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A New Approach of Image Registration for Biomedical Images Using Saliency Information

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Abstract

In this paper we propose a Markov Random Field based Automatic Registration method. This is an elastic registration method that uses the combination of saliency and gradient information. This Intensity-based registration of images is done by linear transformations, based on a discrete Markov random field (MRF) formulation. Here, the challenge arises from the fact that optimizing the energy associated with this problem requires a high-order MRF model. Currently, methods for optimizing such high-order models are less general, easier to use, and efficient, than methods for the popular second-order models. Automatic registration of dynamic contrast enhanced magnetic resonance (DCE-MR) images is a challenging task due to the rapid changes of the images which are characterized by intensity changes over time, thus posing challenges for conventional intensity-based registration methods. Saliency information contributes to a contrast invariant metric to identify similar regions inspiteof contrast enhancement. Saliency is used in optimization framework to identify relevant pixels for registration, thus reducing the computation time. Experimental results on real patient images demonstrate superior registration accuracy with a combination of saliency and gradient information over other similarity metrics.

Keywords: Markov Random fields (MRFs), Automatic registration, saliency, Dynamic Contrast Enhanced Magnetic Resonance images (DCE-MR).

Introduction

Image registration is a vital problem in medical imaging. It has many potential applications in clinical diagnosis (Diagnosis of cardiac, retinal, pelvic, renal, abdomen, liver, tissue etc disorders). It is a process of aligning two images into a common coordinate system thus aligning them in order to monitor subtle changes between the two. Registration algorithms compute transformations to set correspondence between the two images.

Registration is the determination of a geometrical transformation that aligns points in one view of an object with corresponding points in another view of that object or another object. The term "view" generically used to include a three dimensional image, a two-dimensional image, or the physical arrangement of an object in space. Three-dimensional images are acquired by tomographic modalities, such as computed tomography (CT), magnetic resonance (MR) imaging, single-photon emission computed tomography (SPECT), and positron emission tomography (PET)[1]. In each these modalities, a contiguous set of two-dimensional slices provides a three-dimensional array of image intensity values. Typical two-dimensional images may be x-ray projections captured on film or as a digital radiograph or projections of visible light captured as a photograph or a video frame. In all cases, we are concerned primarily with digital images stored as discrete arrays of intensity values. In medical applications, which are our focus, the object in each view will be some anatomical region of the body.

Image processing methods, which are possibly able to visualize objects inside the human body, are of special interest. Advances in computer science have led to reliable and efficient image processing methods useful in medical diagnosis, treatment planning and medical research. In clinical diagnosis using medical images, integration of useful data obtained from separate images is often desired. The images need to be geometrically aligned for better observation. This procedure of mapping points from one image to corresponding points in another image is called Image Registration. It is a spatial transform[2]. The reference and the referred image could be different because were taken at different times, Using different devices like MRI, CT, PET, SPECT etc (multi modal). From different angles in order to have 2D or 3D perspective (multi temporal).

Image registration finds its applications in various fields like remote sensing (multispectral classification), environmental monitoring, change detection, image mosaicing, weather forecasting, creating super-resolution images, integrating information into geographic information systems (GIS), in medicine (combining data from different modalities e.g. computer tomography (CT) and magnetic resonance imaging (MRI), to obtain more complete information about the patient, monitoring tumor growth, treatment verification, comparison of the patient's data with anatomical atlases ,in cartography (map updating) and in computer vision (target localization, automatic quality control).

Automatic Registration Module: Intensity windowing: The intensity windowing is a technique used to identify the enhancement mapping solely of a pixel (x,y). It provides the contents of sub image gray levels, whose pixel values fall on minimum and maximum levels. This technique is employed in the identification of computerized tomography to identify objects in images. One of the well known methods for improving the contrast is by windowing. Windowing describes the process of extending a certain range of pixel / voxel values in the image to fill the entire range of the display.

Voxel Reformation: Voxel reformation is a technique based on multiplanar reformation. It is the simplest method of reconstruction. A volume is built by stacking the axial slices.

Edge or Corner Detection: Before pixel gray between the reference image and matched image has weak correlation, the edge images have strong correlation. Thus, corner matching can be realized in the edge maps, subsequently, image registration is accomplished. The traditional edge detection method is sensitive to noise, so the application is not effective. In recent years, more and more new technologies are introduced to the edge detection, such as mathematical morphology method, wavelet transform methods, the neural network and fractal methods.

