Proceedings of the World Congress on Electrical Engineering and Computer Systems and Science (EECSS 2015)
Barcelona, Spain – July 13 - 14, 2015
Paper No. 310

Quantitative Evaluation of Skull Stripping Techniques on Magnetic Resonance Images

Farahnaz Hosseini, Hossein Ebrahimpourkomleh
Department of Computer Engineering,University of Kashan
6KM ghotbravandiBlvd,Kashan, Iran
farahnazhosseini@grad.kashanu.ac.ir;Ebrahimpour@kashanu.ac.ir

Mehrnaz KhodamHazrati
Department of Electrical and Computer Engineering,University of Florida
Gainesville, Fl. USA
m.hazrati@ufl.edu

Abstract -Magnetic resonance (MR) brain images are often employed to diagnose diseases or to detect abnormalities such as brain tumors inhuman beings. Whole brain segmentation, also known as skull stripping, is an essential pre-processing step to reduce unwanted information and to remove non-brain backgrounds from these images. Automated and intelligent skull stripping techniques can facilitate and expedite the entire process of extracting accurate diagnostic information from MR images. This paper presents a nonparametric approach to quantitatively evaluate the skull stripping methods such as brain surface extractor (BSE), brain extraction tool (BET) and a new approach based on the wavelet transform. We applied these methods to three datasets obtained from Sina and Beheshti hospitals in Iran for detecting and eliminating the skull region. By calculating the Hausdorff distance between each image and the manually segmented image as a gold standard, we provide a qualitative framework to compare the performance of the three algorithms.

***Keywords*:** Human brain images, MRI, Skull stripping, Hausdorff distance, Wavelet transform, BET, BSE.

1. Introduction

Magnetic Resonance Imaging (MRI) is an extremely valuable tool for detection of brain abnormalities such as brain tumors. Artefacts and undesired tissues affect the quality of processing and may lead to diagnostic confusion. Thus, one of the important steps in the processing of brain images is skull stripping where the brain tissue is completely segmented from the skull. It is done for the purpose of clearing away non-brain backgrounds and reducing unwanted information from the MR images.

Since the manual segmentation is very time consuming and prone to errors, various methods have been developed to automatically remove extra-cerebral tissues without human intervention. In recent years, several semi-automatic and automatic skull stripping techniques were introduced in the literature. Approaches such as brain extraction tool (BET) (Smith, 2012), the brain surface extractor (BSE) (Shattuck et al, 2001), and the hybrid watershed (HWA) (Segonne et al, 2004) have been applied widely for this purpose.

In general, the automatic skull stripping can be categorized into three major methods: morphology, deformable model and intensity based methods. There are a few certain metrics that are used to evaluate the performance of the segmentation algorithms. The segmentation accuracy indices such as Tanimoto coefficient or correlation are usually used to evaluate the general performance of a method. A threshold value is mainly applied using the Otsu method (Otsu, 1979) which minimizes the within-class variance between two classes. We conducted a comprehensive literature review on the available methods to study the comparison factor.

Atkins et al. (1998) proposed a method based on the regionthat integrates anisotropic diffusion filtering, gray level thresholding, binary morphology and active contour models snakes. Their method created a mask based on a threshold that was determined by fitting a single Gaussian curve to the histogram of the image.Two images, weight T1 and T2, was tested. The accuracy of their method depends on the threshold value, and with choosing the threshold equal to 0.5 for T1 weighted images, their method worked better than the image intensity alone.

Boesen et al. (2003) compared four methods of skull stripping (McStrip, SPM, BET, and BSE). Based on their comparison, BSE and BET were faster than SPM and McStrip. Skull stripping in SPM is performed by masking out the brain region after calculating a threshold based on both gray and white matter of the brain image. When compared to McStrip manual operation, it showed higher accuracy on T1 images.

A technique was introduced by Ségonneet al. (2004)for skull stripping based on watershed algorithm and deformable surface. They computed different coefficients to compare the performance of various segmentation techniques. Risk evaluation and Jaccard similarity were used to evaluate their method which is a measure of probability of a miss and probability of false detection. Later, Ségonneet al (2014) provided a very simple but powerful method for skull removal. Their method is based on the combination of watershed algorithm and deformable to determine the boundary of the brain in the T1 images.

