Medical Image Registration using Normal Vector and Intensity Value

Y.P. He
Med-X Research Institute
Shanghai Jiao Tong University
Shanghai, China
Email: yphe@sjtu.edu.cn

L.X. Gu
Med-X Research Institute
Shanghai Jiao Tong University
Shanghai, China
Email: gulixu@sjtu.edu.cn

***Abstract*—Medical image registration plays a vital role in many applications such as diagnosis and image guided intervention. So far, the mainstream of medical image registration algorithms are based on intensity values of the images, eg. mutual information. However, spatial feature of the image is another important component deserved to be considered. In this paper, we propose a novel metric combing spatial and intensity scale information, which lies on the similarity features of normal vector and intensity value of the corresponding localization of two aligned images. The experiments reveal that the proposed metric achieved better accuracy comparing with the metric based only on intensity information.**

Keywords-Medical Image Registration; Sptial Information; Normal Vector.

I. INTRODUCTION

Medical image registration allows for image fusion, i.e., to integrate images from different sensors and from existing image databases into one representation [1]. The main motivation lies that different imaging modalities provide different information, i.e., anatomical or functional information, or different properties of the underlying tissues. These aligned images allow clinicians to gather information between anatomical structures and pathology or physiology. Thus, fused image data can improve medical diagnosis, surgery planning and simulation as well as intraoperative navigation [1]. The objective of medical image registration is to find a geometrical transformation that aligns points in one object with corresponding points in another object or just another view of the similar one. In recent years the mainstream algorithms are mostly voxel-based, which relies on the similarity of corresponding voxels' intensity. One of these, mutual information [2], has shown to be a successful measure since it was introduced in 1995. However many researchers have realized some disadvantages of mutual information, which result in failures in some registration applications. Mutual information is highly non-convex and has typically many local maxima. The reason is that MI ignores any spatial information of the images [3]. A possible solution is to include significant spatial information which depicts the structures and the correlation of the inter-subject positions. Many researchers have spent much work on this scheme and proposed some remarkable ideas. In some of these ideas, the spatial information is represented by using intensity gradient which is computed from the neighbor voxels. Pluim et al. [4] proposed a novel metric combing intensity value mutual information and gradient information, to solve the ill-result of mutual information when the image resolution, say samples used, is low. Mert et al. [5] proposed a method to include spatial information by using spatial feature vectors which demonstrates better accuracy and robustness. Higher-order mutual information is also applied into registration by D. Rueckert [6].

As mentioned, the gradient is always used to represent the spatial information. However, Zhuang et al. [7] used the normalized gradient vector, normal vector, instead. The Normal Vector Information, which is derived from the similarity of the corresponding normal vectors, to align images. The experiments reveal that Normal Vector Information can achieve better robustness and accuracy than mutual information. One of the disadvantages of Normal Vector Information lies that it only utilized the spatial information without any intensity information. In this thesis, we propose another novel registration similarity metric, which combines spatial information with gray scale information. The representation of spatial information with gradient is adopted. The similarity of the corresponding vectors is measured to be the alignment criteria. The experimental results show that our metric can largely improves the accuracy especially the mono-modality registration.

II. METHOD

In this section, we will first introduce the mathematics explanation of medical image registration. The concept will guide our work to search the true correspondence between two images. Next, we will demonstrate the incorporation of spatial and gray intensity information after illustrating normal vector as a method to represent spatial information.

A. *Mathmatics Explanation*

The task of medical image registration is to find the correspondence between two images. The two images represent the same or share some part of objects. In our registration framework, we refer one of the images as the reference image which is fixed during registration process. The other one of the two images to align can be considered to be derived from the reference image with an imaging function and noise. The intensity distribution can be presented as equation (1) [8]:

$$v(x,y) = f_{x,y}(u(t(x,y))) + W(x,y); \forall (x,y) \in \Omega \quad (1)$$

In the above equation, u and v are the two images to be aligned. $t(x,y)$ is the transformation, which determines the correspondence between the two images. $f_{x,y}(*)$ is the imaging function determine the relation between the gray values of the two images. And $W(x,y)$ is the random noise added. The problem of medical image registration then can be indicated as the search process of finding the corresponding transformation $t(x, y)$ between the given two images.