Feature Extraction: The 3-D boundary surface of an anatomic object or structure is an intuitive and easily characterized geometrical feature that can be used for medical image registration. Surface-based image registration methods involve determining corresponding surfaces in different images (and/or physical space) and computing the transformation that best aligns these surfaces.

Geometric Transformation: Geometric transformation is a technique used to solve visual tasks. The main goal of this method is to find a set of representative features of geometric form to represent an object by collecting geometric features from images[3]. One popular approach is the development of so-called Interest point detectors. These tend to be based on two-dimensional geometric features often referred to as Corners that are used for the selection of interest points using the Corner detector method and then extract descriptors at these locations for an image retrieval application.

Iterative closest point searching: Algorithm used to minimize the distance between two variant points, which is commonly used in real time.Input points from two raw scans, initial estimation of the transformation, criteria for stopping the iteration.

Process of Thresholding: Thresholding is the simplest method of image segmentation. From a grayscale image, thresholding can be used to create binary images. During the thresholding process, individual pixels in an image are marked as “pixels” if their value is greater than some threshold value (assuming an object to be brighter than the background) and as "background" pixels otherwise. This convention is known as threshold above.

Calculation of Registration Accuracy: A quantitative evaluation of registration accuracy is necessary to judge the effectiveness of any algorithm. The results of registration are generally compared with reference (or ground truth) parameters that help us determine the accuracy of the algorithm. However, it is difficult to get ground truth parameters for elastic registration because each pixel may have different displacement vectors. A common approach is to simulate deformations of known magnitudes and use the magnitude of recovered parameters to calculate the error. Simulated deformations may not replicate deformations found in real-world data. Moreover, simulated deformations could be biased (either favourably or unfavourably) toward certain registration frameworks.

Methodology

Saliency -Based Automatic Registration: Salient points are the prominent points in a scene or image that defines how a particular region is different from its neighbors based on some certain features such as intensity, color, edge orientation, etc. The registration steps are done by Calculation of data penalty as a function of saliency and gradient information from the input images, Calculation of smoothness from the registration labels, Identification of important pixels, Minimization of energy function using MRF based optimization framework, Registration through final transformation labels[4].

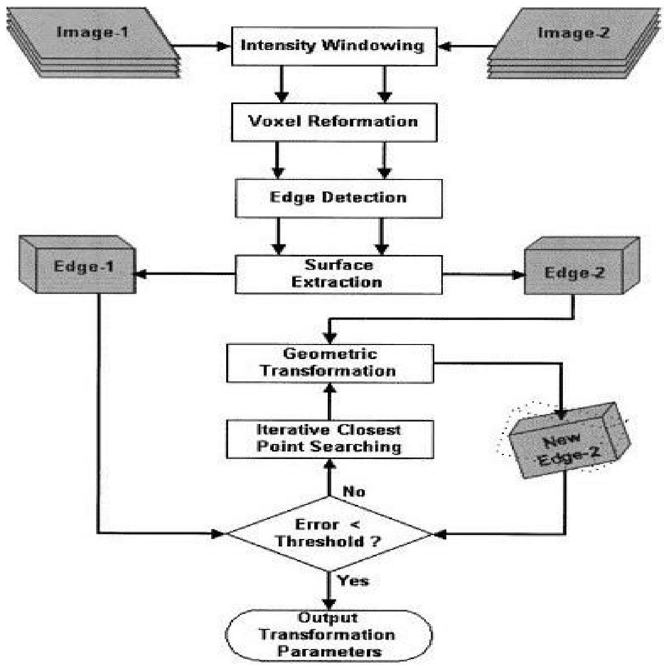

Figure-1
Automatic Registration module

Each and every steps mentioned here are automatic. The experimental results with real patient data show that by exploiting the invariance of the similarity metric our algorithm provides very good registration results.

Since our saliency map is based on the principles of neurobiology, it is a robust similarity metric in the face of contrast enhancement and noise. In combination with gradient information, it increases registration accuracy. Saliency in smoothness formulation adds to the method's robustness. Saliency being more reliable than edge magnitude is more effective to determine whether neighboring pixels in *If* belong to the same object or not. Saliency information helps in reducing computation with the identification of pixels relevant for registration (less than 50% of original number)[5]. A coarse-to-fine approach reduces the number of labels and hence, the computation time. We avoid manually drawn contours, hence reduce the false detections.

