Brain Misalignment Correction Based on Vascular Structures Segmentation in Tumor Surgery using Normalized Gradient Field

Elisée Ilunga Mbuyamba

Universidad de Guanajuato, División de Ingenierías, Campus Irapuato-Salamanca, Carretera Salamanca Valle de Santiago km 3.5+1.8, Comunidad de Palo Blanco, 36885 Salamanca, GTO, México

e.ilungambuyamba@ugto.mx

Juan Gabriel Aviña Cervantes

Universidad de Guanajuato, División de Ingenierías, Campus Irapuato-Salamanca, Carretera Salamanca Valle de Santiago km 3.5+1.8, Comunidad de Palo Blanco, 36885 Salamanca, GTO, México

avina@ugto.mx

Abstract

A possible treatment of brain tumor consists in a surgery performed by neurosurgeons who open the skull (called craniotomy). By navigating through the brain, they reach the tumor tissues and try to remove the maximum possible. The task is tricky because of the small operation field delimited by the craniotomy, also because of the difficulty to differentiate the brain healthy tissue surrounding the tumor and the brain misalignment that occurs. An additional tool for intraoperative imaging represents therefore a crucial element to guide the navigation through the brain safely and improve the resection task. Based on blood vessels segmentation, we proposed a methodology for the correction of brain displacement during resection. This misalignment of the brain was resolved by using a Normalized Gradient Field (NGF) that allows to register segmented vessels with a good accuracy. After to test our method on data phantom and patient data, the result were validated in an average of 90%.

Key Words: Brain misalignment, brain tumor, image segmentation, vascular structures.

1. Introduction

The surgery of brain tumor is widely supported by image-guided surgery to provide critical information and to increase the accuracy in this task. The navigation system allows to match preoperative data (MRI: Magnetic Resonance Image, CT: Computed Tomography) with a physical space and its tracking system enables to locate the points on a patient in the image via a pointer [1-3]. During surgery the use of the navigation system become inaccurate because of the misalignment of the brain, and several techniques was proposed to correct this problem [4-7]. The segmentation of anatomical structures like blood vessels was proposed in [8, 9] to compensate the brain shift using Doppler ultrasound (Doppler US) and preoperative MRA (Magnetic Resonance Angiography) data. Intraoperative ultrasound imaging is preferred with respect to other intraoperative imaging modalities because of its low price and its simplicity [10].

In the context of blood vessels used as pattern for driving registration, several techniques was introduced for segmentation propose. The simplest approach for segmentation is the thresholding [11, 12] followed by its sophisticated version, region growing [13]. The first method suffer of many drawbacks such as: it fails in the presence of smooth edge, of varying intensity and sensible to the noise. The second one has the problems of leakage when the boundary is blurred and the difficulty to set a threshold value confining the target. To overcome the limitation of the firsts methods, several techniques are used such as hybrid genetic algorithm and Artificial Neural Network Fuzzy (ANFIS) [14] in brain tumors segmentation, graph cut with shape priors [15, 16] and active contour model introduced by [17] which used an explicit type of curve representation. The level set approach [18] was proposed to address the curve parameterization issue of the last method. Vessels segmentation is achieved also by using the Hessian operator as presented by Frangi in [19].

In this work, we used segmented vascular structures in preoperative cT1MR (contrast T1-weighted MR) and iCEUS (intraoperative Contrast Enhancement Ultrasound) images to correct the brain misalignment with respect to the initial registration performed with the navigation system. This paper is organized as follows: section II describes the blood vessels segmentation, the similarity measure used to correct brain misalignment and the proposed methodology. The section III presents the results of tests performed on the patient data. The last one concludes the analysis.

2. Methods

2.1. Correlation Coefficient (Normalized Cross Correlation)

Also called Pearson's correlation coefficient, it is defined as:

$$NCC = \frac{1}{\sigma_x \sigma_y} \sum_i (x_i - \bar{x})(y_i - \bar{y}) \qquad (1)$$

Where $\bar{x}$ and $\bar{y}$ are respectively the mean of image X and Y. On the other hand, σ_x and σ_y are the standard deviations X and Y.