Forkert et al. (2008) introduced a method which contains three main steps: 1) The first phase contains pre-processing and noise removal, 2) In the second phase, extracted boundary points of the brain are calculated, 3) The third phase is the correction method. They used 18 data sets automatically and the average segmentation accuracy was 99.18%.

Somasundaramet al. (2010) came up with a method based on clustering for detecting the brain boundaries inside the skull. A 2D growing scheme was used to connect together the clusters and also remove the skull area.Prasad et al (2011) applied deformable organism scheme to successfully stripped skull using images T1 weight. Speier et al (2011) used Robex method for skull stripping. Their results showed this method was better than BSE, BET and HWA. They used T1 weight images taken from Glioblastoma patients. Wang et al (2011) proposed a method, a combination of Atlas, and a deformable method. Galdameset al. (2011) presented a skull stripping based on deformable model and histogram analysis. Their method is applied in two steps: pre segmentation and the deformable method which is based on thresholds and morphological operator.

Balanet al. (2012) proposed a method based on histogram analysis and compared the segmentation accuracy between their proposed method and two widely used techniques, namely BSE and BET. Based on this factor, they reported that their proposed method outperforms these methods. Pratibha(2013) compared two methods of skull stripping (BET, BSE) over two datasets containing T1, T2. They showed that BSE outperforms BET in segmentation of brain images.

In 2013, Roy et al. presented a simple and effective automatic skull removal method that comprises of both statistical and computational elements. This paper evaluatesa modified version of fully automated parameter free approach proposed by (Roy et al, 2013) and compared it with already established methods using three different datasets. The proposed method is able to detect the boundary of the brain and to separate brain from skull and background areas with a high acceptance rate. The algorithm is based on wavelet transformation and the convex hull algorithm.

The aim of this work is to present a quantitative measure to evaluate the available algorithms. Here, we suggest that the Hausdorff distance between each image and a gold standard provides useful information to quantitatively evaluate each method. Finallywe compared the performance of the above algorithm as well as BSE and BET methods in a qualitative way.

2. Datasets

Three different datasets were used in this study. These databases contain 21, 20 and 11 slices of brain MR images, respectively. They are standard datasets in the axial imaging which have been provided in Sina and Beheshti hospitals of Iran.

3. Skull Stripping Algorithms Brain Extraction Tools

This paper evaluated and compared three different types of brain extraction tools, namely, brain surface extraction (BSE), brain extraction tool (BET), and a modified version of the recently introduced wavelet-based approach linked to convex hull algorithm

3. 1. Brain-surface Extraction Software (BSE)

BSE applies a series of mathematical morphological operators to the edge map found in the edge detection step before detecting the brain region. The first step is called erosion with a 3D cross element, which expands the edges into each voxel that shares a face with an edge voxel. The result is that small connections less than 2 voxels wide will break. For images with resolution of 1mm, this corresponds to a 2mm structure. This is sufficient to erode most cranial nerves and to eliminate most noise related connections between the brain and scalp portions of the MRI. With finer resolution images, it may be necessary to increase the erosion size up to 2 in order to separate the brain. In the next step, BSE segments the eroded edge map into several connected regions that are bounded by the edges. BSE then analyses these regions to select a candidate brain region based on the size of the connected region, the average intensity of the connected region and the position of the centroid of the connected region. Here BrainSuite software is used to extract and parameterize the inner and outer surfaces of the cerebral cortex and to segment and label grey and white matter structures. This software can automatically process magnetic resonance images. This tool can remove none brain particles from the brain (Web-1).

3. 2. Brain Extraction Tool

Brain Extraction Tool or BET was introduced by Smith (2002) as an accurate and robust method which utilizes an automatically evolving deformable model to fit the brains' surface. The algorithm finds intensity values in images and defines a threshold for separating brain and none brain areas. By calculating the intensity histogram, values with the highest and lowest intensity in images are found and consequently a threshold is defined. In the next step, a triangular tessellation of a sphere's surface is initialized inside the brain, and allowed to slowly deform, one vertex at a time.If this step doesn't clean surface satisfactory, then the algorithm runs again by a higher smoothness constraint. Finally, the outer surface of the skull is removed (Pratibha, 2013).In this study, we used Mango (Multi-image Analysis GUI)which is a famous viewer and analytical tool for segmentation of brain. The BET plug in installed in this program was used to strip of skull in our datasets.