Saliency has the following advantages over scale space maps: i. Less sensitive to noise and intensity change, ii. Lower computation time; and 3. Close agreement with human eye.

We achieve registration using a combination of gradient and saliency information because intensity information can be misleading for contrast enhanced images. It proves to be robust and identifies similar pixels in spite of contrast enhancement. Edge orientation information complements saliency information in the registration process. For the saliency maps to reflect the local information, we modify the original model by using a local neighborhood of a pixel instead of a Gaussian pyramid to determine a pixel's saliency. Feature maps corresponding to intensity and edge information are computed for each image. Let $F(s)$ denote the feature value at pixel S in feature map *F*. The neighborhood of S is denoted by N_S Thus, to calculate how different a pixel is from its surroundings with respect to a certain feature.

Markov Random Fields: The energy function of an MRF takes the following form

$$E(x) = \sum_{s \in P} D_S\, x_s + \sum_{(s,t) \in N} V_{st}(x_s, x_t) \quad (1)$$

where P denotes the set of pixels, x_s denotes the label of pixel s ∈ P; *N* is the set of neighboring pixel pairs. Displacements along the two axes is given by

$$x_s = \{x_s^1, x_s^2\} \quad (2)$$

Where, x is the entire set of the pixels, D_S is a unary data penalty function derived from observed data that measures how well label x_s fits pixel s.

Saliency is a reflection of a pixel's conspicuity in its neighbourhood. The high saliency difference between 2 pixels in I_f indicates lesser similarity, suggesting the possibility of higher relative displacement between them. We determine a threshold saliency difference that identifies whether neighbouring pixels are similar. If the saliency difference is above the threshold, the pixels are allowed to have a higher relative displacement, in this case maximum of 3 pixel units. Similarly, pixels with the saliency difference below the threshold are constrained to have a lower relative displacement, i.e., maximum of √2 units. The threshold determines whether 2 pixels are similar or different based upon the difference of their saliency values.

Combination of Saliency and Gradient information: Saliency is not always a perfect contrast invariant feature, and may occasionally assign different saliency values to corresponding pixels in a pair of contrast enhanced images. The changing intensity could influence the saliency maps, especially for perfusion images. Although gradient orientation information acts as a more robust contrast invariant metric, the contribution of intensity toward saliency cannot be completely ruled out. As a result, we give greater importance to gradient orientation information when calculating saliency maps. Thus, we may infer that intensity information could have a role in the limitations of saliency for registration. Another common characteristic observed in perfusion MRI is the change in intensity of the background due to artifacts arising from image acquisition. This may lead to different saliency maps for images from similar stages of contrast enhancement. Although this is not observed very frequently, it can lead to misregistration between images. The goal of registration is to match each pixel in the floating image to the most similar pixel in the reference image, and the feature depends on the type of images being registered. MRFs are used for discrete labelling problems and a smooth solution is obtained by constraining the relative displacement between neighbouring pixels to be within a specified range, so that they have similar displacement labels. A combination of gradient and saliency information is used to register DCE images because intensity information can be misleading for registering contrast enhanced images. Gradient information is also a contrast invariant metric for rigid registration but it is sensitive to noise. Although both metrics have individual limitations in registering images, their combination is highly accurate and robust. Smoothness is imposed by penalizing discontinuities in the deformation field such that neighbouring pixels from the same object (or organ) have similar displacements while neighbouring pixels belonging to different objects are allowed to have different displacements.

Results and Discussion

Registration Framework: The results for registration frame work are calculation of saliency maps, calculation of data penalty as a function of saliency and gradient information, calculation of smoothness through iterative closest point searching, identification of important nodes, minimization of energy function, registered image from the final transformation labels are shown sequentially.

