

Brain Tumor Segmentation using K-Means Based Level Sets

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Abstract: Image processing is an active research area in which medical image processing is a highly challenging field. Medical imaging techniques are used to image the inner portions of the human body for medical diagnosis. Brain tumor is a serious life altering disease condition. Image segmentation plays a significant role in image processing as it helps in the extraction of suspicious regions from the medical images. In this paper we have proposed segmentation of brain MRI image using K-means clustering algorithm followed by level set method which avoids the misclustered regions that can inevitably be formed after segmentation of the brain MRI image for detection of tumor location.

Keywords: Image Segmentation, MRI, K-means clustering, Level set method.

INTRODUCTION

Cerebrum tumor is a standout amongst the most well-known mind infections, has influenced and crushed numerous lives. As per study International Agency for Research on Cancer (IRAC), it is evaluated that more than 126,000 peoples are diagnosed for mind tumor every year around the world. The death rate is around 97,000 every year. The measurable reports indicates low survival rate of mind tumor patients despite the fact that cerebrum tumor infections has been the focal point of consideration of a large number of inquiries about more than quite a few years, around the globe. In the Cerebrum is considered as a bit part of the body and has an extremely complex structure.

Brain tumor:

The mind comprises of for the most part two sorts of tissues: gray matter (GM) and white matter (WM). The cerebrum likewise contains a cerebrospinal fluid (CSF) that comprises of compounds, glucose, support and white platelets. A mind tumor is generally an anomalous mass of tissue in which a few cells grow and duplicate wildly obviously unregulated by the instrument that control typical cells. The development of a tumor possesses space inside the skull and meddles with typical mind action. A tumor can bring about harm by moving the mind or pushing against the skull, by expanding weight in the cerebrum, and by attacking and harming nerves and sound cerebrum tissues. Mind tumors are arranged in light of the kind of tissues required in the cerebrum.

The situating of the tumor in the cerebrum, whether it is kind tumor or threatening tumor and other distinctive contemplations. Cerebrum tumors are the strong part that spread all through the encompassing tissues or disort the

encompassing structures. The diverse sorts of cerebrum tumors are Gliomas, Medulloblastoma, Lymphoma, Meningioma, Craniopharyngioma, Pituitary adenoma.

Imaging modalities:

The primary constituents of our body are water and bones. Some hint of components, for example, iodine, iron and so on are additionally present in certain particular parts of our body, for example, thyroid or blood. The fundamental standard of medicinal imaging lies in the proficient utilization of various properties of these body constituents. The imperative cerebrum imaging modalities are x-rays, computed tomography(CT), positron emission tomography (PET), single-photon emission tomography (SPECT), ultrasound magnetic resonance imaging(MRI) and Cerebral angiography. The x-ray which was created by Wilhelm in 1895, depends on the estimation of the transmission of x-ray, through the body.

Be that as it may, because of the abnormal state of radiations transmitted by x-ray, it might bring about maladies, for example, tumor, skin ailments or eye waterfall. In the x-ray based computer assistance tomography(CT), image is reproduced from a substantial number of x-rays.

If there should be an occurrence of positron emission tomography(PET),radio nuclides are infused into patient's body which join to a particular organ. SPECT is an atomic drug based tomographic imaging strategy and it utilizes gamma beams. It is fit for delivering 3D images. Ultrasound is the best methodology for examination of delicate body tissues. It gauges the impression of ultrasonic waves transmitted through the body. Cerebral angiography is a sort of angiography that permits

identification of mind variations from the norm by giving images of veins in and around the cerebrum.

MRI:

Magnetic Resonance Imaging (MRI) is a non-obtrusive strategy and can be utilized securely as regularly as fundamental for cerebrum imaging. MRI images are utilized to create nitty gritty and exact pictures of human organs from various angles for diagnosing anomalies. There are two sorts of MRI high field for delivering high quality images and low field for MRI for littlest analysis condition. MRI images can be utilized by doctors for visualizing even hair line splits and tears in wounds to muscles, ligaments and other delicate tissues. The fundamental rule of MRI depends on the absorption and emission of energy in radio free range of electron magnetic spectrum. Magnetic resonance imaging (MRI) is brilliant for indicating anomalies of the mind, for example, tumor, various sclerosis or injuries, stroke, discharge. Exact anatomical three-dimensional (3D) models got from 2D MRI therapeutic image information helps in giving accurate and exact demonstrative data about spatial connections between basic anatomical structures, for example, vascular structures, articulate cortical zones and so forth and other obsessive discovering which generally were vague by the exposed eye. MRI is normally utilized for mind tumor imaging due to the accompanying reasons:

1. It does not utilize any ionizing radiations like CT, SPECT and PET.
2. Its contrast resolution is higher than aforementioned strategies.
3. Ability of MRI gadgets to produce 3D space images empowers them to have a superior tumor confinement.
4. Its capacity in securing of both anatomical and useful data about the tumor amid the same sweep.