3. 3. Wavelet-based Approach

We have modified the algorithm introduced in (Huttenlocher et al, 1993),in order to find the best stripped image based on a quantitative measure along with brain extraction tools and brain surface extraction methods. This algorithm contains six steps: Bineralization, wavelet transformation, interpolation, labelling and filtering algorithm which is composed of convex hull. In this study, we compared the effect of different parameters to determine the optimum setting based on a quantitative measure. These steps are shown in Figure 1.

A) Binary image

   In the first step, the original image is binerized in order to remove background and grey levels. Bineralization decreases the size of the image and therefore speeds up the process of identifying the image in the next steps.

B) Applying wavelet algorithm

   In the original algorithm two-dimensional wavelet decomposition was applied using db1 wavelet. We studied a wide range of mother wavelets based on the original brain image and then applied the wavelet algorithm in two levels. It causes the unwanted information to be blurred in the image and also reduces the dimensions of the image.

C) Image interpolation
The image obtained after wavelet transformation has smaller size compared to the original image. In order to retrieve the original image size an interpolation step is required. The next step for identify the parts of the skull is labelling.

D) Labelling
This section is supposed to remove the additional places in the image. We have labelled the parts of the image so that all the adjacent parts and pieces are numbered. It also finds the largest label and sets it to zero. In other words, the brain is the greatest piece which is kept and the small pieces around the skull are eliminated.

E) Convex hull algorithm
In the last step, after labelling, the edges of the image that are soft get removed. We applied the convex hull algorithm on the image to perfectly extract the mask. Figure 1 demonstrates the algorithm of the skull stripping algorithm based on (roy et al, 2013).

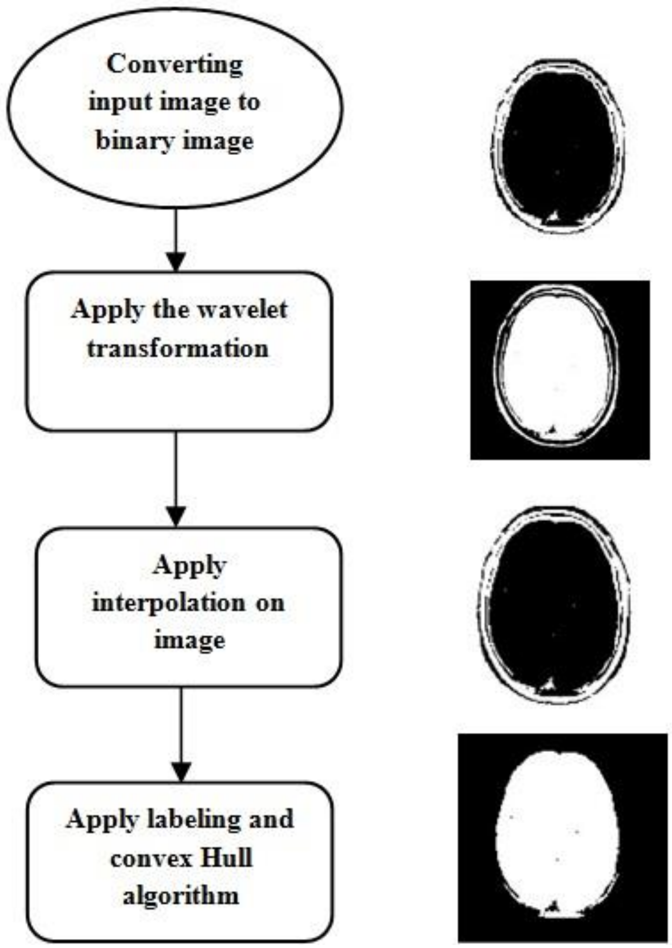

Fig. 1.Scheme of the skull stripping algorithm based on (Roy et al, 2013)

4. Convex Hull Algorithm

The smallest convex set which comprises *S* in the Euclidean space is convex hull of the set *S*of points. As a formal situation, the convex hull can be described as cross point all convex sets which consist *S* or as the convexes combinations of all dots in *S*. It can be visualized as a rubber stripe pulled around *S*when *S* is a bounded subset (Berg et al, 2000). According to the second description, convex hulls can be generalized by stretching from Euclidean spaces to true vector spaces (Knuth et al, 1992).