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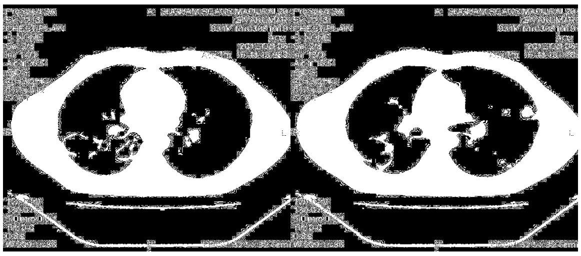

Figure-1
Intensity windowing

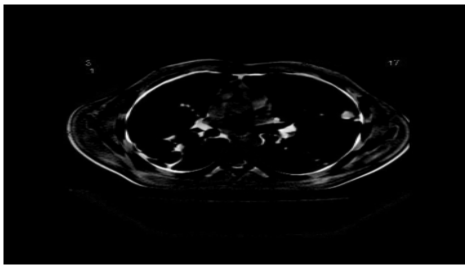

Figure-4
Difference Map

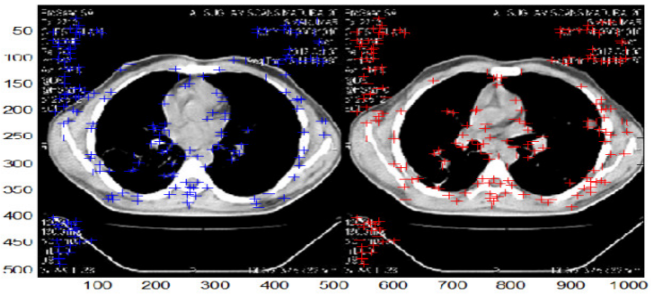

Figure-2
Saliency information

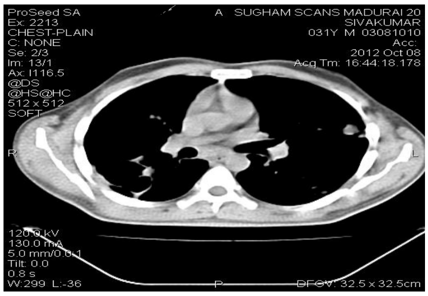

Figure-5
Registered Image from the Transformation Labels

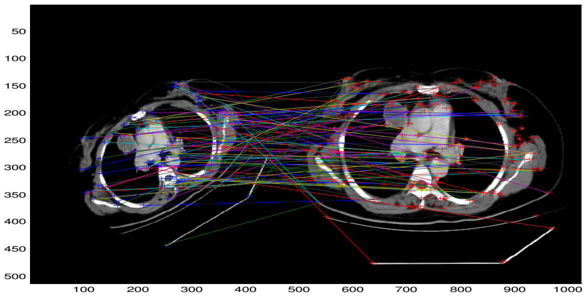

Figure-3
Matches

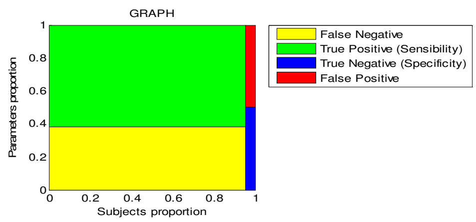

Figure-6
Performance Evaluation

Table-1
Performance Analysis

		Before Registration	After Registration				
			Int	Sal	GI	GSI	FFD
Pre	NMI	1.54	1.57	1.59	1.61	1.65	1.60
-	WC	0.58	0.51	0.31	0.26	0.18	0.28
pre	Err(mm)	2.9	2.6	1.8	1.5	0.8	1.5
Pre	NMI	1.44	1.48	1.54	1.59	1.69	1.43
-	WC	0.63	0.57	0.32	0.25	0.17	0.46
Post	Err(mm)	3.8	3.6	1.9	1.6	0.8	1.6
Pre	NMI	1.53	1.59	1.64	1.71	1.79	1.67
-	WC	0.56	0.51	0.30	0.22	0.17	0.42
post	Err(mm)	3.1	2.0	1.6	1.3	0.7	1.5
	NMI	1.44	1.51	1.54	1.61	1.74	1.56
Overall	WC	0.62	0.54	0.32	0.23	0.17	0.42
	Err(mm)	3.7	2.3	1.8	1.6	0.7	1.6

