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A note on graph theory techniques for brain tumor detection

Yegnanarayanan Venkataraman

Department of Mathematics, Kalasalingam Academy of Research and Education (KARE), Tamilnadu, India

ABSTRACT

Brain Tumors are detected in people of all age groups. It leads to various complications that are both physiological and psychological. Graph theory techniques are employed to study both functional and structural behavior of brain networks. In this article we discuss the pertinence of the computation of graph structural parameters and explain how perceptual clustering techniques enable the detection of the low/high grade of tumor and the pace with which it progresses and how Graph cut approaches are exploited to probe vision related factors like similarity and proximity and indicate the possibility of application to stereo, image re-impose, texture concoction and image departmentalization.

Keywords: graphs, graph cut, clustering, brain networks, tumor departmentalization

INTRODUCTION

Children and adults are susceptible to brain tumors and mostly it culminates in disability linked to alarming complications that are of cognitive, medical and psychosocial in nature (Ostrom et al., 2017). Research has indicated that these effects with direct reference to brain pathology are coupled with the tumor itself. A normal way of assessing the effect of pathology and its treatment on the human brain is to probe structural and functional network connectivity. A latest review of 25 functional connectivity probes of brain tumor on adult patients deduced reduced connectivity strength that are functional in nature across natural brain networks and witness rapid activation of atypical patterns (Fox & King, 2018).

ON THE ROLE OF GRAPH THEORY (GT)

GT is concerned with the study of networks linked to various disciplines. It has witnessed tremendous growth in the area of neuroimaging and it permits for the design of brain networks through brain vertices and edges, their joining [1]. Edges are denoted by values explaining the degree of structural connectivity among vertices. Depending on edges, metrics of isolation, amalgamation, and centrality can be found to elucidate the network properties at both global and local level [2] for metric computation.

A notable positive point of graph-based metrics is that they are not method dependent and hence can be compared with other studies. Another pertinent concept that can be measured with graph theory relates to that of small-world phenomenon which is deemed to stand for the highly efficient organization. It combines local clustering between vertices of a network to create cliques and least length paths that globally connect all vertices of the network revealing vertices are joined with a few intermediate steps [1]. It is likely an oversimplification to interpret a higher or lower value of most metrics as necessarily a positive or negative Sustained endeavor to classify links among graph dependent metrics and behavioral functioning is crucial to speculate outcomes. Graph theory is involved in the study of

Corresponding author:
V. Yegnanarayanan
E-mail: yegna@klu.ac.in

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clinical populations that comprises stroke, epilepsy and brain injury. Latest literature surveys examining brain networks in have observed that patients displayed a shift away from small-world networks [3-4]. In the case of epilepsy, it is observed that increased clustering, characteristic path length, and segregation [5-7]. Hub disruption are responsible for various neurological conditions and can adopt to higher cognition asking for integration [1,8]

PERCEPTUAL CLUSTERING

Wertheimer brought out the pertinence of perceptual clustering and conglomeration in vision and enumerated vital factors like proximity and similarity that led to visual clustering. But, various issues related to computation of perceptual clustering are yet to be fully addressed. Several alternatives are suggested to split an image into distinct subsets. Naturally one can ask how to a) choose the right method, b) identify the criterion to be optimized, c) develop a suitable step by step procedure for optimization. This approach is apt for medical image departmentalizing, for perceiving and delineating debonair objects, grasping the geometric features of the organs, like position of the tumor. Exact brain tissue departmentalizing from Magnetic Resonance Imaging (MRI) is a pertinent issue in several medical image system applications in the study of certain brain disorders. One instance is to analyze and evaluate the effects of certain pharmaceutical treatments being carried out in clinics. The approaches depending on elastic deformable models [9] have demonstrated the effect due to small and local shape changes, specifically for normal tissue departmentalization. One can see [10,11,12] for approaches depending on Gaussian intensity models, Markov random field models, supervised or unsupervised classification etc., A region departmentalization depending on a graph cut supports image split. This can be coined as a generalized eigenvalue problem. The notion of optimality of the graph cuts were successfully applied to stereo, image restoration, image departmentalization.

GRAPH CUT

Graph-cut is a step-by-step procedure to find a globally optimal departmentalization solution. It is also refereed as Min-cut considered as interchangeable to Max-flow. The vertex set of a graph G = (V, E) can be split into two disjoint sets, X, Y, $X \cup Y = V$, $X \cap Y = \emptyset$ by deleting edges joining the two parts. The degree of dissimilarity among these two parts can be determined as total weight of the edges that have been deleted. In graph theory terminology it is refereed as the cut. Cut (X, Y) = Σ w(x, y) x ϵ X, y ϵ Y. The notion of optimality related to the cuts is discussed through eigenvalue allocation to each cut. Problems of this type were well analyzed in the field of graph theory. However, for the optimization it is very hard. Graph cut approaches were applied to stereo, image reimpose, texture concoction and image departmentalization. We will provide here a crisp note on graph cuts for image departmentalization.

