

CT and MRI Brain Images Registration for Clinical Applications

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Abstract

Registration is particularly challenging when fusing imagery from different sensors with different resolutions. Ridges are useful geometrical features for image registration. In this paper, first the performance of Gaussian and Butterworth high pass filters is analyzed on sharpening of images, then ridges are detected from CT and MRI brain images by using scale space primal sketch, and finally cross correlate the two 3D CT and MRI volumes for registration. Results are presented on number of images. The visual comparison shows that filters at cutoff frequency 100 MHz shows better quality. The comparative analysis show that Butterworth filter of order four yields more sharper images as compared to Gaussian filter. Finally, visual results after registration of MRI and CT images of the brain are presented, which can be useful in planning certain types of neurosurgical and ENT surgical procedures.

Keywords: Ridges; Registration; Gaussian; Butterworth; Crosscorrelate

Nomenclature: CT: Computed Tomography; MRI: Magnetic Resonance Imaging; PET: Positron Emission Tomography; SPECT: Single Photon Emission Computed Tomography; Prophylactic cranial radiotherapy (PCR)

Introduction

Image registration is a vital problem in medical imaging. Image registration is the process of geometrically aligning two or more images acquired from different viewpoints that is multiview registration, at different times that is multi temporal registration, by different sensors that is multimodal registration. In multi view analysis the images may differ in translation, rotation, scaling or more complex transformations mainly due to camera positions, while in multi temporal analysis, images of the same scene may be acquired at different times or underdifferent lighting conditions, and finally in multi modal analysis, images are acquired by different type of sensors and imagers. The abundance of existing algorithms has gained a lot of attention among the researchers due to its necessity in various applications such as remote sensing, image mosaicing, image fusion (surveillance, historical monument preservation), medicine (change detection, tumor growth monitoring and computer vision. The details of existing proposed algorithms can be found in references [1]. Different imaging modalities bring complementary information that can be advantageously used to establish a diagnosis or assist the clinician for therapeutic gesture. To locally compare two or more measurements of different nature, a number of registration algorithms had been developed, especially in brain imaging.

The tomography imaging modalities such as MRI and CT entered the wide spread clinically used during 1980's. These two modalities are based on very different physical principles and the images they produce have different properties. MR and CT scanners both produce images of anatomical structure, but the images they generate look quite different. The striking difference between the two is that, bone structure (cortical) appears bright in CT, so is black in MR. MR images tend to have much higher contrast between grey matters. There are many instances in which it would be desirable to integrate the information obtained from two or more studies of the same patient. Application areas of multimodality matching include radio therapy and nuclear medicine [2]. In radiation therapy planning, a CT scan is needed fordose distribution calculations while the contours of the target lesion are often best outlined on MRI [3,4]. In nuclear medicine, determination of the anatomical location of dysfunctional areas and studies in functionalstructural relationships are facilitated by integration of functional and morphological information, and anatomical information may be used to improve PET or SPECT reconstructions. Since information gained from two images acquired in the clinical track of events is usually of a complementary nature, proper integration of useful data obtained from the separate images is often desired. The first step in the integration process is to bring the modalities involved into spatial alignment, a procedure referred to as registration/matching as shown in Figure 1. After registration, a fusion step is required for the integrated display of the data involved. In this paper we will concentrate just on registration of CT and MRI brain images. This type of registration is very useful in radiation therapy planning [2] and skull base surgery [5] (Figure 1).