LITERATURE SURVEY

Strategies, for example, thresholding, the area region growing, statistical models, active control models and clustering have been utilized for image segmentation. In view of the complex intensity distribution in medical images, thresholding turns into a troublesome errand and regularly comes up short [1]. In the region growing developing strategy, thresholding is joined with network [2].

Fuzzy c-means is a well known strategy for medical image segmentation however it just considers image intensity there by creating inadmissible results in noisy images [3]. A cluster of algorithms are proposed to make FCM powerful against noise and in homogeneity however regardless it not perfect.

Exact estimation of the probability density function (PDF) is crucial in probabilistic order. Non-parametric methodology does not make any suspicion in getting the parameters of PDE there by making it exact yet costly. In parametric methodologies, a function is thought to be a

PDF. It is anything but difficult to accuracy and does not real information distribution. Learning vector quantization (LVQ) is a supervised aggressive learning strategy that gets choice limits in input space based on training data.

Self-organizing maps (SOM) is an unsupervised clustering that maps inputs which can be high dimensional to one or two dimensional discrete lattice of neuron units. The input data is composed into a few examples as indicated by a similarity factor like Euclidean distance and every pattern assigns to a neuron. Every neuron has a weight that relies on upon the pattern assigned to that neuron.

Watershed transform is a gradient based segmentation method where diverse inclination qualities are considered as various statures. A hole is made in every local minimum and submerged in water, the water will ascend until local maximums. At the point when two water way meet, a dam is worked between them. The water rises steadily until all points in the map are drenched. The image gets segmented by the dams. The dams are called watersheds and segmented regions are called catchments basins [8][9]. Its quick usage technique is proposed by [9] and [10]. The over segmentation issue still exists in this technique [8][9].

The region growing begins with a seed, which is chosen in the focal point of the tumor region. Amid the region growing stage, pixels in the neighbor of seed are included to region based on homogeneity criteria there by resulting in connected region.

The active control model is a system for delineating an object outline from a noisy image and depends on a curve, $x(s)=[x(s),y(s)]$, defined in the image area where s in range of $[0,1]$ is an arc length. It twists in a way that minimizes an energy function. The internal energy and is utilized to control the pressure and unbending nature of the misshaping curve. The external energy is utilized to control the deforming curve toward the target [11].

A Markov random field, Markov network or undirected graphical model is an arrangement of arbitrary variables having a Markov property portrayed by an undirected graph. It is a statistical model used to show spatial relations that exist in the neighbour of pixels [12].

In graph cut based methodologies, the issue of image segmentation is considered as a graph partitioning issue and a worldwide paradigm that measures both total dissimilarity among the distinctive groups and the total similarity inside then is utilized. A proficient strategy in view of generalized Eigen value.

The principle challenge lies in segmentation of cerebrum with anatomical deviation like tumor with various shape, size, area and intensities. The tumor not just changes the piece of cerebrum which tumor exists additionally some of the time it impacts shape and intensities of different structures of the mind. Therefore the presence of such anatomical deviation makes utilization of earlier data about power and spatial distribution testing.

PROPOSED METHOD

Level set method:

Utilizing a partial differential equation (PDE) - based technique and unravelling the PDE condition by a numerical plan, one can segment the image. Curve propagation is a popular technique in this class, with various applications to object extraction, objects tracking, and stereo reconstruction. There are basically three strategies under the PDE Level Set strategy, Parametric Method, Fast Marching method. Level Set Method is one of the developing image segmentation systems for medical image segmentation. The level set strategy is a numerical method for following interfaces and shapes.

The essential idea of the level set strategy is to represent contours as the zero level set of an implicit function characterized in a higher dimension, ordinarily referred to as the LSF, and to advance the level set function as indicated by an partial differential equation (PDE). In typical PDE strategies, images are thought to be continuous functions tested on a grid. Active contours were acquainted all together with segment the images in images utilizing dynamic curves. Geometric active contour models are ordinarily determined utilizing the Euler - Lagrange equation. In level set formulation of moving fronts (active contour), the fronts, meant by, are represented by the zero level arrangement of a level set function.