Suppose that $t_1, \ldots, t_n$ are the data points then the aim of clustering is to split the data set into various smaller sets in such a way that the elements in the same set are similar and elements in distinct sets are dissimilar to each other. The data can be epitomized as a graph G = (V, E, W) where V stands for the vertices that epitomizes the data points t_i, E the edge set with weights allotted by a weighted adjacency matrix A = (a_{ij}) i, j = 1,...,n. An edge joining two vertices u_i and u_j carries a weight that is greater than or equal to zero. If $a_{ij} = 0$ then we say that the vertices u_i and u_j are not linked. The degree of a vertex $u_i \in V$ is defined as $d_i = \Sigma a_{ij}$ j = 1, ..., n. Observe that, this sum runs only over all vertices adjacent to u_i. The degree matrix D is conceived as the diagonal matrix with the degrees $d_1, \ldots, d_n$ on the diagonal. A divide of similarity graphs depends on symbolizing the local neighborhood links among the data points. Different similarity graphs were suggested in spectral clustering. For this one can use the ε -neighborhood graph. All links with distances below a threshold ε are set to 1. That is, we set $\Sigma a_{ij} = 1$ if $\forall$ (i, j) d (i, j) < ε. When the input data are epitomized as a similarity graph with the adjacency matrix A, the easiest way to departmentalize the image is to build a bipartition of the graph. The normalized Cut Ncut is normally employed to iron out this problem. The yardstick to be minimized for splitting an image into A and B is: Ncut(A,B) = ((1/Vol(A)) + (1/Vol(B)))$\sum a_{ij}$ with $i \in A$, $j \in B$ where Vol(A) = Σd_i where $i \in A$ and $A \in B = V$, $A \cap B = \emptyset$, A and B are subsets of V(G), $B = A^c$. Minimizing Ncut amounts to determining a cut of small weight among two subsets with strapping internal links. It is known that optimizing the Ncut yardstick is NP hard. Laplacian matrix is employed to solve the optimizing problem. In the occurrence of k-split, the clustering involves picking the subsets of the partition as X, ..., X_k which minimizes: cut (X, ..., X_k) = $\sum_{i=1}^{k}$ cut (X_i, $X_i X_i^c$).

A Graph Cut based procedure for tumor departmentalization

Step 1: Build a weighted graph G = (V, E, W) by deeming the image pixels as vertices. We introduce an edge among two pixels. $a_{ij} = (\exp(\| X(i) - X(j) \|_2^2 / SI^2)*(\exp(\| Y(i) - Y(j) \|_2^2/SY^2)$ if SI $\| Y(i) - Y(j) \| < r$ and 0 otherwise, where at pixel i X(i) denotes the gray level value, Y(i) denotes in an image the position of pixel i, A_{ij} acts as similarity measure among the pixels i and j , r the cutoff distance from i to j, SI denotes a constant linking to the gray level and SX a constant linking to the distance.

Step 2: Split the graph into parts with the similar pixels in the same part and dissimilar pixels in distinct parts and determine the similarity matrix A =|a_{ij}| and the degree matrix D = |d_i|= Σ_i a_{ij}. These two matrices A and D are pertinent for determining the generalized eigenvector to minimize the graph cut.

Step 3: Use the Laplacian matrix L = D – A and (D- A)z = λDz to find the eigenvalues and eigenvectors.

Step 4: redo bipartition iteratively. Stop when the Ncut value is more than a previously set value.

DISCUSSION

Graph analysis is employed to probe the brain tumor population, despite the availability of limited literature on the topic. The brain tumor population is an apt set amenable for analysis involving graph-based metrics due to its ability to tackle network disruption confederated with local/global effects of tumors and that of radiation and demyelination. Aerts et al. [13] contributed a crisp overview on graph theory-based probe about brain tumor patients. They remarked that the current research at those times pointed to reduced isolation and diminished global conglomeration in LGG refereed as low-grade glioma. Over the same time period another investigation of HGG called grade glioma was announced. But it reported no variation among HGG and controls. All probes made a good use of DTI, fMRI, MEG or EEG and employed graph theoretic probe to scrutinize brain networks in affected population of brain tumors. As of now only one detailed probe involving graph theory has been carried out [14]. It is observed that the effects on brain networks are distinct and incomparable among patients who are adults and one who escaped childhood brain tumors. This is because adult brain tumors happen post neurodevelopment. Hallquist and Hillary and Yeh et al [15,16,17] gave respectively an excellent knowhow on various issues that are methodological found in neuroscience network with particular concentration on functional graph analysis.