2.2. Mutual Information (MI)

Based on information theory, mutual information evaluates the statistical dependence between two image intensity distributions. It should reach the maximal value when the two images to register are correctly aligned. In information theory, entropy is defined as the measure of the uncertainty in a random variable and the Shannon entropy is defined as:

$$H(X) = -\sum_i^n p_i \log p_i \qquad (2)$$

Where $H(X)$ is called the entropy of the random variable X and p_i the probability mass function.

The mutual information $MI(X,Y)$ between two random variables X and Y is described as:

$$MI = H(X) + H(Y) - H(X,Y) \qquad (3)$$

$$H(X,Y) = -\sum_{i,j} p(x_i, y_j) \log p(x_i, y_j) \tag{4}$$

Where $H(X,Y)$ called Joint entropy of X and Y images.

2.3. Normalized Gradient Field (NGF)

Assuming that two images are considered to be similar, if intensity changes occur at the same locations, the Normalized Gradient Fields (NGF) has been proposed by [20].

The NGF is calculated as follows

$$n(I,x) = \begin{cases} \dfrac{\nabla I(x)}{\|\nabla I(x)\|} & \nabla I(x) \neq 0 \\ 0 & otherwise \end{cases} \tag{5}$$

Where $\nabla I(x)$ is the gradient of the image $I(x)$.

By considering two related points x in X (fixed image) and T(x) in Y (moving image), the NGF similarity measure is based on the angle formed by the two resulting vectors n(X, x) and n(Y, x). Since the gradient fields are normalized, the inner product (dot-product) of the vectors is related to the cosine of this angle, while the norm of the outer product (cross-product) is related to the sine.

The alignment analysis is validated by the distance measures:

$$d^c(Y,X) = \|n(X,x) \times n(Y,x)\|^2 \tag{6}$$

$$d^d(Y,X) = < n(X,x), n(Y,x) >^2 \tag{7}$$

Where d^c and d^d are respectively the cross-product and the dot-product.

2.2. Methodology proposed

Since a brain displacement occurs after the craniotomy and during tumor resection, the correction of the initial registration is required. The vascular structures was used as a reference to achieve the correct alignment during surgery. The first tests have been performed on the phantom data. With a CEUS image a little misaligned to the CT image, we used the vascular structures to perform the alignment. The method consist firstly by a segmentation of vascular structures in both modalities, and followed by a registration task of these segmented elements. The registration provided a transformation matrix that allows the overlapping of images. When this matrix is applied to the CT image, the alignment error converge to zero. The methodology for correcting the brain shift is illustrated in the Fig. 1. The registration on the second step has been performed using the Normalized Gradient Field (NGF) as similarity measure.

This correcting process can be described as follows:

1. Manually definition of the Region of interest (ROI) on the images,
2. Define the Threshold value by the user and compute the segmentation,
3. Start the registration of the segmented structures using a NGF,
4. Display the final solution.