Fusing the two different modalities from different images referred as multimodal registration. Most medical image registration methods have been developed for use in the head, where correct and



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Received November 12, 2013; Accepted January 20, 2014; Published January 29, 2014

Citation: Dogra A, Patterh MS (2014) CT and MRI Brain Images Registration for Clinical Applications. J Cancer Sci Ther 6: 018-026. doi:10.4172/1948-5956.1000243

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precise registration of two modalities is clinically important. Medical imageregistration can be divided into extrinsic registration method and intrinsic registration methods [6]. Extrinsic registration method are based an artificial marking devices whereas intrinsic registration methods are based on patient related image properties. Extrinsic methods as described in [6] is based on artificial object attached to the patients and some object which are visible in all of the modalities. Such object are, invasive non-invasive markers and fiducial object (stereo active frame) [7,8]. The drawback of extrinsic registration methods are invasive character of marker object and cannot include patient related image information, the nature of the registration transformation is often restricted to be rigid. Whereas intrinsic registration methods are based on image information. In intrinsic methods, the registration of images is based on landmarks, [9-11] segmentation based [12-14] or voxel property based [15-17]. The major drawback in landmark based registration methods is that user interaction is required for identification of the landmarks. Segmentation based registration methods are quite popular till now since segmentation is easy to perform and computational complexity relatively low. Voxel based methods operate in the images grey value. In voxel based registration methods either reduce the image grey value content or use the full image content throughout the registration process. In our proposed algorithm, the method is based on intrinsic registration methods using voxel based property. Firstly the two CT and MR data sets are Sharpened by Gaussian and Butterworth high pass filters, and these high pass filters are analyzed qualitatively and quantatively. For quantative analysis calculated means square error. The purpose of sharpening onto the MR data sets is to show better delineation of anatomy and pathology and better edge enhancement of bony structures in CT images. In second steps ridges are extracted onto the two data sets by scale space primal sketch. In our application of CT/MR registration, skull ridge in most prominent in a CT images and skull trough or called inverse ridge isprominent in MR images. So images ridgeness seems to serve a usefulfeature. In third step, cross correlate the two ridgeness volumes. Theregistration is passed on cross correlation of grey value. Using thegrey value of two feature images directly, hence avoid segmentation. The advantages of this method are it is fully automatic and no user interaction is required but computationally demanding.

Image sharpening by Gaussian high pass and Butterworth high pass filter

Image sharpening is done to remove the noise from the significant image. High pass filters [18] give emphasis to the higher frequencies in the image. The high pass image is then added to the original image so as to obtain a sharper image. It may be interesting to experiment with width and frequency threshold of the Butterworth or the Gaussian high pass filters. Here we will only demonstrate the image sharpening by Gaussian and Butterworth high pass filter and conclude which image can be used further in image processing tasks. By taking $D_0=50$, 100, 150, 200 and n=2 and 4 (where D_0 is cutoff frequency, n is the order of the Butterworth filter). Figure 2(a) shows original MRI image and figure 2(b)-(j) shows the result of GHPF and 2nd order BHPF, varying the cutoff frequency D₀=50, 100, 150, 200. Similar examples can be shown with GHPF and 4th order BHPF, again varying the cutoff frequency D₀=50, 100, 150, 200 as results depicted in Figure 3. As the cutoff frequency increases the filtering become milder, while increasing the cutoff frequency from 50 to 200, sharpening becomes milder in both the cases (GHPF and BHPF). But as order of the Butterworth filter is changed, then there is no such difference between the enhanced images.



images by BHPF are much sharper than GHPF. So 4th order BHPF $(D_0=100)$ processed images can be used for further image processing tasks like edge detection and ridge detection. For quantitative analysis MSE is calculated, MSE is error metric used to compare image quality [18]. Computing MSE between input images and reconstructed images depicts that reconstructed images by BHPF possess better images quality than GHPF as MSE here indicates change and this change



Figure 3: Image sharpening by GHPF and 4th order BHPF with D0=50, 100, 150, 200. (a) 4th order BHPF, D0=50, (b) GHPF, D0=50, (c) 4th order BHPF, D0=100, (d) GHPF, D0=100, (e) 4th order BHPF, D0=150, (f) GHPF, D0=150, (g) 4th order BHPF, D0=200. (h) GHPF, D0=200.

MSE Between Original MR and Sharpened MR images	GHPF	2 nd order BHPF
<i>D</i> ₀ =50	195.1878	224.2108
<i>D</i> ₀ =100	88.1401	107.3320
D ₀ =150	40.9014	53.5254
<i>D</i> ₀ =200	21.1840	27.0158

Table 1(a): Calculation of MSE.