The level set strategy was initially presented by Osher and Sethian. The level set strategy is a numerical and hypothetical tool for engendering interfaces. The essential idea is to begin with a closed curve in 2D or a surface in 3D and permit the curve to move perpendicular to itself at a recommended speed. In image preparing the level set strategy is most regularly utilized as a segmentation tool through engendering of a contour by utilizing the properties of the image. One of the main applications was to detect edges in an image, yet in later applications textures, shapes, hues and so forth can be identified. In the level set technique, an interface C is represented implicitly as a level set of a ϕ , called level set function, of higher measurement. The geometric characteristics and the movement of the front are computed with this LSF. The interface is presently represented implicitly as the zero-th level set (or contour) of this scalar function. Over whatever remains of the image space, this LSF is characterized as the signed distance function from the zero-th level set. In particular, given a closed curve C, the function is zero if the pixel lies on the curve itself, else, it is the signed minimum distance from the pixel to the curve. By tradition, the distance is viewed as negative for pixels outside C and positive for pixels inside C. The LSF ϕ of the closed front C is defined as follows, [13]:

$$\phi(x, y) = \pm d((x, y), c) \quad (1)$$

Where $d((x, y), C)$ is the distance from point (x, y) to the contour C, and the sign positive or negative are picked

if the point (x, y) is inside or outside of interface C. The interface is currently represented implicitly as the zero-th level set (or shape) of this function:

$$c = \{(x, y) / \phi(x, y) = 0\} \quad (2)$$

Such an implicit representation has various preferences over a parametrical approach. The most striking case is topological changes happening during the propagation, ordinarily when two flames burn together the developing interfaces converge into one single engendering front.

The function ϕ , which fluctuates with space and time (that is, $\phi = \phi((x, y), t)$ in 2D) is then developed utilizing a PDE, containing terms that are either hyperbolic or parabolic in nature.

So as to illustrate the origin of this PDE, we next consider the evolution of the function ϕ as it evolves in a directional normal to itself with a known speed F. Here, the normal is arranged as for an outside and an inside. The possibility of the level set technique is to consider the developing interface C $((x, y), t)$ as the arrangement of zero-values of the function $\phi(\phi(C((x, y), t), t) = 0)$. We can write:

$$\frac{\partial \phi(x, y)}{\partial t} + \nabla \phi \frac{\partial c((x, y), t)}{\partial t} = 0 \quad (3)$$

We discover then the condition of level set presented by Osher and Sethian for ϕ :

$$\frac{\partial \phi(x, y)}{\partial t} = F |\nabla \phi| \quad (4)$$

Where F indicates a constant speed term to push or pull the contour.

A specific case is the movement by mean curvature, when $F = \text{div}(\phi / \|\nabla \phi\|)$ is the curvature of the level-curve of ϕ going through (x, y) .

A geometric active contour model taking into account the mean curvature movement is given by the accompanying evolution equation[7]:

$$F = \text{div}(\nabla \phi / \|\nabla \phi\|) \quad (5)$$

The constant v is a correction term, which is a picked so that the amount $(v + \epsilon k(\phi(x, y)))$ remains positive. This constant might be curvature as a force pushing the curve toward the object, when the curvature gets to be null or negative. Additionally, $v > 0$ is an imperative on the area inside the curve, increasing the engendering speed.

Where k indicates the mean curvature of the LSF given by

$$\frac{\partial \phi(x, y)}{\partial t} = |\nabla \phi(x, y)| (\epsilon k(\phi(x, y)) + v) \quad (6)$$

$$k(\phi(x, y)) = \text{div} \left(\frac{|\nabla \phi|}{\|\nabla \phi\|} \right) \quad (7)$$

Where ϕ_x and ϕ_{xx} indicate the first-and second-order partial derivatives of $\phi(x, y)$ admiration to x, and ϕ_y and ϕ_{yy} signify the same respect to y. The part of the curvature term is to control the normality of the contours as the internal energy term does in the classic snakes model, and ϵ controls the balance between the consistency and robustness of the contour evolution.