B. Normal Vector

Spatial information can be depicted by many formats [3]. Here, we derive the normal vector at every sampled voxel from gradient to represent spatial information of corresponding point. The selection of gradient is because locations with a strong gradient are assumed to be the boundary of different tissues. The correspondent variation of intensity value at such boundaries can’t be utilized or represented in gray scale information only metric. The gradient is computed on a spatial scale by a Gaussian kernel. The sigma of Gaussian function is set to be 1.5. The only difference between normal vector and gradient vector lies that normalization is applied to normal vector. So we gain the equation to derive the normal vector through all the sampled voxel as equation (2).

$$NV(x, y, z) = Normalize(Gradient(x, y, z)) \quad (2)$$

The normal vectors of the corresponding locations between the aligned images are assumed to have close relationship. Mostly, the intensity distributions at the corresponding point have approximately same or opposite variation tendency. Thus, we generate the normal vector images from the absolute values of normal vectors on images. Even if the images have huge difference in intensity distribution, the normal vector images can expose the similarity of the spatial information just like Figure 1.

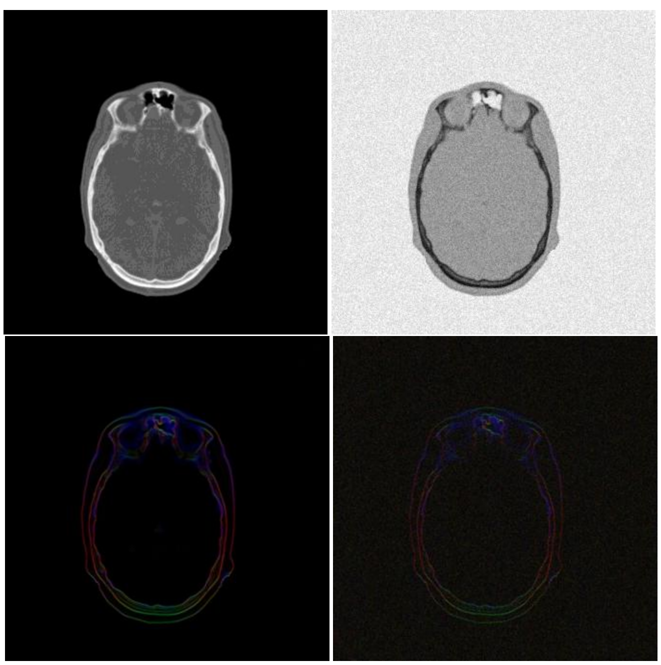

Figure 1. Normal vector reveals the similarity. The upper row is the original images, and the below row is the normal vector images.

In figure 1, we reversed the intensity value of first image and added noise which makes the intensity value distribution has huge difference with the original image. We just can conclude that the normal vector images of this two images have almost the same form and intensity value distribution. Normal vector images can be a sufficient tool for representing spatial information.

C. Integrating Intensity Component

The normal vectors are well representation of spatial information of neighbor voxels on the image. While the main target of this thesis is to incorporate the spatial information with gray scale information. The most straightforward method is to incorporate the intensity value with the 3D normal vector which is showed in Figure 2.

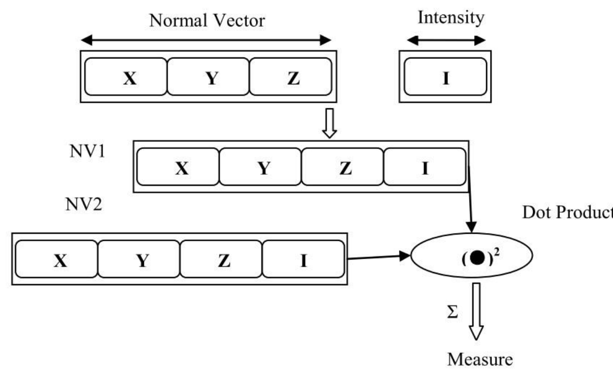

Figure 2. Illustration of integrating intensity component

The 4D vector consists with 3 components from normal vector and the other one is directly derived from the intensity value of current voxel. One problem of the direct incorporation is that the 4 different vector components have large difference of scalar range. As mentioned above, the 3 components from normal vector are normalized which make them no large than 1. While the voxels’ intensity values can be large even to 1000. Thus, we first normalize the voxel intensity value through dividing the maximum intensity value of the whole image extent. Secondly, we apply a ratio to the intensity value component. The ratio can be considered as the importance factor of intensity value versus normal vector. It's reasonable to use larger intensity ratio in mono-modality registration applications and smaller in multi-modality ones. Experimental results reveal that intensity ratio also can be manipulated to adjust the function smoothness and sharpness.