MSE Between Original MR and Sharpened MR images	GHPF	4 th order BHPF
<i>D</i> ₀ =50	195.1878	243.6108
<i>D</i> ₀ =100	88.1401	118.1366
D ₀ =150	40.9014	60.6080
<i>D</i> ₀ =200	21.1840	25.3916

Table 1(b): Calculation of MSE.

is greater in BHPF as compare to GHPF. As we increases the cut offfrequency the MSE decreases and imply that as the cutoff frequency increases the sharpening become milder. The calculated MSE shown in Table 1(a) and (b).

Ridges and Valleys

Ridges

In general ridges are rough top of anything or narrow elevation. To understand the concept of ridge we will make it clear by the use of the term in geography and physical geology. Basically ridge is a geological feature consisting of a chain of mountains or hills that form a continuous elevated crest for some distances shown in Figure 4. For elongated objects, the notion of ridges is a natural tool. A ridge descriptor computed from a grey level image can be seen as generalization of a medical axis. From a practical viewpoint, a ridge can be thought of as a one dimensional curve that represent axis of symmetry and in addition has an attribute of local ridge width associated with each ridge point. Unfortunately however, it is algorithmically harder to extract ridge features from general classes of grey level images then edge, corner or blob features. Nevertheless, ridge descriptors are frequently used for extractions in aerial image [19] and for extracting blood vessels in medical images. Figure 5 shows clearly prominent ridge.



Figure 4: Mountain Ridge in Japan.



Definition of ridges and valleys in n dimensions

In its broadest sense, the notion of ridge generalizes the idea of a local maximum of a real-valued function. A point X0 in the domain of a function $f:\mathbb{R}n \to \mathbb{R}$ is a local maximum of the function if there is a distance $\delta > 0$ with the property that if X is within δ units of X0, then $(X)<(X_0)$. It is well known that critical points, of which local maxima are just one type, are isolated points in a function's domain in all but the most unusual situations (i.e., the non-generic cases)[20]. Consider relaxing the condition that $(X)<(X_0)$ for X in an entire neighborhood of X_0 slightly to require only that this hold on a n - 1 dimensional subset. Presumably this relaxation allows the set of points which satisfy the criteria, which we will call the ridge, to have a single degree of freedom, at least in the generic case. This means that the set of ridge points will form a 1-dimensional locus, or a ridge curve. Notice that the above can be modified to generalize the idea to local minima and result in what might call 1-dimensional valley curves.

This following ridge definition follows the book by Eberly [21] and can be seen as a generalization of some of the abovementioned ridge definitions. Let $U \subset \mathbb{R}n$ be open an open set, and $f:U \to \mathbb{R}$ be smooth. Let $X_0 \in U$. Let $\nabla_{X_0} f$ be the gradient of f at X_0 , and let $H_{X_0}(f)$ be the $n \times n$ Hessian matrix of f at X_0 . Let $\lambda_1 \leq \lambda_2 \leq \cdots \leq \lambda_n$ be the n ordered Eigen values of $H_{X_0}(f)$ and let $\ominus i$ be a unit eigenvector in the Eigen space for λ_i (For this, one should assume that all the Eigen values are distinct).

The point X0 is a point on the 1-dimensional ridge of f if the following conditions hold:

$\lambda_n - 1 < 0$, and $\nabla_{x_0} f . ei = 0$ For i = 1, 2, ..., n - 1





This makes precise the concept that f restricted to this particular n - 1-dimensional subspace has a local maxima at X_0 .



Figure 9: Sharpened MRI images by 4th order BHPF with cutoff frequency $\ensuremath{\text{Do}}\xspace=100.$



This definition naturally generalizes to the k-dimensional ridge as follows: the point X_0 is a point on the k-dimensional ridge of f if the following conditions hold:

1. $\lambda_n - k < 0$, and

2. $\nabla_{x_0} f.ei = 0$ For i = 1, 2, ..., n - k

In many ways, these definitions naturally generalize that of a local maximum of a function. Properties of maximal convexity ridges are put on a solid mathematical footing by Damon and Miller.

