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Robust Brain MRI Segmentation for 3D Printing Applications

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Abstract: In this paper, we introduced a technique for efficient simulation, Optimization, and Replication of patient specific procedures and prosthetics for neurosurgery applications the recent advances in computing power and additive manufacturing have made possible. Two important applications are detection and applying additive manufacturing towards brain analogues are in vivo brain modelling and finite element modeling for brain injury simulation. The drawback of efficiently Segmenting imaging data for use in finite element model or 3D printing is still remained. In this, for efficient brain MRI segmentation , we are combining statistically based segmentation with partial differential equation based methods using neuromechanical models, in this we use non-linear filtering, k-mean clustering, active contour modelling techniques for segmentation of brain MRI images. The results of these processes lead us to simulate brain procedures and prosthetics on a patient level using segmented image

Keywords: MRI, non-linear filtering, k-mean clustering, Active contour modelling, postprocessing(erode, dilate), gamma filtering

I. INTRODUCTION

The main aim of our project is to segment the brain. In this, we efficiently segment the medical imaging data for the use in simulation modelling and statistical analaysis. Generally segmenting an image by using CT or MRI scan requires considerably time consuming and expensive, specialized software.

And many hours of work to segment a single image sequence. In image processing by segmenting a image in medical field have some challenges .The image is effected by noisy data, low contrast , and large variations between patients.

In the neurosurgery and neurology applications had made advances in finite element modeling and 3D printing have made possible for the accurate simulation and construction of patient specific brain models with clear images. However to generate a finite element surface models for 3D printing requires the efficient segmentation of brain MRI images. To segment the brain MRI images is difficult to segment because of low level contrast between the brain tissue ,and other surrounding tissue, cerebrospinal fluid which is present in brain. In this ,we are mainly concentrating on segmenting for 3D printing applications ,specially it is created for clear brain images (for patients).since this area is less developed in printing applicationS. However to generate a finite element surface models for 3D printing requires the efficient segmentation of brain MRI images.

II. LITERATURE SU RVEY

There are several segmentation techniques for segmenting the image they are (i) Statistical techniques in which fuzzy c mean is used. Since it can segment(fuzzy)the image effectively and also some other statistical techniques are more advanced and demands lot of computation.(ii) partial differential equation method in which active contour model is used for energy minimization and level set method. It is one of the most effective equation based technique in the partial differential equation .mathematically we can calculate the active contour model based on distance between two neuronsand minimizing the folding energ ,here we are using the latter model

The equation is given below

$$Ec/1-Vc^2(t4/12)\ d4v/ds2+ptcd2v/ds2=q$$

(iii)some of the deterministic models of EDGE detection based on wavelet transform or other transform methods in the wavelet method by taking the discreat wavelet transform of the image and combining this to find the edges in the image where as energy minimization methods is used to reduce the energy in edge contour.

III. PROPOSED METHOD

A few strategies for picture division have been genius postured, which can be generally isolated into factual systems and halfway

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differential condition based methods. The most prominent factual method is fluffy c-implies arrangement, since it can viably section the picture into independent classes of signal. Other measurable strategies are more cutting-edge and computationally concentrated, for example, convolutional neural systems. For fractional differential condition techniques, there are many models in view of vitality minimization and level set strategies. A standout amongst the best fractional differential condition based strategies is dynamic shape models, which fit spline with negligible vitality to the picture forms. There are additionally numerous deterministic models of edge location in light of wavelet change or other change techniques. Wavelet-based techniques work by taking the discrete wavelet change of the picture and consolidating these to discover the edges in the picture, while vitality minimization strategies regard the edge form as an adaptable plate and look to limit its vitality.

A. Technical Approach and Mathematical Framework

1) *Active Contour Model:* Dynamic form models look to limit the vitality standard of the shape. Since cortical collapsing will actually likewise look for the locally insignificant vitality state, there is an inborn association between dynamic forms and cortical collapsing. Since parameterizing a shape turns out to be computationally troublesome because of conceivable topological changes in the form as it develops between emphasess, we rather utilize a level set approach from and regard the shape as the zero level arrangement of higher measurement work _:

V(s)={(x,y)|(t=0,x,y)=}

$$\frac{\partial \phi}{\partial t} = \delta_\epsilon(\phi)\left[\mu \,\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right) - \nu - \lambda_1(u_0 - c_1)^2 + \lambda_2(u_0 - c_2)^2)\right] = 0$$

where c1, c2 are necessary elements of _, _1 = _2 = 1, _ = 0, and _ controls the solidness of the shape. The nonlinear PDE can be discritized and tackled iteratively to merge to a nearby least (i.e. @_=@t = 0), which will be the locally ideal dynamic shape. This specific dynamic form model was picked in light of the fact that it is not subject to a substantial edge slope. Because of the low complexity between dim matter and cerebrospinal liquid, the edges in mind X-ray will have a low inclination, so a without edge model is perfect for cerebrum X-ray division.