In order to derive a suitable scalar metric in a maximization similarity registration framework, we introduced the intersect angle to depict the similarity of the corresponding intensity-normal vectors. The basis is that when two images are aligned, the corresponding points’ normal vector and intensity value should have the almost same or negative direction which results the similarity of the 4D vector pair. The cosine of intersect angle can be used to measure the similarity. For the possibility of negative directions on the corresponding localizations between the reference and floating images, the metric is summed up with the squares of cosine like equation (3).

$$
\begin{aligned}
measure &= \sum \cos^2 \langle V_1, V_2 \rangle = \sum (V_1 \bullet V_2)^2 \\
&= \sum (|V_{1x}| \cdot |V_{2x}| + |V_{1y}| \cdot |V_{2y}| + |V_{1z}| \cdot |V_{2z}| + |V_{1i}| \cdot |V_{2i}|)
\end{aligned} \tag{3}
$$

V_1 and V_2 are the 4D vectors of the corresponding localization. V_{1x} , V_{1y} , V_{1z} , V_{1i} is the 3 components of the normal vector and the intensity respectively.

III. RESULTS

In this section, the performance of our metric and mutual information will be compared. First, the registration functions of our method and mutual information are demonstrated using the same dataset. Then both the mono- and multi-modality experiments are carried out to demonstrate the accuracy.

A. *Registration Function*

We simulated the registration function with two same images which is pre-transformed with a rigid transformation.

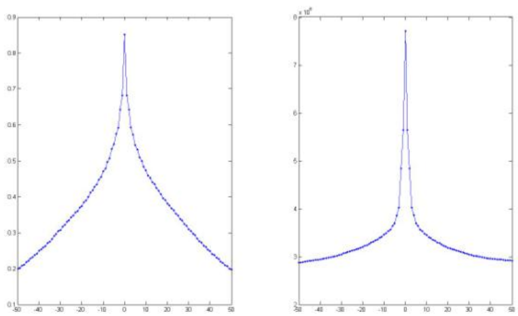

Figure 3. Comparison of registration functions. Left is of mutual information and right is of our metric.

From figure 3 we can see that our metric gains even sharp function which means the difference of our measure in misaligned and aligned position is even great. It can result into high success ratio of registration.

B. *Mono-modality Experiment*

We carried out the rigid experiment on the BrainWeb [9] dataset. The images in BrainWeb are pre-aligned. The MR_PD and MR_T1 images are chosen to simulate the fixed and moving image. We first applied a rigid transformation to the moving image to get the misaligned images. Thus, the true misalignment is known and can be treated as golden criteria. The translations of the transformation are randomly achieved from -10.0~10.0, and the rotation angle are randomly gained from -10.0º~10.0º. 20 tests are carried out to make the comparison, and the average errors with the true misalignment are listed at table 1.

TABLE 1. MONO-MODALITY RESULTS

Metric	Transform					
	Rot.X	***Rot.Y***	***Rot.Z***	***Trans. X***	***Trans. Y***	***Trans. Z***
MI	0.6057	0.5087	0.4943	0.2196	0.1834	0.1941
Our Metric	0.0302	0.0294	0.0441	0.0080	0.0091	0.0183

The mono-modality registration experiment shows that our metric can gain better accuracy than the mutual information metric. The correlation between the corresponding normal vectors can enhance the similarity function of two images and improve the accuracy of mono-modality registration.

C. *Multi-modality Experiment*

We still use the BrainWeb dataset to simulate the accuracy of our metric on multi-modality registration application. We first negated the floating image with the equation (4) to manually produce the different modality image [5].

$$I_{new} = I_{max} + I_{min} - I_{old} + W \tag{4}$$

I_{max} and I_{min} are the maximum and minimum of the original floating image intensity value. I_{old} and I_{new} are the old and manually-produced gray values. The effect of the equation is to turn round the gray values as illustrated in figure 3.

