Hybrid Clustering Technique for Enhanced MRI Brain Image Segmentation to Identify Vestibular Schwannomas

---

Yves Greatti, Heather Grimaudo

EN.585.703.81.FA24 Applied Medical Image Processing
Course Project Update

Project Title: “Hybrid Clustering Technique for Enhanced MRI Brain Image Segmentation to Identify Vestibular Schwannomas”

Introduction

Medical imaging segmentation is a fundamental form of image processing that identifies different tissue types by exploiting differing signal intensities to create a clear separation between regions of interest. In clinical practice, imaging segmentation of MR imaging of the brain is essential for delineating normal/healthy brain tissue from tumors, identifying neurodegenerative changes like hippocampal atrophy in Alzheimer's disease, assessing the degree of stroke burden in the setting of acute stroke and consideration for mechanical thrombectomy, and presurgical planning for neurosurgeons. Various segmentation methods have been used in MR imaging, including manual segmentation by a radiologist, which is time-consuming and subjective, thresholding, which does not work well with regions of low contrast, clustering algorithms (k-means, fuzzy C-means), atlas-based segmentation, and deep learning or AI-based segmentation[1], [2], [3], [4].

Our project aims to utilize clustering algorithms to optimize the segmentation of MR imaging of the brain that demonstrate a unilateral vestibular schwannoma, a benign tumor arising from cranial nerve VIII, or the vestibulocochlear nerve. Specifically to segment the normal brain tissue and tumor. Vestibular schwannomas usually have a regular spherical shape and avid homogenous contrast enhancement on T1 contrasted sequences, so this tumor was chosen as an object that will appear starkly different from normal gray and white matter of the brain.

From a clinical perspective, research consistently demonstrates a robust correlation between smaller tumor sizes—classified as lower Koos grades—and improved post-surgical outcomes in vestibular schwannoma resection [5]. Consequently, advancements in imaging modalities, such as auto segmentation and volumetric analysis, which enable early detection of small tumors and precise monitoring of growth, are poised to significantly enhance patient outcomes. Clinicians such as neuroradiologists, neurosurgeons, and radiation oncologists can use optimized segmentation methods to more closely follow these tumors and make informed clinical decisions regarding surgical intervention and conservative management.

Related Work

The fuzzy C-means (FCM) clustering algorithm is an unsupervised machine-learning-based algorithm commonly used in imaging segmentation[4]. Its limitations include sensitivity to noise and its initial parameters. There have been recent hybrid approaches claiming to improve FCM and increase its robustness to noisy images and adaptability[6], [7], [8], [9].

Objective

Our project will first implement the algorithm described in reference [6] - a hybrid image segmentation method based on fuzzy C-mean and modified bat algorithm. We will then validate its performance in different datasets. Finally, we will compare them with performances obtained with more traditional or recently established segmentation algorithms. If time permits, we will implement *de novo* algorithms described in [7], [8] or [9] and compare their performances with the algorithm in [6].

Methodology

- **Implement and Evaluate the Modified Fuzzy Bat Algorithm (MFBA):** Reproduce the MFBA-based Fuzzy C-means (MFBAFCM) algorithm discussed in the paper[6]. This step involves integrating the MFBA optimization into the FCM clustering for MRI brain image segmentation.

- **Noise Robustness Testing**: Assess the robustness of the MFBAFCM algorithm on MRI brain images with varying noise levels and non-uniform intensity. This would showcase its effectiveness in handling common MRI images.
- **Algorithm Comparison**: Compare the performance of MFBAFCM with our course-provided **k-means** implementation and other clustering-based segmentation methods, such as standard Fuzzy C-means (FCM) and recent algorithms from the literature.
- **Segmentation Accuracy Metrics**: Use different clustering validity and segmentation accuracy metrics such as Dice Similarity Coefficient (DCS) or other clustering metrics to evaluate the segmentation performance.
- To help with this task, we can utilize annotation pipelines such as FreeSurfer (https://surfer.nmr.mgh.harvard.edu/) or FSL (https://fsl.fmrib.ox.ac.uk/fsl/docs/), or similar tools. We will then compare the segmentation performances of these tools with our implementation of MFBAFCM.
- **Visualization**: Generate visual plots of segmentation results using MRI images to demonstrate the improvements brought by the proposed method.

Datasets

The Cancer Imaging Archive (TCIA):

- **Vestibular-Schwannoma-SEG | Segmentation of Vestibular Schwannoma from Magnetic Resonance Imaging: An Open Annotated Dataset and Baseline Algorithm.** A collection of 242 patients with unilateral vestibular schwannomas, including T1-weighted post-contrast sequences, high-resolution T2-weighted sequences, and manually segmented T1-weighted post-contrast sequences to outline the tumor. The segmentation was performed by both the treating neurosurgeon and radiation oncologist for radiosurgery planning [10].
  (https://www.cancerimagingarchive.net/collection/vestibular-schwannoma-seg/)
  - We will be using T1-weighted post-contrast sequences and manually segmented sequences.