CONCLUSIONS

Employing graph theoretical approaches to explain brain network attributes in the framework of brain tumors is yet in its initial stages of development. However, it is a fast upcoming area of enquiry with huge window for stimulating discoveries. Observations have indicated to disturbances functional imbalance in brain network structure with regards to several measurements of centrality and conglomeration despite inconsistency in results concerning direction and magnitude of affects. Other important factors like graph cuts and associated procedure for departmentalization with live impacts on networks comprise the low /high grade of tumor and the pace with which it progresses. With continued effort on further probes, one can uncover various facts concerning the resiliency and plasticity of brain amidst disruption and reveal new knowhow regarding how treatments impact the brain and its network.

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Rubinov M, Sporns O. Complex network measures of brain connectivity: uses and interpretations. Neuroimage. 2010 Sep;52(3):1059-69. doi: 10.1016/j.neuroimage.2009.10.003. Epub 2009 Oct 9. PMID: 19819337.

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REFERENCES

1. Bullmore E, Sporns O. Complex brain networks: graph theoretical analysis of structural and functional systems. *Nature reviews. Neuroscience,* 2009; 10(3), 186–198.
2. Rubinov M, Sporns O. Complex network measures of brain connectivity: uses and interpretations. *NeuroImage,* 2010; *52*(3), 1059–1069.
3. Caeyenberghs K, Verhelst H, Clemente A, Wilson PH. Mapping the functional connectome in traumatic brain injury: What can graph metrics tell us?. *NeuroImage*, 2017; 160, 113–123.
4. Imms, P., Clemente, A., Cook, M., D'Souza, W., Wilson, P. H., Jones, D. K., & Caeyenberghs, K. (2019). The structural connectome in traumatic brain injury: A meta-analysis of graph metrics. *Neuroscience and biobehavioural reviews,* 2019; 99, 128–137.
5. Dennis EL, Jahanshad N, McMahon KL, de Zubicaray GI, Martin NG, Hickie IB et al. Development of brain structural connectivity between ages 12 and 30: a 4-Tesla diffusion imaging study in 439 adolescents and adults. *NeuroImage*, 2013; 64, 671–684.

6. Bernhardt BC, Bonilha L, Gross DW. Network analysis for a network disorder: The emerging role of graph theory in the study of epilepsy. *Epilepsy & behavior: E&B*, 2015; 50, 162–170.
7. Pedersen M, Omidvarnia AH, Walz, JM, Jackson GD. Increased segregation of brain networks in focal epilepsy: An fMRI graph theory finding. *NeuroImage. Clinical*, 2015; 8, 536–542.
8. Crossley NA, Mechelli A, Scott J, Carletti F, Fox PT, McGuire P et al. The hubs of the human connectome are generally implicated in the anatomy of brain disorders. *Brain: a journal of neurology*, 137(Pt 8). 2014; 2382–2395.
9. Pitiot, A., Toga, A. W., & Thompson, P. M. Adaptive elastic segmentation of brain MRI via shape-model-guided evolutionary programming. *IEEE transactions on medical imaging*, 2002; 21(8), 910–923.
10. Styner M, Brechbühler C, Székely G, Gerig G. Parametric estimate of intensity inhomogeneities applied to MRI. *IEEE transactions on medical imaging*, 2000; 19(3), 153–165.
11. Van Leemput K, Maes F, Vandermeulen, Suetens P. A unifying framework for partial volume segmentation of brain MR images. *IEEE transactions on medical imaging*, 2003; 22(1), 105–119.
12. Warfield SK, Kaus M, Jolesz FA, Kikinis R. Adaptive, template moderated, spatially varying statistical classification. *Medical image analysis*, 2000; 4(1), 43–55.
13. Aerts H, Fias W, Caeyenberghs K, Marinazzo D. Brain networks under attack: robustness properties and the impact of lesions. *Brain: a journal of neurology*, 2016; 139(Pt 12), 3063–3083.
14. Na S, Li L, Crosson B, Dotson V, MacDonald TJ, Mao H, King TZ. White matter network topology relates to cognitive flexibility and cumulative neurological risk in adult survivors of pediatric brain tumors. *NeuroImage. Clinical*, 2018; 20, 485–497.
15. Hallquist MN, Hillary FG. Graph theory approaches to functional network organization in brain disorders: A critique for a brave new small-world. *Network neuroscience (Cambridge, Mass.)*, 2018; 3(1), 1–26.
16. Yeh CH, Jones DK, Liang X, Descoteaux M, Connelly A. Mapping Structural Connectivity Using Diffusion MRI: Challenges and Opportunities. *Journal of magnetic resonance imaging: JMRI*, 2021; 53(6), 1666–1682.
17. van den Heuvel MP, Sporns O. Network hubs in the human brain. *Trends in cognitive sciences*, 2013; 17(12), 683–696.