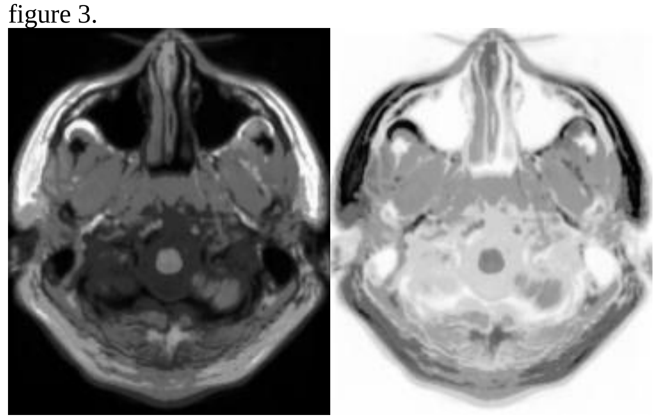

Figure 4. Demonstration of artificial multi-modality images

The reference image and the negated floating image then are conveyed to the registration process. We applied the same registration comparison process to the multi-modality experiment as the mono-modality. The errors are listed at table 2.

The multi-modality experiments results indicate that our metric gains not so satisfactory accuracy comparing to mono-modality registration. The main reason lies that the intensity value component has not much similarity in the multi-modality images, especially in our artificially-created images whose gray values are negated from each other. While thanks to the similarity of the normal vectors at the corresponding localizations, our metric do not compromise the accuracy of mutual information method.

TABLE 2. MULTI-MODALITY RESULTS

Metric	Transform					
	Rot.X	***Rot.Y***	***Rot.Z***	***Trans. X***	***Trans. Y***	***Trans.Z***
MI	0.4372	0.5589	0.5432	0.3898	0.3636	0.4461
Our Metric	0.5840	0.4697	0.3956	0.5404	0.4522	0.5101

IV. DISCUSSION

Many revised metrics based on mutual information or entropy are proposed which have achieved better results. In this paper, we proposed a novel metric based on the intensity value and the normal vector (information about image structure). The intensity value and corresponding normal vector are encapsulated into a 4D vector (if the image is 3D). The similarity of the pairwise vectors on the reference and floating images are measured to be the alignment criteria. From the experiment results, the accuracy comparing mutual information is improved. While many researches show that entropy is a very good tool to measure the similarity between images, our novel metric has not utilized the powerful entropy tool. The future work will be focused on the method to fully utilize the entropy tool on the 4D vectors. In our preliminary experiments, we found that the ratio of intensity component which determines the importance of intensity value similarity impacts the smoothness of registration function and accuracy of alignment. Thus, how to find the best ratio on a specific registration application remains further research.

ACKNOWLEDGMENT

This paper was partially supported by National Natural Science Foundation of China, Grant No. 60872103 and Shanghai Municipal Research Fund with grand No. 10440710600. The authors would also thank all the members in the Image Guided Surgery and Therapy Laboratory of Shanghai Jiao Tong University for their helps.

REFERENCES

[1] K. Rohr, “Elastic registration of multimodal medical images: A survey,” *KI*, vol. 14, no. 3, pp. 11–17, 2000.

[2] P. Viola and W. M. Wells, “Alignment by maximization of mutual information,” *International Journal of Computer Vision*, vol. 24, no. 2, pp. 137-154, 1997.

[3] J. P. W. Pluim, J. B. A. Maintz, and M. a Viergever, “Mutual-information-based registration of medical images: a survey.,” *IEEE transactions on medical imaging*, vol. 22, no. 8, pp. 986-1004, Aug. 2003.

[4] J. P. W. Pluim, J. B. A. Maintz, and M. A. Viergever, “Image registration by maximization of combined mutual information and gradient information,” *Ieee Transactions on Medical Imaging*, vol. 19, no. 8, pp. 809-814, 2000.

[5] M. Sabuncu, “Spatial information in entropy-based image registration,” *Biomedical Image Registration*, pp. 132-141, 2003.

[6] J. Hawkes and D. L. G. Hill, “Non-rigid registration using higher-order mutual information,” *Image (Rochester, N.Y.)*, vol. V, no. 2011, 2000.

[7] Y. P. He and L. X. Gu, “Medical Image Registration using Information of Normal Vector and Intensity Value.”

[8] B. Zitova and J. Flusser, “Image registration methods: a survey,” *Image and Vision Computing*, vol. 21, no. 11, pp. 977-1000, 2003.

[9] R. K. Kwan, a C. Evans, and G. B. Pike, “MRI simulation-based evaluation of image-processing and classification methods.,” *IEEE transactions on medical imaging*, vol. 18, no. 11, pp. 1085-97, Nov. 1999.