- **Vestibular-Schwannoma-MC-RC | Segmentation of Vestibular Schwannoma from Magnetic Resonance Imaging: An Annotated Multi-Center Routine Clinical Dataset.** A 60 T1-weighted post-contrast and T2-weighted sequences, 64 only T1-weighted post-contrast sequences, and 303 only T2-weighted sequences [11].
  (https://www.cancerimagingarchive.net/collection/vestibular-schwannoma-mc-rc/)
  - We will be using T1-weighted post-contrast sequences.

Expected Outcomes

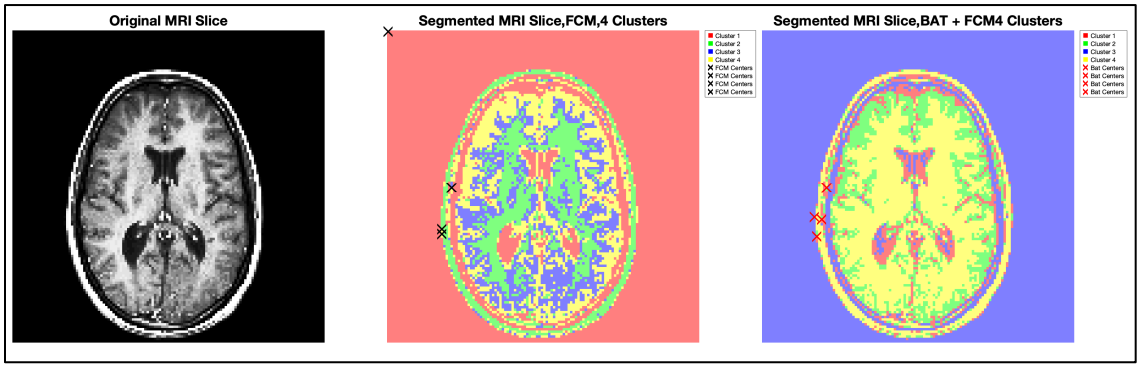
The modified segmentation algorithm, MFBAFCM, should perform superiorly in auto segmenting vestibular schwannomas compared to standard FCM and other brain segmentation approaches, including intensity-based approaches. If time permits, we will include hybrid approaches such as contour-based or metaheuristic machine learning. Due to the lack of infrastructure for model training and tuning, as part of this project, we will not consider deep learning algorithms.

Milestones – Update - Timeline

☑ Dataset(s) identification and acquisition (Beginning-October)

☑ MFBAFCM implementation (Mid-October)

1. We are investigating the impact of the initial cluster centroids on the FCM algorithm. It does not show significant improvement to the quality of the segmentation.



The visual result is confirmed by our quantitative analysis. To evaluate the quality of clusters used in segmentation, we employ the following four metrics:

- **Partition Coefficient (PC)**: This metric quantifies the overlap between clusters, with higher values indicating better-defined clusters.
- **Classification Entropy (CE)**: Like PC, CE measures the fuzziness in cluster assignments. Lower values are preferred as they suggest more distinct cluster boundaries.
- **Partition Index (SC)**: This index measures cluster validity based on individual cluster characteristics, normalized by the fuzzy cardinality of each cluster. A higher SC value indicates better separation between clusters.
- **Fuzzy Separation Index (S)**: This metric assesses the separation quality of clusters. Higher values imply clearer boundaries and less overlap.
- The results from the BAT + FCM algorithm, as compared to the standalone FCM algorithm, suggest that the current implementation is not improving the clustering metrics as expected:

Algorithm	PC	CE	SC	S
FCM	0.90	0.19	0.003	0.027
BAT + FCM	0.82	0.36	0.014	0.66

The current fitness function in BAT and FCM:

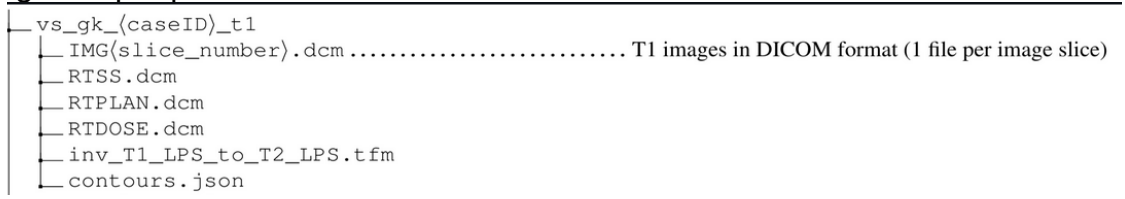
Fitness = [intra-cluster distance + partition index (SC)] / partition coefficient (PC)

We attempted several modifications to encourage the BAT + FCM algorithm to explore the solution space more thoroughly and achieve better clustering results. Our primary objective was to prevent early convergence and push the FCM algorithm to perform additional iterations. Specifically, we implemented the following adjustments:

1. **Introducing Randomness in Initial Centers**: To encourage FCM to explore further, we added a small amount of randomness to the initial cluster centers selected by the BAT algorithm. This perturbation was intended to prevent FCM from converging too quickly and to encourage a deeper search for optimal solutions.
2. **Setting a Minimum Number of Iterations for FCM**: We enforced a minimum iteration count within FCM, regardless of the early convergence behavior.
3. **Combining Fitness Functions**: We combined the original FCM objective function with a weighted term based on the custom fitness function defined earlier. This hybrid approach was designed to balance intra-cluster compactness with inter-cluster separation, theoretically promoting both well-defined and distinct clusters.

