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HYBRID NON-RIGID IMAGE REGISTRATION USING MUTUAL INFORMATION AND THE VISCOUS FLUID ALGORITHM

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ABSTRACT

Recently there has emerged a need to compute multimodal non-rigid registrations in a lot of clinical applications. To date, the viscous fluid algorithm is perhaps the most adept method at recovering large local mis-registrations that exist between two images. However, this model can only be used on images from the same modality as it assumes similar intensity values between images. This paper presents a solution to this problem by proposing a hybrid non-rigid registration using the viscous fluid algorithm and mutual information. The mutual information is incorporated via the use of a block matching procedure to generate a sparse deformation field which drives the viscous fluid algorithm. Although successful, the hybrid approach suffers from interpolation artifacts which prevent sub-voxel deformations and limit the accuracy of the algorithm.

1. INTRODUCTION

Non-rigid image registration is an essential tool required for overcoming the inherent local anatomical variations that exist between images acquired from different individuals or atlases. The majority of these non-rigid algorithms assume the existence of similar intensities between images, restricting their use to intra- or mono-modality registrations. Recently, however, there has emerged a need to compute multimodal non-rigid registrations in a lot of clinical applications. The most prominent application of this is in the registration of pre-operative and intra-operative images. This allows the display of pre-operative anatomical and pathological tissue discrimination in the interventional field [1].

An important concept that arouse in the computer vision field during the mid 1990's was an entropy-based measure known as mutual information (MI). This measure has its roots in information theory and has demonstrated its power and robustness for use in multimodality registration in the rigid domain repeatedly. The strength of this measure lies in its simplicity as it does not assume the existence of any particular relationship between image intensities. It only assumes a statistical dependence.

MI has been incorporated into a non-rigid registration by several researchers. The main distinction between the proposed methods lie in the way the MI is calculated. This is accomplished either globally or locally [2]. However, to date MI has never been incorporated with a physical continuum model, (such as the elastic or viscous fluid algorithm). The viscous fluid algorithm is a popular approach which is capable of recovering large local mis-registrations. It also ensures that the deformation field is physically smooth. However, like most other non-rigid registrations, it assumes similar intensity values between images.

This paper proposes a novel hybrid non-rigid registration using the viscous fluid algorithm and MI. Some MI preliminaries are outlined in Section 2. Section 3 will describe non-rigid image registration including the viscous fluid algorithm and a general block matching approach which is used to incorporate the MI. Section 4 will then present the hybrid non-rigid algorithm including some results in Section 5. Finally, the paper is concluded in Section 6.

2. MUTUAL INFORMATION PRELIMINARIES

MI is an information theoretic measure and was proposed for use in image registration by two independent groups, Viola et al. [3] and Collignon et al. [4], in 1995. The basic concept behind the use of this measure is to find a transformation, which when applied to an image, will maximise the MI between the two images. The success of MI lies in its simplicity as it is considered to be quite a general measure. It makes very few assumptions regarding the relationship that exists between different images. Assumptions regarding linear correlation or even functional correlation are not made. It only assumes a statistical dependence.

There are two main definitions of MI used in the literature. Both are based on Shannon's entropy, whose origins lie in communication theory. The first definition relates the

MI between two random variables to their marginal, joint and/or conditional entropies. These relationships are summarised by the expressions,

$$\begin{aligned} I(x,y) &= h(x) + h(y) - h(x,y) \\ &= h(x) - h(x|y) \\ &= h(y) - h(y|x) \end{aligned} \quad (1)$$

where $h(x)$, $h(y)$ are the marginal entropies, $h(x,y)$ is the joint entropy and $h(x|y)$, $h(y|x)$ are the conditional entropies. These entropies are generally calculated by evaluation of the following entropy integrals for the marginal and joint entropies respectively (for the continuous case),

$$\begin{aligned} h(x) &= \int_{-\infty}^{\infty} p(x) \log p(x) \mathrm{d}x \\ h(x,y) &= \int_{-\infty}^{\infty} p(x,y) \log p(x,y) \mathrm{d}x \mathrm{d}y \end{aligned} \quad (2)$$

where $p(x)$ and $p(x,y)$ represent the marginal and joint probability density functions respectively. The second definition of MI that is commonly used is not defined in terms of entropy. Rather it has been formulated using the Kullback-Leibler measure [5] and is given by,

$$I(X,Y) = \sum_{x,y} p_{X,Y}(x,y) \log \left(\frac{p_{X,Y}(x,y)}{p_X(x) P_Y(y)} \right) \quad (3)$$

MI is a measure of the degree of dependence of the random variables X and Y. When formulated using the Kullback-Leibler measure in equation 3, the MI measures the distance between the joint distribution $p_{X,Y}(x,y)$ and the distribution associated with complete independence, i.e. $p_X(x).p_Y(y)$ [6]. This measure is bounded below by complete independence and bounded above by one-to-one mappings.