Including an extra term, called stopping function, to the speed function in the geometric active contour model proposed by Caselles et al. Give:

$$k(\phi(x, y)) = \frac{\phi_{xx}\phi_y^2 - 2\phi_x\phi_y\phi_{xy} + \phi_{xy}\phi_x^2}{(\phi_x^2 + \phi_y^2)^{3/2}} \quad (8)$$

Where $g(I(x, y))$ indicates the stopping function, i.e. a positive and decreasing function of the image angle. A basic case of the stopping function is given by :

$$\frac{\partial \phi(x, y)}{\partial t} = g(I(x, y))(\epsilon k(\phi(x, y)) + v) |\nabla \phi(x, y)| \quad (9)$$

The contours move in the ordinary course with a velocity of $g(I(x, y))(v + \epsilon k(\phi(x, y)))$, and subsequently stops on the edges, where $g(\cdot)$ vanishes. The shape term κ keeps up the consistency of the forms, while the consistent term v quickens and keeps the shape development by minimizing the encased territory.

Geodesic dynamic form model was proposed by Caselles et al. Taking care of this geodesic issue is comparable to looking for the consistent condition of the level set advancement condition given by :

$$g(I(x, y)) = \frac{1}{1 + |\nabla I(x, y)|} \quad (10)$$

Piecewise-consistent dynamic form model was proposed by Chan and Vese utilizing the Mumford-Shah division model. Piecewise-steady dynamic shape model moves deformable forms minimizing vitality capacity as opposed to seeking edges. A steady approximates the factual data of picture force inside a subset, and an arrangement of constants, i.e. a piecewise-steady, inexact the insights of picture power along the whole space of a picture. The vitality capacity measures the distinction between the piecewise-steady and the genuine picture force at each picture pixel. The level set development condition is given by :

$$\frac{\partial \phi(x, y)}{\partial t} = g(I(x, y))(k(\phi(x, y)) + v) |\nabla \phi(x, y)| + \nabla g(I(x, y)) \cdot \nabla \phi(x, y) \quad (11)$$

Where μ_0 and μ_1 separately signify the mean of the picture power inside the two subsets, i.e. the outside and within forms. The last apportioned picture can be spoken to as an arrangement of piecewise-constants, where every subset is spoken to as a consistent. This technique has demonstrated the quickest joining speed among locale based dynamic forms because of the basic representation.

K- Means clustering:

The k-means algorithm assigns each point to the cluster whose center (also called centroid) is nearest. The centre is the average of all the points in the cluster that is, its coordinates are the arithmetic mean for each dimension separately over all the points in the cluster.

The algorithm steps are:

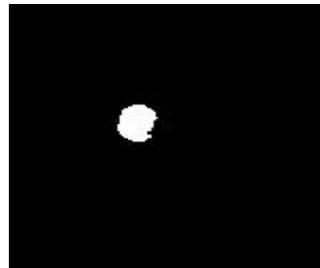
- Choose the number of clusters, k.
- Randomly generate k clusters and determine the cluster centers, or directly generate k random points as cluster centers.
- Assign each point to the nearest cluster center.
- Recomputed the new cluster centers.
- Repeat the two previous steps until some convergence criterion is met (usually that the assignment hasn't changed).

RESULT

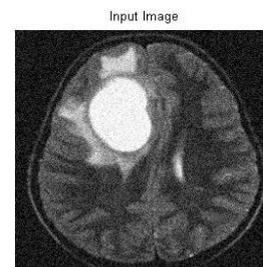
Input image :

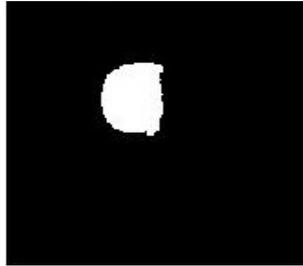


Output image:



Input image1:



Output image1:

CONCLUSION

Image segmentation is the most typical and latest research area in the field of image processing for the last decade. In spite of the availability of a large variety of state-of art methods for brain MRI segmentation, it is still a tough task and there is a need and wide scope for future research to improve the precision and accuracy of segmentation methods. Introducing new methods and combining different methods can be the future schema for making improvement in brain segmentation methods. Because of the today's research in biological world, increasing new knowledge about the relationship between different disorders with anatomical deviation is coming up. So, brain segmentation is gaining importance in using as the first stage in tools for detection and analyzing anatomical deviation. In this paper, we present a comparative study (review) of different approaches used for medical image segmentation. The method presented in this paper is used with new approaches of image segmentation for the better accuracy and precision of results.

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