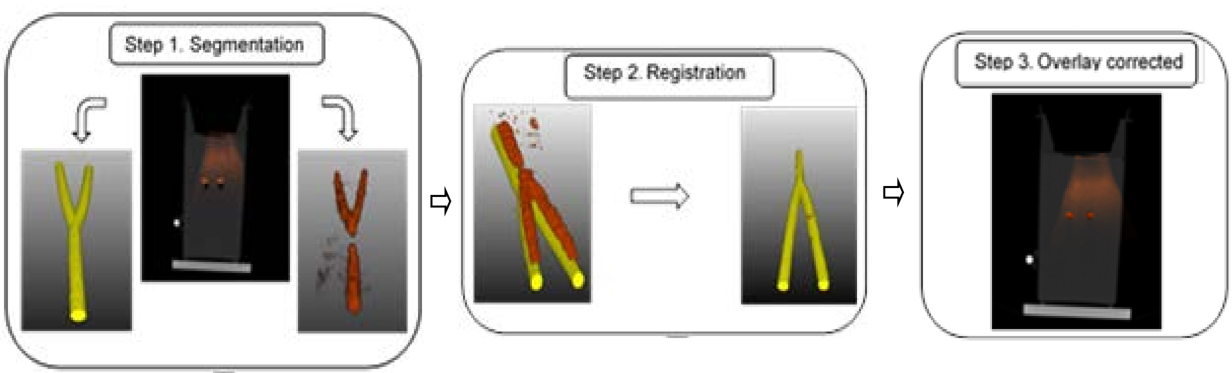
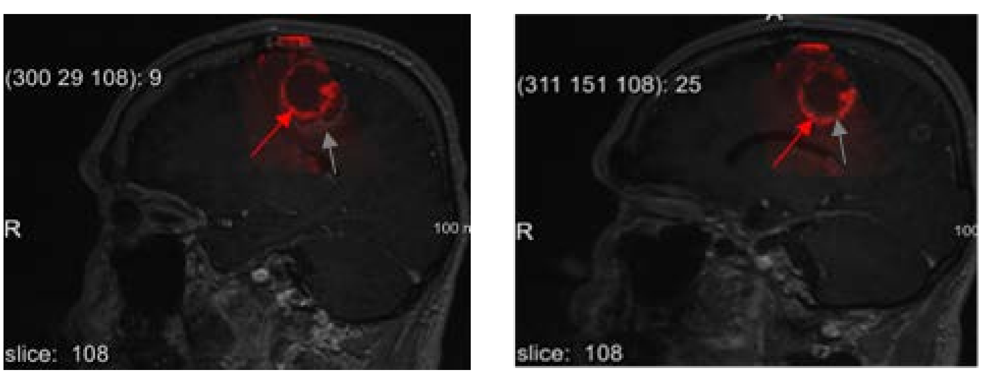


Fig. 1. Proposed methodology for correcting misalignment.

3. Results

This section shows the results obtained in each application, and the implementation was done with an Intel Celeron, 1.5 Ghz and 2 GB of memory. The algorithms have been implemented using MeVisLab tool and ITK C++ (Insight Segmentation and Registration).

Since the brain shift can be corrected using blood vessels, the Fig. 2 presents a result obtained with patient data. At the same position or slice, the Fig. 2 (a) shows the misalignment between the cT1MR image and the CEUS data occurred during brain tumor resection. By applying the method of vessels-based registration to correct the brain shift, the obtained result is illustrated in the Fig. 2 (b). The brain misalignment is observed by the non-overlapping of tumor margins in intraoperative cT1MR image compared to the intraoperative CEUS image.



(a) (b)

Fig. 2. (a) Overlay of cT1MR and iCEUS data with brain displacement, (b) cT1MR and iCEUS data superimposed after the brain misalignment correction based on blood vessels.

The Frangi vesselness filter followed by the Otsu thresholding and the region growing methods provided a good result of segmentation. Basing of the extracted blood vessels within the ROI defined in the images, they was used to carry out the registration. The segmented vessel in cT1MR is merged with the CEUS image in the Fig 3.

The first row shows how the concerned vessel are misaligned in the both images, and the second one illustrates how they are matched after our proposed method.

The correct overlapping of anatomical structures, especially of the vessels, was not only visually checked, but it was also validated with the Jaccard index $J(A,B)$ and the Dice index $D(A,B)$ adopted as metrics. In the table 1 the comparison of metric results are compared. Due to the difference of images compared, cT1MR and CEUS, the good result of overlaying will not be represented by 100%. The reference is considered as the result obtained by the expert and it represents the best superimposing result that could be achieved.