The two original MI techniques, proposed by Viola et al. [3] and Collignon et al. [4], both use different formulations for the MI. Viola's approach is based on the entropy formulation of MI, as given by equation 1, and Parzen windows which is used to estimate the probability densities of the image intensities. Collignon et al. [4] however, formulates MI in terms of the Kullback-Leibler measure or Shannon's information, as given by equation 3, and estimates the densities by normalisation of the 2D frequency histograms. This is given by $p(x,y) = \frac{1}{N} h(x,y)$, where N is the number of samples. The marginal densities $p(x)$, $p(y)$ can be obtained by a summation over the x and y axes of the joint density respectively.

3. NON-RIGID IMAGE REGISTRATION

A rigid registration is composed solely of a rotation and translation and literally preserves the 'rigid' body constraint, i.e. a body is rigid and must not undergo any local variations during the transformation. This type of registration is distance preserving and is adequate for many applications in medical imaging including multimodality and intra-patient registration. However, for inter-patient registration or patient-atlas matching, non-rigid algorithms are required. In a non-rigid approach, the 'rigid' body constraint is no longer acceptable as it does not account for the non-linear morphometric variability between subjects [7], i.e. there exists inherent anatomical variations between different individuals resulting in brain structures that vary in both size and shape. These non-rigid algorithms allow one image to deform to match another image, thus overcoming any local variations.

A non-rigid registration defines a deformation field that gives a translation or mapping for every pixel in the image. This is generally described by the following relationship.

$$I_f \circ T(\mathbf{x}) = I_f(\mathbf{x} - \mathbf{u}(\mathbf{x})) = I_r \quad (4)$$

In the above expression, I_f is referred to as the floating image that is undergoing the deformation while I_r is the reference image. T denotes the non-rigid transformation which equates to a translation of every pixel $\mathbf{x}$ in the floating image by a certain displacement defined by the displacement field $\mathbf{u}(\mathbf{x})$.

There are many ways of estimating the required displacement field $\mathbf{u}(\mathbf{x})$ in equation 4. This includes deformable models, optical flow, elastic and viscous fluid models, spline warps, truncated basis function expansion methods, and also local registration approaches [2]. This paper however, presents a hybrid non-rigid registration using both the viscous fluid algorithm and a local approach. These are described in the following sections.

3.1. Viscous Fluid Algorithm

The viscous fluid model stems from early work involving the use of elastic models. Both approaches, often referred to as physical continuum models, ensure that the deformation field is physically smooth. The distinct disadvantage of the early elastic model is that it often does not allow complete registration due to the internal restoring forces that increase linearly with the deformation. This inhibits the generation of any large local deformations. This observation was noted by Christensen [8] who proposed the use of the viscous fluid model instead. Christensen argued that the viscous fluid model can handle large deformations without breaking the image topology. This is accomplished by allowing the internal restoring forces to relax as the image deforms over time.

In terms of the model of elasticity, deformations $\mathbf{u}(\mathbf{x})$ are linked to external forces by the linear operator of elasticity. However, in the viscous fluid model, these operations are

carried out on the instantaneous velocity field $\mathbf{v}(\mathbf{x}, t)$ instead of the displacement field. The Navier-Stokes viscous fluid partial differential equation used by Christensen [8] is shown below.

$$\alpha\nabla^2\mathbf{v}(\mathbf{x}, t) + (\alpha + \beta)\nabla(\nabla^T \cdot \mathbf{v}(\mathbf{x}, t)) + \mathbf{b}(\mathbf{x}, \mathbf{u}(\mathbf{x}, t)) = 0 \quad (5)$$

where $\mathbf{v}(\mathbf{x}, t)$ is the instantaneous velocity of the displacement field $\mathbf{u}(\mathbf{x}, t)$ at time t. The term $\mathbf{b}(\mathbf{x}, \mathbf{u}(\mathbf{x}, t))$ represents the applied forces and the parameters α and β are the viscous fluid coefficients. This is solved at each time step and, similarly to the elastic model, the driving forces are derived from image differences and intensity gradients.

To date, the viscous fluid registration algorithm is perhaps the most adept method at recovering large local misregistrations that exist between two images. However, like the elastic algorithm, the viscous fluid model can only be used on images from the same modality as it assumes similar intensity values between images. This is due to the use of measures such as the SSD to produce driving forces for the algorithm.

3.2. Block Matching

Non-rigid registration can also be made possible through local registration approaches and several methods exist to accomplish this. One common method, known as block matching, is where a grid of control points are defined on an image which are each taken as the centre of a small window. These windows, which usually overlap their neighbours, are then translated to maximise a local similarity criterion. The location of the maximum can be found through an exhaustive search or with the use of local optimisation strategies. The location of the maximum then represents the existence of a corresponding window in the second image, the centre of which being the homologue point of the corresponding grid point defined in the first image. Thus, this block matching approach can be used to generate two corresponding sets of control points (or landmark points) between two images. This information can then be used to generate a sparse deformation field with the translations known at each of these grid points. An example of a sparse field generated using block matching procedures is shown in Figure 1.