Conclusion

In dynamic contrast enhanced magnetic resonance images, the organ under test is scanned repeatedly and rapidly following a bolus injection of a contrast agent. Changes in pixel intensity corresponding to the same tissue across the image sequence provide valuable functional information about the organ being imaged. However, perfusion MR image sequences suffer from motion induced by patient breathing during acquisition. Therefore, registration must be performed on time-series images to ensure the correspondence of anatomical structures in different frames. Due to the vast amounts of data acquired in dynamic perfusion MRI studies, automatic registration is strongly desirable. This paper focuses on automatic registration of medical images. The algorithm exploits image features that are invariant to a rapidly changing contrast agent for the construction of templates. We have obtained encouraging registration results with real patient datasets. We have presented automatic registration with MRF framework that combines saliency and gradient information for elastic registration of dynamic contrast enhanced magnetic resonance images. This makes it suitable for elastic registration where matching local information is crucial. A combination of saliency and gradient information with automatic registration overcomes their individual limitations and resulting in good registration performance. The optimization framework was used to speed up the registration process. Experiments were conducted on real patient datasets showing considerable improvement in registration accuracy in terms of average registration errors.

In future work, we aim to improve the method for ultimate registration of 3-D datasets and also make it suitable for other types of MRI data as well as various imaging modalities by using Complex Random Field method.

References

1. Glocker B., Komodakis N., Navab N., Tziritas G. and Paragios N., Dense image registration through MRFs and efficient linear programming, *Med. Image Anal.*, **12(6),** 731–741 **(2008)**.

2. Boykov Y. and Veksler, Fast approximate energy minimization via graph cuts, *IEEE Trans. Pattern Anal. Mach. Intell.*, **23(11),** 1222–1239 **(2001)**

3. Holden M., A review of geometric transformations for nonrigid body registration, *IEEE Trans. Med. Imag.*, **27(1),** 111–128 **(2008)**

4. Itti L., Koch C. and Niebur. E, Model of saliency-based visual attention for rapid scene analysis, *IEEE Trans. Pattern Anal .Mach. Intell.,* **20(11),** 1254–1259 **(1998)**

5. Itti L. and Koch C., A saliency-based search mechanism for overt and covert shifts of visual attention, *Vis. Res.*, **40,** 1489–1506 **(2000)**

6. Kadir T. and Brady M., Saliency, scale and image description, *Int. J. Comput. Vis.*, **45,** 83–105 **(2001)**

7. Rohde G., Aldroubi A. and Dawant B., The adaptive bases algorithm for intensity based nonrigid image registration, *IEEE Trans. Med. Imag.*, **22(11),** 1470–1479 **(2003)**

8. Rueckert D., Sonoda I., Hayes C., Hill D.L.G., Leach M.O. and Hawkes D.J., Nonrigid registration using free-form deformations: application to breast MR images," *IEEE Trans. Med. Imag.*, **18(8),** 712–721 **(1999)**

9. Shekhovtsov A., Kovtun I. and Hlav´ac V., Efficient MRF deformation model for non-rigid image matching, *Comput.Vision Image Understand.,* **112(1),** 91–99 **(2008)**

10. SunY., Jolly M.P. and Moura J., Contrast-invariant registration of cardiac and renal MR perfusion images, in *Proc. Med. Image Comput. Comput.-Assisted Intervention (MICCAI)*, 903–910 **(2004)**

11. J.P., Image matching as a diffusion process: an analogy with Maxwell's demons, *Med. Image Anal.,* **2,** 243–260 **(1998)**

12. Woods R.P., Mazziotta J.C. and Cherry S.R., Mri-pet registration with automated algorithm, *J. Comput. Assist. Tomogr.,* **17(4),** 536–546 **(1993)**

13. Dinkar A., Bhattacharyya S., Kumar D., Kumar A., Gupta P., Banerjee G.1 and Singh M., Pneumonia caused by Candida Kefyr ion pediatric patient with acute Lymphoblastic Leukaemia: Case Report", *Inernational Research journal of Engineering sciences,* **1(1),** 18-19 **(2013)**

14. Uma R. and Pravin B, Invitro Cytotoxic Activity of Marsilea Quadrifolia Linn of MCF-7 Cells of Human Breast Cancer *International Research Journal of Medical Sciences*, **1(1),** 10-13 **(2013)**

15. Budi Setiyono, Mochamad Hariadi and Mauridhi Hery Purnomo, "Investigation of Superresolution using Phase based Image Matching with Function Fitting", *Research Journal Engineering Sciences,* **1(3),** 38-44 **(2012)**