2) *Brain Geometry:* Because the brain is a three dimensional function, we can also treat each individual slice of the brain as a level set □(x; y) of a higher dimensional function (x; y; t). Take □(x; y)i = f (x; y; t)jt = h_ig, i 2 Z and h _ step size between brain MRI slices, and define conv(supp□(x; y)) _ convex hull of the support of □(x; y). If □0 _ largest MRI slice (by cross sectional area), we take h = 1, and there are n slices, we have:

$$\mathrm{conv}(\mathrm{supp}\ \Gamma_0) \subseteq \mathrm{conv}(\mathrm{supp}\Gamma_{\pm 1}) \subseteq \cdots \subseteq \mathrm{conv}(\mathrm{supp}\ \Gamma_{\pm n})$$

This property (approximately) holds for all brain slices, so we can exploit this property for efficiently segmenting the brain. That is, if we manually segment □0, we can propagate the convex hull of each successive slice to remove unwanted features outside supp□i as well as provide an accurate initial value for the active contour segmentation, which in turn accelerates the convergence.

3) *Image Segmentation Algorithm:* The proposed algorithm uses the active contour model proposed by [11]. In this algorithm, we combine gamma filtering with iterated active contour segmentation to improve the final segmentation result. Additionally, the algorithm employs statistical techniques to further remove unwanted background features and morphological post-processing to improve the 3D printing properties. The goal is to create a robust brain MRI segmentation system by combining these techniques. The algorithm is given below. Manually segment thickest slice and initialize as □0 for All slices above and below □0 do Segment Sn by S0n = Sn _ conv(supp□n□1) Gamma filter: S0n = (Sn _ conv(supp□n□1))2:0 Initialize _0 = conv(supp□n□1) while active contour not converged do Propagate active contour on image S0n end while S0n = (Sn _ conv(supp□n□1))1:5 Initialize _0 0 = _converged Repeat active contour iteration Perform k-means clustering with k = 4 Record minimum centroid end forkavg = average lowest centroid of k-means data Threshold each slice by kavg Morphological post processing on segmented slices.

The algorithm is given below. Manually segment thickest slice and initialize as □0 for All slices above and below □0 do Segment

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IV. SIMULATION AND RESULTS

After physically dividing the underlying cut, initial phase in fragmenting a transitional cut is to stack the X-ray picture from the picture grouping. The X- ray grouping contains 120 pictures, and the voxel size was 1mm3

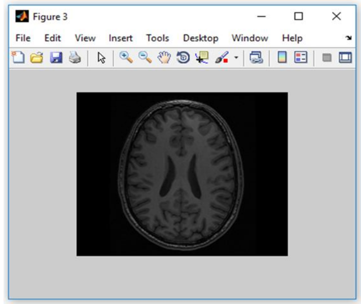

fig1: Intial image

We can generally section the crude X-ray picture utilizing the arched frame of the cover from the past cut. Since the support of each progressive cut is a subset of the past cut, we can utilize this property to proficiently expel the skull from the picture.

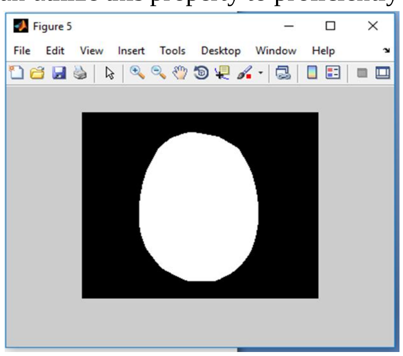

fig2: Intial mask

We can generally section the crude X-ray picture utilizing the arched frame of the cover from the past cut. Since the support of each progressive cut is a subset of the past cut, we can utilize this property to proficiently expel the skull from the picture.
Initialize _0 0 = _converged Repeat active contour iteration Perform k-means clustering with k = 4 Record minimum centroid end for kavg = average lowest centroid of k-means data T.