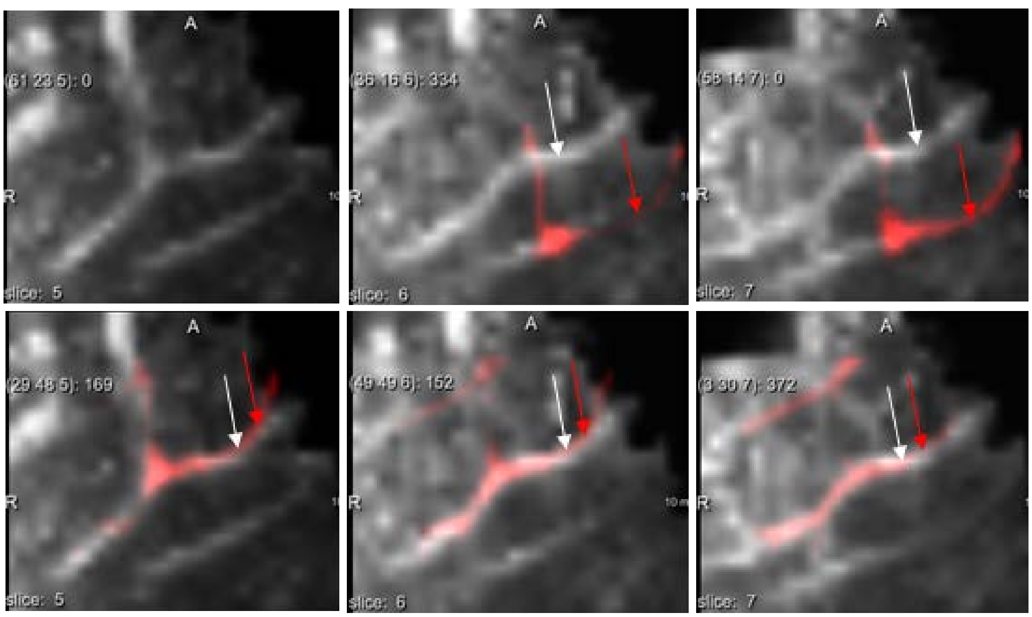


Fig. 3. In the first line: segmented MRI vessels in red are merged with CEUS image misaligned. The second line present the result obtained after the correction.

$$J(A,B) = \frac{A \cap B}{A \cup B} \quad (8)$$

$$D(A,B) = \frac{2(A \cap B)}{A + B} \tag{9}$$

Comparative Studies	Jaccard Index (%)	Dice index (%)	Processing time (s)
NGF vs Expert	91,73%	91,74%	28,6
NMI vs Expert	70,39%	70,40%	6,966666667
NCC vs Expert	62,42%	62,37%	10

Table 1. The NGF, NMI and NCC results are compared with the result of the expert.

4. Discussion

Considering in this study vascular structures marked by a bifurcation or some angles, the NGF similarity measure performs the registration of blood vessel with a high accuracy than the others, but it is computationally expensive. Even in presence of a poor quality of the medical image, NGF is still robust. According to the application, the NMI is a good alternative in computation time by keeping an acceptable accuracy of the result.

5. Conclusions

Various approaches are used to align preoperative image with intraoperative data for increasing accuracy in surgery task. In this work, a method based on segmentation of vascular structures have been presented in the context of brain tumor surgery. In the obtained results, the use of blood vessels as a reference patterns and the NGF have shown the capability to correct the misalignment of cerebral structures. Despite its computing long time, the NGF is robust to perform the registration of vessels in presence of noises. The choice of a bifurcation is an advantage for this similarity measure. Based on the computing of angles, it achieve the good performance when other methods fail.

Acknowledgements

This work has been supported by the National Council of Science and Technology of Mexico (CONACYT) under the grant number 493442. We are also thankful to the concyteg and the "Programa Integral de Fortalecimiento Institucional 2012 (PIFI-2012)" for their support to this work. The authors would like to thank the University Hospital, department of Neurosurgery, Universität Leipzig in Germany for the collection of data.

6. References

[1] Watanabe E, Watanabe T, Manaka S, Mayanagi Y, Takakura K. Three dimensional digitizer (neuronavigator). Surg Neurol 1987; 27:543–547.

[2] Kato A, Yoshimine T, Hayakawa T, Tomita Y, Ikeda T, Mitomo M, Harada K, Mogami H. A frameless, armless navigational system for computer-assisted neurosurgery. J Neurosurg 1991; 74:845–849.

[3] Reinhardt H, Trippel M, Westermann B, Gratzl O. Computer aided surgery with special focus on neuronavigation. Comput Med Imaging Graph 1999;23: 237–244.

[4] A. Hagemann, K. Rohr, H.S. Stiehl, Coupling of fluid and elastic models for biomechanical simulations of brain deformations using FEM, Medical Image Analysis, Volume 6, Issue 4, December 2002, Pages 375-388, ISSN 1361-8415.