5. Hausdorff Distance

Hausdorff distance is a metric for gauging the closeness between two subsets in a metric space. Based on this definition, we have compared the distance between cleaned images and a reference image in our datasets. Sample images are shown in the result section. The calculated distance between two images can be interpreted as a similarity index. The mathematical definition is as follows (Agarwal et al, 2010):

Consider two sets A and B.A*B→ R that Distance between components in the sets of A and B are considered. For a ∈ A every member of the set B is considered and also for every member of the set B, b∈ B to the set Hausdorff distance is calculated.

The Hausdorff distance directional between A and B is defined as:

$$h(A,B) = sup_{a \in A}\, d(A,B)$$

And the Hausdorff distance between image A and image B is calculated as follows:

$$H(A,B) = max\ [h(A,B), h(B,A)]$$

The distance of each component calculates their Hausdorff with members of the other set, which is the minimum Hausdorff distance. One of the weaknesses of Hausdorff distance is being sensitive to outliers in the data. One of the possible methods of root-mean-square is the Hausdorff distance between images A and B which is determined by:

$$h_R(A,B) = \frac{\int_A (d^2(a,B)da)^{1/2}}{\int_A da}$$

Where A is the automatically skull stripped region and B is the brain region of the manually stripped image. In order to calculate the maximum distance:

$$h_R(A,B) = max\{h_R(A,B), h_R(B,A)\}$$

Finally, Hausdorff distance is calculated:

$$h_s(A,B) = \frac{\int_A (d(a,B)da)}{\int_A da}$$

6. Result and Discussion

In this article, the skull region and non-brain background have been removed by applying three selected methods. Skull stripping results are illustrated in Figure 2 for sample images from each dataset. The results of BSE show that some of non-brain tissues are not skull stripped. According to given parameters as can be visualized in Figure 2, BET removed the skull of the brain better than BSE. Table 1 describe metrics used for the following tests. Table 2 shows comparison metrics for BET and BSE and db1-wavelet on Hausdorff distance. Table 1 shows the parameters used for BSE and BET.

In the first dataset, the db1 wavelet method has not been able to remove the skull perfectly from all images and also as shown above, it has not done perfectly the removal of the skull in the second dataset which is one of the drawbacks of this method. As shown in Table 2, the average Hausdorff distances using BET method are considerably smaller than the other two methods in dataset 2 which shows this method has successfully removed the skull. When comparing these three methods, it can be seen that BET outperforms BSE and db1 wavelet in segmentation of brain image. Figure 3 shows the comparison of brain extraction tools by the averaged Hausdorff distances over all three datasets. The results show that the wavelet based method was not able to fully detect and remove the skull in some images , however, the skull in some images was perfectly stripped.

