshold, which implies that tuning the parameters of polyaffine can no longer recover the local deformation, extra control points need to be placed in the misaligned region for the higher resolution level.

3. RESULTS

The algorithm was run on a series of 10 small field of view T2-weighted MR datasets, of which 5 were pre-CRT and 5 were post-CRT (provided by Oxford Radcliffe Hospitals). Each of our datasets is comprising $512 \times 512 \times 25$ voxels of size $1\text{mm} \times 1\text{mm} \times 3\text{mm}$. Although the result is shown in 2D images, the algorithm can be extended to a 3D case.

Fig.3 shows the registration result on one of the patient datasets. Three anatomical landmarks, the centre of two hip bones and the coccyx as shown in fig.3(a) and fig.3(b), are provided by the shape representation [2]. These landmarks are initialized as the control point of the polyaffine transformation. From the difference image before and after the registration, the major spatial misalignments in the hip joints and the mesorectum are largely corrected, as shown in fig.3(d)

and fig.3(e). Increasing iterations with a small change of the polyaffine parameters as shown in Fig.3(f), there observes a ‘high central spike’ which implies that the phase mutual information is very sensitive to a tiny local change. This also suggests that the phase-based registrations are able to capture feature relationship that is generally not available in intensity-based methods.

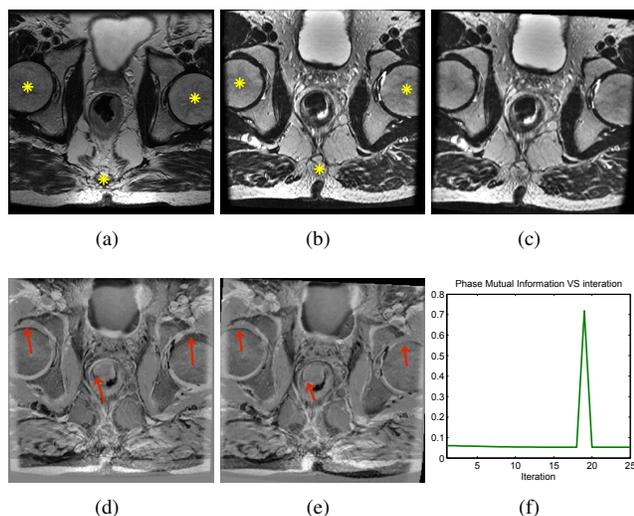


Fig. 3. The pre-CRT (a) and post-CRT (b) colorectal MRI images superimposed with the anatomical landmarks provided by the graphical representation [2]. (c):the aligned (or warped) post-CRT colorectal image. (d): the difference image before the registration. (e):the difference image after the registration and red arrows show the major spatial corrections. (f):phase mutual information vs iteration curve.

Validation of registration accuracy is a difficult task, because ground truth is not generally available. In colorectal image registration, a global measure of registration accuracy is not really what is required; the main interest is the target registration error in the mesorectal region. We use a set of the anatomical landmarks provided by the graphical representation [2] in order to validate the registration. We stress that these landmarks are NOT available to the registration algorithm; but to assess its performance. These identified anatomical landmarks can be overlaid to a temporally aligned post-CRT image to directly measure the target registration error(TRE). As shown in Table 1, the root mean square (RMS) TRE of five datasets was 2.92 ± 0.23 mm.

Patients	1	2	3	4	5	Mean
(mm)	2.98	2.99	3.17	2.74	2.68	2.92

Table 1. The registration accuracy of five patient datasets

4. DISCUSSION

In this paper, a nonrigid registration of the pre- and post-CRT colorectal MR images has been proposed. The result has shown an accurate registration to particular anatomical regions, such as the hip bones and rectum (mesorectum). On an Intel Pentium dual-core processor with 3.20GHz and 2G ram, the running time for the registration algorithm in our experiments is less than 6 minutes for 20 iterations. We expect less computation by developing a faster PDFs estimation with NP windows. For a more accurate registration in the mesorectum, the result in our experiments can serve as an initial registration and then our previous adaptive registration algorithm [3] can be applied to this clinical region using an image mask. This is our future research.

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