[5] Prashanth Dumpuri, Reid C. Thompson, Benoit M. Dawant, A. Cao, Michael I. Miga, An atlas-based method to compensate for brain shift: Preliminary results, Medical Image Analysis, Volume 11, Issue 2, April 2007, Pages 128-145, ISSN 1361-8415.

[6] Oskar Škrinjar, Arya Nabavi, James Duncan, Model-driven brain shift compensation, Medical Image Analysis, Volume 6, Issue 4, December 2002, Pages 361-373, ISSN 1361-8415.

[7] Songbai Ji, Alex Hartov, David Roberts, Keith Paulsen, Data assimilation using a gradient descent method for estimation of intraoperative brain deformation, Medical Image Analysis, Volume 13, Issue 5, October 2009, Pages 744-756, ISSN 1361-8415.

[8] I. Reinertsen, F. Lindseth, G. Unsgaard, D.L. Collins, Clinical validation of vessel-based registration for correction of brain-shift, Medical Image Analysis, Volume 11, Issue 6, December 2007, Pages 673-684, ISSN 1361-8415.

[9] I. Reinertsen, M. Descoteaux, K. Siddiqi, D.L. Collins, Validation of vessel-based registration for correction of brain shift, Medical Image Analysis, Volume 11, Issue 4, August 2007, Pages 374-388, ISSN 1361-8415.

[10] Comeau, R.M., Sadikot, A.F., Fenster, A., Peters, T.M., 2000. Intraoperative ultrasound for guidance and tissue shift correction in image-guided neurosurgery. Medical Physics 27 (4), 787–800.

[11] Sahoo, P. K. et al., "A survey of thresholding techniques," Computer Vision, Graphics, and Image Processing, 41: 233-260 (1988).

[12] M. Usman Akram, Shoab A. Khan, “Multilayered thresholding-based blood vessel segmentation for screening of diabetic retinopathy”, Engineering with Computers, 2011

[13] B. E. Chapman, J. O. Stapelton, and D. L. Parker, “Intracranial vessel segmentation from time-of-flight MRA using preprocessing of the MIP Z-buffer: accuracy of the ZBS algorithm,” Medical Image Analysis, vol. 8, no. 2, pp. 113–126, 2004.

[14] Minakshi Sharma and Sourabh Mukharjee, “Brain Tumor Segmentation using hybrid Genetic Algorithm and Artificial Neural Network Fuzzy Inference System (ANFIS),” International Journal of Fuzzy Logic Systems (IJFLS), Vol.2, No.4, October 2012.

[15] Hui Wang and Hong Zhang, “Adaptive shape prior in graph cut segmentation,” in proceeding of the 17th IEEE International Image Processing, (ICIP 2010), pp.3029-3032, Sept 2010.

[16] N. Vu and B.S. Manjunath, “Shape prior segmentation of multiple objects with graph cuts”, in proceeding of IEEE Conference on Computer Vision and Pattern Recognition, (CVPR 2008), pp.1-8, June 2008.

[17] Kass, M., Witkin, A., Terzopoulos, D.,”Snakes: Active contour models”, International Journal of Computer Vision 1(4) (1988) 321-331.

[18] Ravi Malladi, James A. Sethian, Baba C. Vemuri, “Shape Modeling with Front Propagation: A Level Set Approach”, IEEE Trans. Pattern Anal. Mach. Intell. 17(2): 158-175 (1995).

[19] Alejandro Frangi, WiroNiessen, Koen Vincken, and Max A. Viergever, “Multiscale vessel enhancement filtering”, Medical Image Computing and Computer-Assisted interventation, MICCAI 98, pages 130–137, 1998.

[20] Haber E. and Modersitzki J., “Beyond mutual information: A simple and robust alternative”. Bildverarbeitung fur die Medizin 2005, ser. Informatik Aktuell, A. H. Hans-Peter Meinzer, Heinz Handels and T. Tolxdorff, Eds. Springer Berlin Heidelberg, 350-354, 2005.

7. Authors

Ing. Elisée Ilunga Mbuyamba es Ingeniero en Computación por la Universidad ISTA República Democrática del Congo.

Dr. Juan Gabriel Avina Cervantes, Doctor en Informática y Telecomunicaciones, Institut National Polytechnique de Toulouse.