4. HYBRID ALGORITHM

The viscous fluid model, although capable of handling large local mis-registrations, can only be used on images from the same modality as it assumes similar intensity values between images. This is due to the use of measures such as the SSD, intensity differences and intensity gradients, which are used to produce driving forces for the algorithm. Thus, the main motivation behind the creation of a hybrid algorithm

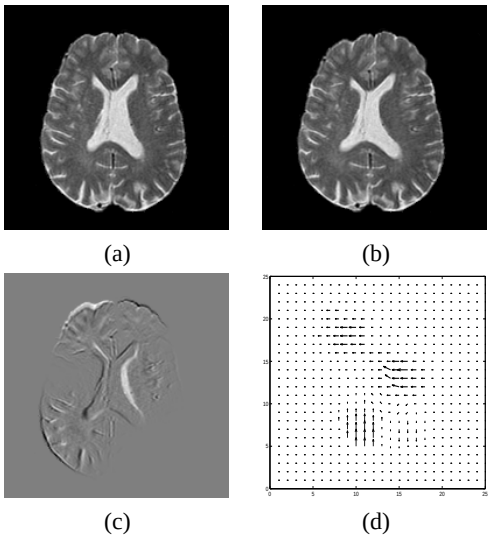


Figure 1: Deformation field calculated using a block matching procedure. (a) Original image, (b) Deformed image, (c) Rescaled difference image, (d) estimated deformation field.

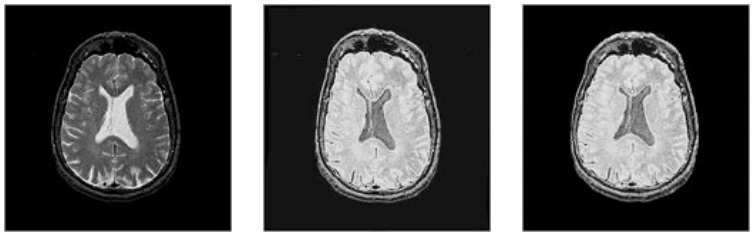
was to incorporate the strengths of both the viscous fluid algorithm and an information theoretic measure such as MI. This would allow the execution of a fluid registration on multimodal images.

In the original viscous fluid algorithm, the driving forces are formulated in the most possible local manner, i.e. the force acting at a particular voxel is derived from the intensity difference and gradients of a point, not a region. However, in the approach of the hybrid algorithm, these driving forces are replaced with those derived from the MI block matching scheme. As mentioned in Section 3.2, the block matching is used to produce two sets of corresponding point sets with known deformations at each point. MI is the similarity criterion used in order to allow for a multimodal registration. The MI is also formulated using the frequency histogram approach and equation 3.

The forces derived from the sparse deformation field are then fed into the viscous fluid algorithm which are used as the driving potentials instead of the original image differences and gradients. The significant difference however lies in the manner in which the forces were calculated. Instead of utilising the intensity difference and gradients of a point, the block matching approach estimates the displacement field and hence the driving forces of a point by incorporating information that is contained in a small region around the point.

5. RESULTS

The hybrid algorithm was tested on a pair of simulated multimodal images with known deformations. The simulated multimodal images were generated from a single MR image which was taken as the reference image and is shown in Fig-



(a) (b) (c)

Figure 2: Simulated multimodal non-rigid registration test. (a) Reference image, (b) Floating Image, (c) Registered version of (b) using the hybrid MI-viscous fluid algorithm.

ure 2(a). The floating image, shown in Figure 2(b), is generated from the reference image with known deformations in various regions of the image. The intensities are also transformed using $I^* = \sin(I \times \frac{\pi}{255})$ to simulate images from different imaging modalities. Figure 2(c) is the registered version of the floating image using the hybrid MI-viscous fluid algorithm.

6. DISCUSSION AND CONCLUSION

The hybrid MI-viscous fluid algorithm presented in this paper is successful in recovering local deformations between multimodal images. However it is susceptible to interpolation artifacts which prevent the estimation of sub-pixel translations. Thus, the estimated deformation field will not vary smoothly, instead it will vary with integer valued steps.

In a typical viscous fluid registration of unimodal images, the estimated deformation field varies smoothly. Thus, for the images shown in Figure 2, there will be a small difference between the estimated deformation field and the actual deformation field applied to the original images. The presence of this residue makes selection of the stopping criteria for the viscous fluid model difficult. The stopping criteria states that the registration will finish once the maximum difference between the target coordinate of a control point with its current position falls below a threshold value. However, with the presence of the residue, a small threshold value will result in a never ending registration while a high threshold value will result in termination of the registration before actual convergence.

The main area of improvement lies in reducing the effects of the interpolation artifacts. This would help improve the accuracy of the registration and may allow for sub-pixel translations. These interpolation artifacts are a direct result of using the block matching scheme which essentially, is limiting the effectiveness of the viscous fluid algorithm. In Section 4, it was discussed how the original driving forces, which were calculated in a local manner, where replaced with those generated from the block matching scheme, which utilises a small region around a control point. Although successful, this prevents the estimation of very fine local deformations. Thus, it is concluded that this hybrid approach would be appropriate for multimodal applications that require a coarse-to-medium registration.

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