# Medical Image Alignment by Normal Vector Information

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**Abstract.** In this paper, a new approach on image registration is presented. We introduce a novel conception- normal vector information (NVI) - to evaluate the similarity between two images. NVI method takes advantage of the relationship between voxels in the image to extract the normal vector (NV) information of each voxel. Firstly, NVI criterion is presented. Then, based on the criterion, we find that NVI related metric has a quite perfect global optimal value on transformation parameter ranges. Finally, registration examples which are based on NVI criterion are provided. The result implies that the feature of smooth value distribution and one global optimal value that NVI metric has makes the optimization procedure much easier to be implemented in image registration.

## 1 Introduction

In image registration there is a need to find and evaluate the alignment of two images for other applications [1], [2]. Image registration is to find a geometric transformation that maps a given moving image into a fixed image [3]. Current popular metrics are mostly based on voxel intensity value of the images, such as mean squares metric, normalized correlation metric and mutual information metric. Those metrics employ the intensity value pair of the fixed image voxel and corresponding moving image voxel to evaluate their similarity in a special space transformation. Both mean square metric and normalized correlation metric work well in image registration but they are restricted to mono-modality applications[1]. Mutual information metric can be applied in multi-modality medical image registration [4]; and much improvement has been achieved on it [5], [6]. However, the feature that the metric has many local maximum values in multi-modality registration makes the optimization difficult (fig.1 (a)). Optimization used in registration based on mutual information should be specially designed to achieve a good performance [7].

In this paper, we propose a new registration method based on NVI. Fig.1 (b) shows that the distribution of mean squares metric in mono-modality is very smooth and has excellent advantages in optimization. Here, we will present a novel criterion that employs the NVI of image to evaluate the similarity between two images. NVI is extracted from normal vector of each image voxel due to their isosurfaces or in image. This metric is not restricted in mono-modality. We will present both theory explanation and relative datasets to prove the feasibility of this method.

[1] The conclusion is drawn from experiments using source of Insight Toolkit (www.itk.org).

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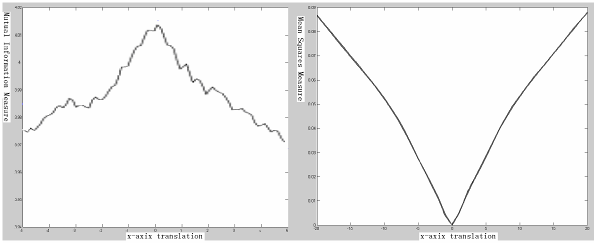
The rest of this paper is organized as follows: in section 2, we introduce NVI criterion use data analysis to show the advantages of NVI metric. In section 3, we offer medical image registration examples.




(a) (b)

**Fig. 1.** Value of metrics to describe how similar two images are aligned plotted against x-axes translation. (a) mutual information metric. (b) mean squares metric.

# 2 NVI Based Similarity

## 2.1 Normal Vector Images

NV can be computed from the direction value of gradient of image [9]. Here, we give each NV component to each pigment of a RGB color to display a NV image.

The left two images of Fig.2 display two T1, T2 MRI images but they are similar in structure. In fact, they are from the some position of one brain but reflect different information. The NV value of each voxel of these two images is calculated and the result is that the NV images are almost the same, as Fig.2 (b) shows. The reason lies in that whatever the image want to reflect of the body function, the imaging result will catch the structure of imaged objects. Next, we will provide the definition of NVI metric and some algorithm used in registration process.

## 2.2 A Formal Definition of NVI Metric

To evaluate the alignment between two images, a direct idea is to calculate how much the NVI of the images are similar. Here we use cosine of the included angle of two NV value to obsess the similarity of two NV. Therefore, the sum of all the cosine value should be the function to represent the similarity of the two NVI images. A NVI metric evaluates alignment of images is presented as below:

$$S(p \mid F, M, T) = \sum_{i=1}^{n} | \cos(\theta(N_{F(xi)}, N_{M(x'i)}) |^{e} \quad (1)$$