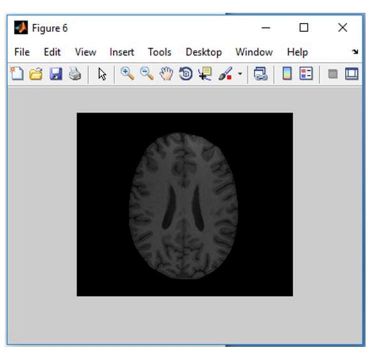

fig3: Intial segmentation

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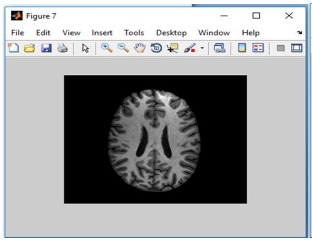
The dynamic form division happens in two stages. To begin with, we apply a gamma channel with extensive to make the white matter predominant in the picture. At that point, we utilize the dynamic form calculation from [11] (utilizing the execution in [12]) to fragment the picture utilizing the gamma channel. The reason for this progression is to fragment fundamentally the white matter, so the lastform will merge to a shape which does not contain the dura mater or other undesirable material. We discovered tentatively that = 2:0 delivered great outcomes for this progression, however any esteem that adequately smothers the dura mater and dark matter would be substantial



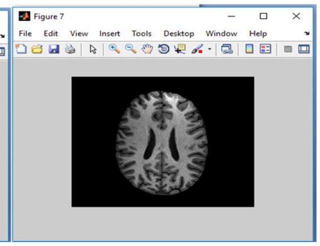
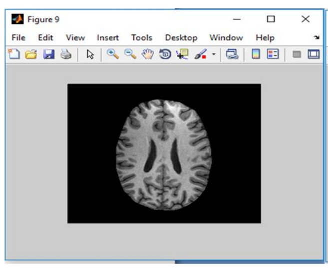


Fig4: gamma filter 1(2.0) Fig5:active contour segmentation1

For the second dynamic form division, we apply a gamma channel with a more direct esteem (= 1:5 for this situation), then section with a similar dynamic shape calculation, utilizing the form found in the past stride as the underlying speculation. The dynamic shape unites to a locally negligible vitality esteem, so the reason for the principal dynamic form division is to locate an underlying speculation for the second division that will meet to the right form. Were we to utilize the curved structure of the past cut as the underlying estimate, undesirable components, for example, the dura mater would be incorporated into the last division, and elements, for example, partition between mind folds would be lost. For this progression, we utilize a more adaptable dynamic shape thanin the past stride i.e. try not topunish arch as emphatically in the shape improvement. From a neuromechanical outlook, a more adaptable form while fragmenting the dim matter is defended because of the lower firmness of dark matter with respect to white matter and common overlap in the mind structure.



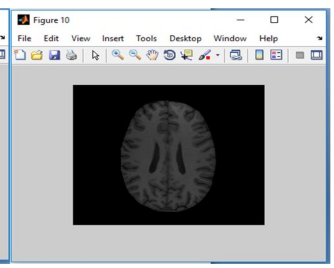
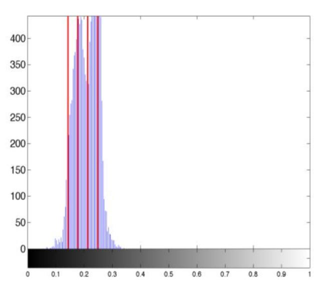
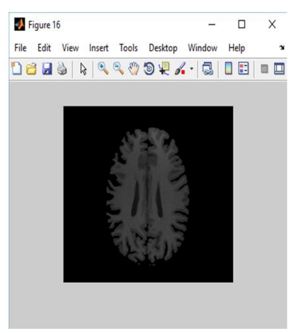


Fig6: Gamma filter 2 (1.5) Fig7:active contour model 2

In the wake of portioning each cut, we perform k-implies bunching on the histogram of the picture utilizing k = 4. For each cut, the most reduced centroid was recorded. The base centroids were then arrived at the midpoint of to locate a normal incentive for the foundation all through the whole picture grouping. Utilizing this normal esteem, the sectioned cuts were thresholded to create to the last parallel veil.