Despite these efforts, the improvements in clustering performance were limited. This suggests that the current custom fitness function may not be adequately promoting cluster separation. To address this, we plan to explore alternative fitness function formulations that better emphasize cluster separation.

2. We have also downloaded the *"Vestibular-Schwannoma-SEG | Segmentation of Vestibular Schwannoma Imaging"* dataset, and we have processed the data so all the images including the contour points of the segmented structure are located together per patient.



3. We are skipping the noisy generation step to focus on the task segmentation.

- ~~*Noisy Image Generation (Mid-November)*~~
- *Experimental Setup (Mid -November)*
- *Experimental Results (Mid - November)*
- *Visualization Plot Creation (Mid -November)*
- *Report Writing (Mid -November)*
- *Presentation Deck Creation (Mid-November)*

References

[1] R. Agrawal and M. Sharma, “Review of segmentation methods for brain tissue with magnetic resonance images,” *Int. J. Comput. Netw. Inf. Secur.*, vol. 6, no. 4, pp. 55–62, Mar. 2014, doi: 10.5815/ijcnis.2014.04.07.

[2] M. Hameurlaine and A. Moussaoui, “Survey of brain tumor segmentation techniques on magnetic resonance imaging,” *Nano Biomedicine and Engineering*, vol. 11, no. 2, pp. 178–191, 2019, [Online]. Available: https://www.academia.edu/download/74098374/f4c662a0062b189ac1a800772476b12caade.pdf

[3] S. Yazdani, R. Yusof, A. Karimian, M. Pashna, and A. Hematian, “Image segmentation methods and applications in MRI brain images,” *IETE Tech. Rev.*, vol. 32, no. 6, pp. 413–427, Nov. 2015, doi: 10.1080/02564602.2015.1027307.

[4] H. A. Jalab and A. M. Hasan, “Magnetic resonance imaging segmentation techniques of brain tumors: A review,” *Arch. Neurosci.*, vol. 6, no. Brain Mapping, Jan. 2019, doi: 10.5812/ans.84920.

[5] D. Armocida, A. Pesce, S. Ciarlo, F. Marzetti, A. Frati, and A. Santoro, “Predictive factors of facial nerve function after medium/large vestibular schwannoma surgery: relationships between time of surgery, dimensions and size of resection,” *Egypt. J. Neurosurg.*, vol. 39, no. 1, Aug. 2024, doi: 10.1186/s41984-024-00319-z.

[6] S. Boulanouar and C. Lamiche, “A new hybrid image segmentation method based on fuzzy C-mean and modified bat algorithm,” *Int. J. Comput. Digit. Syst.*, vol. 9, no. 4, pp. 677–687, Jul. 2020, doi: 10.12785/ijcds/090415.

[7] H. Abdellahoum, N. Mokhtari, A. Brahimi, and A. Boukra, “CSFCM: An improved fuzzy C-Means image segmentation algorithm using a cooperative approach,” *Expert Syst. Appl.*, vol. 166, no. 114063, p. 114063, Mar. 2021, doi: 10.1016/j.eswa.2020.114063.

[8] D. Wei, Z. Wang, L. Si, C. Tan, and X. Lu, “An image segmentation method based on a modified local-information weighted intuitionistic Fuzzy C-means clustering and Gold-panning Algorithm,” *Eng. Appl. Artif. Intell.*, vol. 101, no. 104209, p. 104209, May 2021, doi: 10.1016/j.engappai.2021.104209.

[9] C. Valliappa *et al.*, “Hybrid-based bat optimization with fuzzy C-means algorithm for breast cancer analysis,” *Int. J. Noncommun. Dis.*, vol. 6, no. Suppl 1, pp. 62–68, Nov. 2021, doi: 10.4103/2468-8827.330652.

[10] J. Shapey *et al.*, “Segmentation Vestibular Schwannoma from Magnetic Resonance Imaging: Open Annotated Dataset Baseline Algorithm (version 2) [SEG Dataset],” in *Cancer Imaging Archive*, 2021.

[11] A. Kujawa *et al.*, “Segmentation of Vestibular Schwannoma from magnetic resonance imaging: An annotated multi-center routine clinical dataset (Vestibular-Schwannoma-MC-RC).” The Cancer Imaging Archive, 2023. doi: 10.7937/HRZH-2N82.