Where, S means the similarity of the two images. Interpolator method is p, fixed image F, moving image M, transformation T. n is the number of voxels that have NV value and are counted. $N_{F(xi)}$ is the normal vector of voxel xi in fix image. $N_{M(x'i)}$ is that of move image. $X'_i = T(X_i)$. $\theta(N_{F(xi)}, N_{M(x'i)})$ is the included angle of the two vectors. $|\cos(\theta)|$ represents the absolute value of the included angle's cosine value. Parameter e stands of an exponent operator. As gradient descent optimizer is easiest way to look for a maximum of a metric, and NV value could be proximately set as the normalized vector value of gradient, then formula used to compute the derivate of NVI metric S with respect to transformation T is offered here:

$$\partial S/\partial(T) = (\partial S/\partial(x_m, y_m, z_m))/(\partial(x_m(T), y_m(T), z_m(T))/\partial(T)) \quad (2)$$

$X'_i = T(X_i) = (x_m, y_m, z_m)$ After some manipulation $\partial S/\partial(x_m, y_m, z_m))$ might be written as follows,

$$\partial S/\partial(x_m, y_m, z_m)) = \frac{2 * M_{fm}}{M_f{}^2 * M_m{}^4} *$$

$$\begin{bmatrix} ((G_{fx} * \frac{\partial V_m{}^2}{\partial x \partial x} + G_{fy} * \frac{\partial V_m{}^2}{\partial y \partial x} + G_{fz} * \frac{\partial V_m{}^2}{\partial z \partial x}) * M_m{}^2 - M_{fm} * (G_{mx} * \frac{\partial V_m{}^2}{\partial x \partial x} + G_{my} * \frac{\partial V_m{}^2}{\partial y \partial x} + G_{mz} * \frac{\partial V_m{}^2}{\partial z \partial x})) \\ ((G_{fx} * \frac{\partial V_m{}^2}{\partial x \partial y} + G_{fy} * \frac{\partial V_m{}^2}{\partial y \partial y} + G_{fz} * \frac{\partial V_m{}^2}{\partial z \partial y}) * M_m{}^2 - M_{fm} * (G_{mx} * \frac{\partial V_m{}^2}{\partial x \partial y} + G_{my} * \frac{\partial V_m{}^2}{\partial y \partial y} + G_{mz} * \frac{\partial V_m{}^2}{\partial z \partial y})) \\ ((G_{fx} * \frac{\partial V_m{}^2}{\partial x \partial z} + G_{fy} * \frac{\partial V_m{}^2}{\partial y \partial z} + G_{fz} * \frac{\partial V_m{}^2}{\partial z \partial z}) * M_m{}^2 - M_{fm} * (G_{mx} * \frac{\partial V_m{}^2}{\partial x \partial z} + G_{my} * \frac{\partial V_m{}^2}{\partial y \partial z} + G_{mz} * \frac{\partial V_m{}^2}{\partial z \partial z})) \end{bmatrix} \quad (3)$$

Where, G=(Gx,Gy,Gz) is the gradient, V is an image voxel. F means Fixed image, M means moving image. Mfm stands of the point multiply of gradient of fixed image and moving image. Mf=|Gf|, Mm=|Gm|

### 2.3 Advantages of NVI Metric

Distribution plots of NVI metric value against rigid transformation are provided to describe the advantages of NVI metric in biomedical registration.

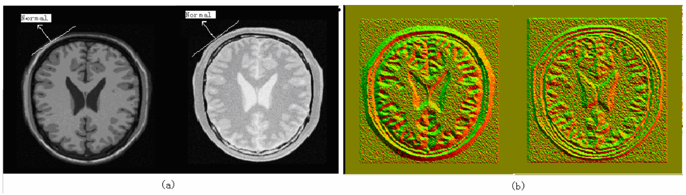
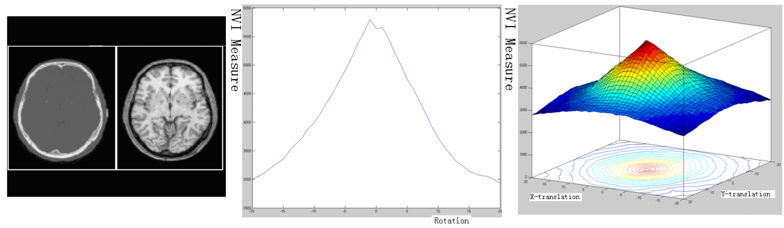



**Fig. 2.** T1, T2 MRI images[2] and their corresponding NVI images are presented. (a) Every location in the image has an isosurface and its normal vector. (b) NVI images of (a) images but does not include the “normal” and arrow.