Their properties in one-parameter families were established by Keller [22].

Result and Discussion

Detection of ridges by using primal sketch

Scale space primal sketch by T. Lindeberg is used for ridge detection. As T. Lindeberg used primal sketch for blob detection. Here it is used for ridge detection. Original CT and MRI images are shown in Figures 6 and 7. These CT and MRI images are sharpened by 4th order Butterworth filter (D_0 =100) as depicted in Figures 8 and 9. Ridges are extracted on these sharpened CT and MRI images by using primalsketch as shown in Figure 10 and 11 and convolve these images withGaussian kernels to increase size. Next step to calculate the scale spacevolume. To compute the scale space volume, followed the steps of T. Lindeberg's methodology given in [23,24]. Here we do not follow thecomplete methodology by him. Therefore only followed the first two steps used by him in his methodology, which is summarized as:

- 1. Generate the scale representation where ridges are extracted at the level of scale and linked across scales.
- 2. Now further step is calculate the scale-space volume for scalespace ridges and obtain the resultant 3D volumes.

Using above steps we compute the 3D volumes of CT and MRI images as depicted in Figures 12 and 13.







Registration of images

After obtaining feature images there is need to register the 3D volumes. The method is based on registering by means of geometrical image features. Now the prior step used before cross correlating to 3D volumes is to minimize the troughness of 3D MRI volume or to maximize the ridgeness of the 3D CT volume for making the registration meaningful. Therefore for minimizing the troughness of 3D MRI volume uses the arithmetic operators. By employing cross-correlation of grey value, using the grey value directly and avoid segmentation of feature images.

The accurate registration of 3D CT and MR ridgeness volume (called L1 and L2) using correlation of grey values, [3,4] minimize c (t) over rigid transformation, c (t) is defined as $c(t) = \Sigma L_0(x, y, z) \in L_1(x, y, z) L_2(t(x, y, z))$. By using the grey values directly avoided segmentation of feature images, thus resort to multi resolution method as a irrational force approach by trying possible function for t is computationally infeasible. This method is called multi resolution correlation method and hierarchical registration. Advantages of this method are that it is fully automatic, there is no user interaction, and user subjectivity is also avoided. Only disadvantage related is high computational effort required. It is fully automatic but computational effort is more. The final registered images are shown in Figure 14.

Applications of CT-MRI registration

The combination of MR and CT images of the head can be useful inplanning certain types of neurosurgical and ENT surgical procedures. In particular the relationship between soft tissue contract provided by MRI and bone detailed provided CT can be useful where



a single modality is insufficient. The matching of CT and MRI images can be very efficient in radiotherapy planning. It is used in prophylactic cranial radiotherapy (PCR). These are the application inside the head now for outside the head. Now for the application outside the head, a non-rigid transformation is normally necessary because of soft tissue deformation resulting from change in patient positioning, Respiration, etc. When registering MR or CT image with PET or SPECT images, some parts of the body such as the pelvis can be treated as a rigid body because careful patient positioning can make tissue deformation smaller than the resolution of the PET or SPECT images. For MR-CT registration, this assumption is not valid. There is nevertheless considerable interest in registration of MR and CT outside the head for staging cancer and planning radiotherapy.

Conclusion

The terms matching and registration are both used to donate the process of determining the transformation that relates the content of two images in a meaning full way. In this paper, we use 3D CT andMR volumes in a multi resolution correlation method. This scheme required no interactive actions and devoid of human subjectivity. This method is fully automatic. The disadvantage with this method is high computations. The final registered image show decreased resolution of the soft tissues as far as diagnostic quality is concerned. However the matching of CT and MR image will be of great help for radiotherapy planning as planning is done on CT system and localization is better onMRI thereby combining the best to features of two different modalities.

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