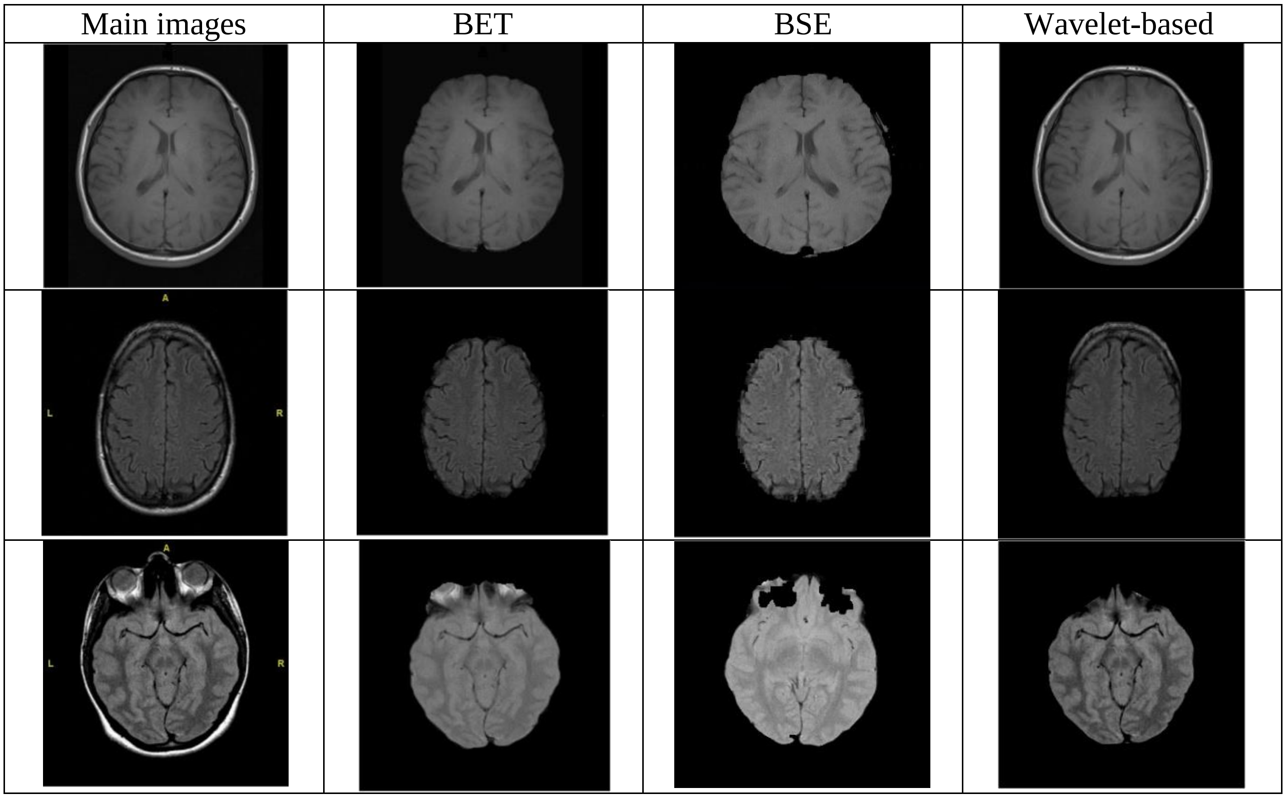

Fig. 2. Illustration of skull stripping results on sample images from each dataset. First column shows the input images ($I_{1,2,3}$) and the second column shows the results of BET method and the third column shows BSE results and finally the last column shows the results of wavelet-based approach.

Table.1. Parameters used in the comparative evaluation

Parameters	***Dataset 1***	***Dataset 2***	***Dataset 3***
Diffuse iterations	3	3	3
Diffuse constant	25	25	25
Edge constant	0.5	0.45	1.02
Erosion size	1	1	1
Fractional intensity Threshold	0.5	0.5	0.5

Table. 2. Comparison of BET, BSE and Wavelet method based on Hausdorff distance (mean value)

Data	***BET***	***BSE***	***Wavelet***
Image I_1	0.7559	0.8178	0.8070
Image I_2	1.5374	1.5374	1.5555
Image I_3	0.8261	0.9856	0.8261

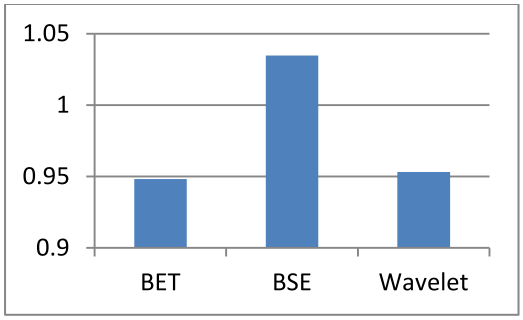

Fig. 3. Comparison of brain extraction tools by the averaged Hausdorff distances over all three datasets

7. Conclusion

Brain segmentation is widely used as the main step in analyzing brain images. Fully automated skull stripping helps extract fast and accurate diagnostic information; however, it can only be realized through robust and reliable processing algorithms. This paper evaluated and compared three different types of brain extraction tools, namely, brain surface extraction (BSE), brain extraction tool (BET), and a modified version of the recently introduced wavelet-based approach linked to convex hull algorithm (Roy et al, 2013). Previously, we have studied the effect of using different mother wavelets in the latter method. Ultimately, we have selected a db1 mother wavelet.

To evaluate the performance of the segmentation algorithms we used the Hausdorff distance as a measure of similarity between the segmented image and the reference image. In average the wavelet-based approach showed the lowest Hausdorff distance in dataset 1 and a comparable value in two other datasets. There are a few segmentation accuracy indices such as Tanimoto coefficient or correlation that are usually used to evaluate the general performance of a method. A threshold value is required in most cases. Our measure is a parameter free index that can be used as a measure of segmentation accuracy on MR segmented images.