We use CT-MRI images to show the distribution of the similarity value by rotating from -20 degree to 20 degree and x, y-axis each translating from -20 to 20 pixels. The metric formula used to calculate the similarity value is the formula (1) provided in section 2.2, and parameter e is set to 2. Fig.3 shows that the NVI metrics have only one maximum value; and all the curves or surfaces plotted against rigid transform parameters are quite smooth. We can expect that optimizers used in looking for an optimal value in NVI registration might be much easier and simpler to implement

[2] These two images are from Insight Toolkit example data. (www.itk.org)

because the perfect feature of the metric. Next section we will demonstrate the advantages using two registration experiments.




(a) (b) (c)

**Fig. 3.** The value distribution of CT-MRI images similarity by NVI metric against rigid transformation. (a) CT-MIR images both in size of 125*125 (b) value plotted against rotation (c) value plotted against x, y axes translation.

## 3 Registration Experiments

In this section we demonstrate medical image registration by NVI metric. Our experiments are based on MS Visual C++ environment and running on a P-IV 2.60 GHz PC, 1.0GB main memory, MS Windows XP.

In our experiments, we adopt bi-linear interpolation when needed and only consider rigid transformation. We use regular gradient descent as the optimizer. We adopt $\partial S/\partial(T)=(S(T_{+1})-S(T_{-1}))/(T_{+1}-T_{-1})$ to approximately compute derivative of S against transformation parameters. This method makes our experiments much easier to implement and the learning rate of each parameter could be set almost the same. The NVI metric formula we provided in section2.2 has the parameter value 2 which is our best experimental value. Here we offer T1 MRI to T2 MRI and CT to MRI registration experiments. The two MRI images employed in this experiment are shown in Fig.2 (a), which are both in size of 221*257. The CT-MRI images employed in this experiment are shown in Fig.3 (a), which are both in size of 125*125. The maximal iterations in both cases are set to 200 steps when the learning rate set to 0.01 for translation parameter, and 0.01 for rotation parameter in T1-T2 MRI example. In CT-MRI example, learning rate is 0.001 for both translation and rotation. The first step length of both examples is set to 5.

In each example, we performed a number of randomized experiments to determine the convergence, accuracy and efficiency. Mono-modality test data is reported in Table.1, multi-modality test data is reported in Table.2. In each example, the initial images are perfectly aligned. We use initial transform(X,Y, $\theta$ ) to establish a misaligned pose. Each 4 experiments (E1, E2, E3, E4) in the two examples have 50 times registration.

- In E1, X, Y translation scope randomly varies from 0 pixel to 10 pixels, angle of rotation randomly varies from 0 to 10 degree;
- In E2, X, Y translation scope randomly varies from 0 pixel to 30 pixels, angle of rotation randomly varies from 0 to 10 degree;

- In E3, X, Y translation scope randomly varies from 0 pixel to 20 pixels, angle of rotation randomly varies from 0 to 20 degree;
- In E4, X, Y translation scope randomly varies from 10 pixel to 20 pixels, angle of rotation randomly varies from 20 to 40 degree.

Initial and Results columns in Table.1 and Table.2 are the average value of the 50 time registration initial value and result value. Column Time offers how many seconds the average test takes in these experiments. Column Steps presents average steps of optimization in these experiments. Column Suc in the two tables means how many times succeed in registration in the 50 registration.