Histogram after segmentation with k-mean centroid fig8: Final segmented image

For 3D printing applications, we do post-processing on the segmented masks to remove artifacts from the thresholding. Specifically, we erode then dilate the mask. Very small or thin regions are usually artifacts and can potentially cause issues when replicating the brain sample via 3D printing since they are usually below the accuracy threshold of most commercially available printers.

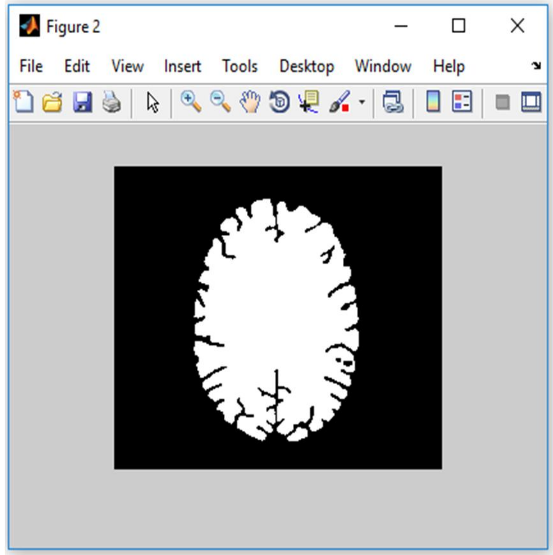


Fig9: Mask after post processing

V. CONCLUSION

This venture built up a calculation that joined non-linear separating, dynamic shape demonstrating, factual thresholding, and morphological post-preparing into a novel calculation that can heartily section cerebrum X-ray pictures. The runtime of the exhibited calculation is fundamentally quicker than manual division and other existing semi-robotized division work processes, and the calculation was still extremely compelling at extracting the significant cerebrum tissue from the X-ray pictures.

The calculation was less viable at expelling the eyes, cerebellum, and dura mater, yet these issues can be effortlessly overcome later on with upgrades in preprocessing the picture. Future work for this ought to concentrate on utilizing more progressed factual procedures in the picture division calculation. Two specific ranges of premium are utilizing more propelled PC vision procedures to distinguish and expel non-cerebrum tissues in the lower mind cuts, and utilize measurable learning strategies to all the more precisely anticipate the geometric development of the cerebrum between cuts as per the Hamilton-Jacobi condition. By and large, nonlinear sifting essentially enhances the execution of dynamic form models in situations with frail edges, and consolidating factual and morphological methods with nonlinear channels and dynamic shapes can effectively portion cerebrum X-ray pictures at a level of exactness reasonable for neurosugery and 3D printing applications.

REFERENCES

[1] M. A. Balafar, A. R. Ramli, M. I. Saripan, and Mashohor, "Review of brain MRI image segmentation methods," Artificial Intelligence Review, vol. 33, no. 3, pp. 261–274, January 2010.
[2] M. B. Panzer, B. S. Myers, B. P. Capehart, and C. R. Bass, "Development of a finite element model for blast brain injury and the effects of CSF cavitation," Annals of Biomedical Engineering, vol. 40, no. 7, pp. 1530–1544, February 2012.
[3] M. Balafar, A. Ramli, M. Saripan, R. Mahmud, and
[4] Mashohor, "Medical image segmentation using fuzzy c-mean (fcm) and dominant grey levels of image," in Visual Information Engineering, 2008. VIE 2008. 5th International Conference on, July 2008, pp. 314–317.
[5] M. Rostami, J. Ghasemi, and R. Ghaderi, "Neural net-work for enhancement of fcm based brain mrisegmen-tation," in Fuzzy Systems (IFSC), 2013 13th Iranian Conference on, Aug 2013, pp. 1–4
[6] S. Khare, N. Gupta, and V. Srivastava, "Optimization technique, curve fitting and machine learning used to detect brain tumor in mri," in Computer Communication and Systems, 2014 International Conference on, Feb 2014, pp. 254–259.
[7] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Ac-tive contour models," International Journal of Computer Vision, vol. 1, no. 4, pp. 321–331, 1988.
[8] S. W. Yoon, H. S. Shin, S. D. Min, and M. Lee, "Medical endoscopic image segmentation with multi-resolution deformation," in 2007 9th International Conference on e-Health Networking, Application and Services. Institute of Electrical & Electronics Engineers (IEEE), June 2007.
[9] Y. Zhang, Z. Dong, L. Wu, S. Wang, and Z. Zhou, "Feature extraction of brain MRI by stationary wavelet transform," in 2010 International Conference on

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