References

Agarwal, P. K., Peled, S. H., Sharir, M., & Wang, Y. (2010). Hausdor_ Distance Under Translation For Pointsand Balls. *Journal of the ACM*, V(N), 1-26.

Atkins, M.S., & Mackiewich, B.T. (1998). Fully Automatic Segmentation Of The Brain In MRI. *IEEE Trans. Med. Imaging*, 17, 98–107.

Balan, A.G. R., Marcela, A.J.M.T., Ribeiro, X., Marques, P. M. A., & Traina, C. (2012). Smart Histogram Analysis Applied To The Skull-Stripping Problem In T1-Weighted MRI. *Computers in Biology and Medicine*, 42, 509–522.

De Berg, M., van Kreveld, M., Overmars, M., & Schwarzkopf, O. (2000). *Computational Geometry: Algorithms and Applications*. Springer. 2–8.

Boesen, K., Rehm, K., Schaper, K., Stoltzner, S., Woods, R., & Rottenberg, D. (2003). Quantitative Comparison of Four Brain Extraction Algorithms. *Conf. on Functional Mapping of the Human Brain*, 19, (2).

Forkert, N. D., Säring, D., Fiehler, J., Illies, T., Färber, M., Möller, D., & Handels, H. (2008). Fully Automatic Skull-Stripping in 3D Time-of-Flight MRI Image Sequences. *Eurographics Workshop on Visual Computing for Biomedicine.*

Galdamesa, F.J., Jaillet, D.F., & Pereza, C.A. (2011). An Accurate Skull Stripping Method Based on Simplex Meshes and Histogram Analysis in Magnetic Resonance Images. *Rapport de recherche RR-LIRIS-019.*

Huttenlocher, D.P., Klanderman, G. A., & Rucklidge, W. J. (1993). Comparing Images Using the Hausdorff Distance. *IEEE Transactions on pattern analysis and machine intelligence*, 15(9).

Kass, M., Witkin, A., & Terzopoulos, D. (1987). Snakes: Active Contour Models. *Int. J. Comput. Vision 1*, 321–331.

Knuth, D.E., & Hulls, A. (1992). *Lecture Notes in Computer Science, 606.* Berlin: Springer Verlag. ISBN:3-540-55611-7.

Pratibha. (2013). Performance Evaluation of Skull Stripping Methods and Tools. *International Journal of Computer Trends and Technology,* 4(9).

Prasad, G., Joshi, A. A., Thompson, P. M., Toga, A .W., Shattuck, D. W., & Terzopoulos, D. (2011). Skull Stripping Eith Deformable Organisms. *IEEE Journal*, 978-1-4244-4128.

Roy, S., Nag, S., Maitra, I. K., & Bandyopadhyay, S. K. (2013). Artefact Removal and Skull Elimination from MRI of Brain Image. *International Journal of Scientific & Engineering Research,* 4(6), ISSN 2229-5518.

Ségonne, F., Dale, A. M., Busa, E., Glessner, M., Salat, D., Hahn, H. K., & Fischla, B. (2004). A Hybrid Approach To The Skull Stripping Problem In MRI. *ELSEVIER NeuroImage,* 22, 1060– 1075.

Shattuck, D.W., Sandor-Leahy, S.R., Schaper, K.A., Rottenberg, D.A., & Leahy, R.M. (2001). Magnetic Resonance Image Tissue Classification Using A Partial Volume Model. *NeuroImage,* 13(5), 856‑876.

Smith, S.M. (2002). Fast Robust Automated Brain Extraction. *Human Brain Mapping,* 17(3), 143‑155.

Somasundaram, K., & Siva Shankar, R. (2010). Skull Stripping of MRI Using Clustering and 2D Region Growing Method. *Image Processing NCIMP.*

Speier, W., Iglesias, J. E., El-Kara, L., Tu, Z., & Arnold, C. (2011). Robust Skull Stripping of Clinical Glioblastoma Multiforme Data. *G. Fichtinger, A. Martel and T. MICCAI, Part III, LNCS 6893,* 659–666.

Wang, Y., Nie, J., Yap, P., Shi, F., Guo, L., & Shen, D. (2011). Robust Deformable-Surface-Based Skull-Stripping for Large-Scale Studies. *G. Fichtinger, A. Martel, and T. Peters MICCAI , Part III, LNCS 6893,* 635–642.

Web sites:
Web-1: www.brainsuite.org