**Table 1.** Registration results of mono-modality images (MRI-MRI)

| E | Initial | | | Results | | | Time | Steps | Suc |
|---|---|---|---|---|---|---|---|---|---|
| | avgX | avgY | avg $\theta$ | avgX | avgY | avg $\theta$ | | | |
| E1 | 4.02 | 4.56 | 4.18 | 0.3372 | 0.3106 | 0.3140 | 10.0 | 6.7 | 50 |
| E2 | 13.62 | 12.28 | 3.9 | 0.3036 | 0.2778 | 0.3222 | 9.8 | 6.7 | 48 |
| E3 | 8.92 | 10.06 | 10.5 | 0.3682 | 0.2622 | 0.3602 | 10.04 | 6.9 | 50 |
| E4 | 13.94 | 14.08 | 31.36 | 0.3308 | 0.3042 | 0.3200 | 8.52 | 5.82 | 50 |

**Table 2.** Registration results of multi-modality images (CT-MRI)

| E | Initial | | | Results | | | Time | Steps | Suc |
|---|---|---|---|---|---|---|---|---|---|
| | avgX | avgY | avg $\theta$ | avgX | avgY | avg $\theta$ | | | |
| E1 | 4.64 | 4.44 | 5 | 0.5395 | 0.5873 | 0.3640 | 10.38 | 30.2 | 50 |
| E2 | 16.76 | 14.38 | 4.92 | 0.5672 | 0.6289 | 0.3631 | 13.34 | 39.14 | 50 |
| E3 | 9.18 | 9.36 | 8.8 | 0.5679 | 0.6160 | 0.3570 | 13.1 | 38.44 | 50 |
| E4 | 14.44 | 14.68 | 30.48 | 0.5493 | 0.6609 | 0.3690 | 22.48 | 67.72 | 50 |

As shown in Table 1, the result of the experiments demonstrates that the alignment procedure is reliable, accurate and efficient in MRI-MRI medical images registration. In Table 2, the result of multi-modality registration is almost as good as that of mono-modality. The accuracy and robustness are nearly equal to the first example. Average time consumption and steps in each experiment are much more than that in mono-modality. The reason is the NVI that effectively used in similarity computing is less in multi-modality registration and the gradient of metric distribution is less steep than that of mono-modality.

## 4 Conclusion

In this paper, we presented a new conception to evaluate the similarity between images. Compared to other existing metrics, NVI metric has an excellent smooth value distribution plotted against transformation, and its optimal value is almost unique so that the optimization work can be easily implemented. Furthermore, NVI criterion is not restricted to mono-modality registration and has an outstanding performance in multi-modality domain as well.

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## References

1. Gu, L.: Dynamic Heart Modeling Based on a Hybrid 3D segmentation Approach. In: Yang, G., Jiang, T. (eds.): Medical Imaging and Augmented Reality. Lecture Note and Computer Science, Vol. 3150. Springer (2004) 237-244
2. Xu, J., Gu, L.: Evaluation of Morphological Reconstruction, Fast Marching and a New Hybrid Segmentation. In: Zhang, J., He, J. (eds.): Computational and Information Science. Lecture Notes in Computer Science, Vol. 3314 (2004) 678-684
3. Brown, L.G.: A Survey of Image Registration Techniques. ACM Comput. Surv., Vol. 24 (1992) 325-376
4. Viola, P., Wells III, W.: Alignment by Maximization of Mutual Information. International Journal of Computer Vision, Vol. 24(2) (1997) 137-154
5. Mattes, D., Haynor, D.R., Vesselle, H., Lewellen, T., Eubank, W.: Nonrigid multimodality image registration. In: Sonka, M., Hanson, K.M. (eds): Medical Imaging 2001: Image Processing, Vol. 4322. SPIE Press, Bellingham, WA (2001) 1609-1620
6. Mattes, D., Haynor, D.R., Vesselle, H., Lewellen, T., Eubank, W.: PET-CT Image Registration in the Chest Using Free-form Deformations. IEEE Transactions in Medical Imaging, Vol. 22, No.1 (2003) 120-128
7. Thevenaz, P., Unser, M.: Optimization of Mutual Information for MultiResolution Image Registration. IEEE Transactions in Image Processing, Vol. 9, No. 12 (2000) 2083-2099
8. Ng, L.: Overview: ITK Registration Methods. SPIE2004: Medical Image Segmentation and Registration With ITK (2004)
9. Hoehne, K.H., Bernstein, R.: Shading 3D-Images from CT Using Gray-Level Gradients. IEEE Trans. Medical Imaging, Vol. MI-5, No. 1 (1986) 45-47