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Comprehensive analysis of technique used for classification of diseases using image processing mechanism

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Abstract
Diseases within the human body are common and technology is playing a vital role in the detection and prevention of diseases at early stage. Technology including image processing plays a critical role in the investigation of deadly disease present within brain. For the detection purpose MRI images are used. Preprocessing, segmentation and classification of MRI image is compulsory in the process of disease detection. This paper presents comprehensive analysis of mechanisms used to perform preprocessing and classification of brain tumor using image processing. Comparative table provides the study of techniques yielding optimal result in terms mean square error and peak signal to noise ratio. Better techniques are extracted for future enhancement using this literature.

Keywords: brain, MRI, segmentation, mean square error, peak signal to noise ratio

1. Introduction

Now a day the image processing has been commonly utilized for many applications. Image Processing can also be utilized in medical images to record and store them. The interpretation of medical image is very time consuming and so to make it fast segmentation is utilized. The image segmentation is way to retain the portion of image that is useful for further interpretation. It divides the image in different portions based on the criteria that utilized for future use.

Medical image segmentation is a key undertaking in numerous medical applications, for example, surgical arranging, post-surgical evaluation, irregularity recognition etc. There are bunches of techniques for programmed and self-loader image segmentation, however, a large portion of them fall flat as a result of obscure noise, poor image differentiation, inhomogeneity and week limits that are common in medical images. Medical images generally contain confused structures and their exact segmentation is fundamental for clinical conclusion [1].

One of such is mind image segmentation which is much entangled and testing yet its precise segmentation is imperative for recognizing tumors, edema, and necrotic tissues. Exact discovery of these tissues is imperative in symptomatic frameworks. Additionally, magnetic resonance imaging (MRI) is a vital imaging procedure for identifying strange changes in various parts of the cerebrum in beginning period. MRI imaging is a prevalent approach to acquire an image of mind with high complexity. MRI securing parameters can be changed in accordance with give distinctive dim levels for various tissues and different sorts of neuropathology. MRI images have great differentiation in contrast with computerized tomography (CT). Consequently, the vast majority of research in medical image segmentation utilizes MRI images [2].

The recognizable proof of brain structures in magnetic resonance imaging (MRI) is essential in neuroscience and has numerous applications such as: mapping of practical initiation onto brain life structures, the investigation of brain advancement, and the examination of neuroanatomical fluctuation in typical brains. Brain image segmentation is likewise helpful in clinical finding of neurodegenerative and mental issue, treatment evaluation, and surgical arranging. There are heaps of strategies for programmed and self-loader image segmentation, however, the greater part of them fall flat as a result noisy images, poor contrast or capturing mechanism problem.

MR imaging (MRI)

MR imaging (MRI), created in 1970, is a noticeable system in helpful imaging. X-beam looking at is by and large protected and not in the slightest degree like other therapeutic imaging modalities, can be used as consistently as fundamental. In addition, it can be changed in accordance with image mind. Clinical MRI relies upon the hydrogen center as a result of their riches in the human body and their attractive resonation affectability. For image course of action, an extensive static attractive field is used to aggravate attractive previews of proton that exist in the hydrogen center from their adjust and observing how troubled minutes loosens up back to their adjust. Regularly, the protons are masterminded discretionarily. However in nearness of a static attractive field, they line up with the field and the net charge of protons slants toward the heading of the field. In nearness of enough imperativeness, it is possible to impact the net polarization to zero. In the loosening up method an affected electronic banner is recorded. The quality and traverse of the banner depend upon three sums:

1. Thickness of protein causing problems like cyst in brain (ρ)
2. Time associated with spin winding: Time it takes to achieve quick polarization (T1).
3. Spin unwinding time: this is the time which causes the overall charging to discharge to zero (T2).

In filtering of a man's body, by utilizing diverse parameters setting, it is conceivable to get three distinct images of a similar body: T1-weighted, T2-weighted, and ρ-weighted. Rest of the paper is organized as follows: section 1 gives the introduction, section 2 gives the literature survey along with comparative analysis of techniques for enhancement of image along with classification mechanisms, section 3 presents the disease parameters used in various mechanisms of segmentation and classification, section 4 gives the conclusion and future scope and last section gives the references.

2. Literature Review

Noise handling is critical in the analysis of medical images. Accurate images without noise will always be need of the hour to detect critical diseases at early stage. The issues in MRI images that can be detected by the application of technology includes:

- Noise
- The slant field (the proximity of effectively fluctuating powers inside tissues)
- The deficient volume affect (a voxel contributes in different tissue sorts)

It is difficult to remove noise from MRI images and state of-craftsmanship methods in emptying the commotion are critical. Methodologies change from standard channels to additionally created channels, from general systems to specific MRI de-noising techniques, for example, given beneath are some of the strategies used for noise handling:

- Linear sifting strategies
- Nonlinear sifting strategies
- Anisotropic nonlinear dissemination separating
- A Markov irregular field (MRF)models
- Wavelet models
- Non-neighborhood implies models (NL-implies)

These methodologies have central focuses and shortcomings. None of the procedures is better than anything others as far as estimation cost, de-noising, nature of de-noising and limit sparing. In this way, de-noising is so far an open issue and de-noising systems require change. Direct channels are sensibly clear [2]. They invigorate estimation of a pixel by (weighted) normal of its neighborhood. These channels lessen commotion however degrade image purposes of intrigue and the edges of the image; in this way, restored image looks clouded. Instead of straight channels, nonlinear diverts have better execution in edge ensuring yet degenerate fine structure; in this way, the assurance of the image is diminished [3].

LVQ (Learning Vector Quantization)

Learning vector Quantization (LVQ) organize is an overseen learning approach that makes sense of how to see tantamount data vectors with the end goal that neurons having place close-by to others in the neuron layer respond to near data vectors. In LVQ the difference in data vectors to target classes are picked by the customer [4]. The LVQ approach used as a piece of this material just with image pixels and this approach used here with no extraordinary model or probability movement. LVQ typically avoids the brain boggling structure by and large happening on account of other neural system strategies. Pictures are taken by cutting edge camera and RGB (Red Green Blue) pictures are changed over into HSV (Hue Saturation Value). On the base of Hue, the LVQ technique is associated with Learning vector Quantization distinguish and see the shading from the images. For each pixel as for its Hue regard input vector examine be organized and input vector check be used with their target classes in getting ready and taking in the LVQ arrange. LVQ figurings couldn't think less about the thickness components of class tests like Vector quantization or probabilistic neural systems do, yet on the base of models it particularly describe as far as possible, a nearest neighbor manage and a victor take everything worldview [5].

Self-Organizing Maps (SOM)

Self-sorting out maps (SOM) is an unsupervised learning framework. It is one of the outstanding frameworks in the neural framework field. It maps inputs which can be high dimensional to perhaps a couple dimensional discrete cross segment of neuron units. It deals with data into a couple of cases as showed by a likeness factor like Euclidean detachment. Every case selects to a neuron. Each neuron has weight that depends to configuration delegated to that neuron. The framework learns regularities and association in its data and adjusts its future response. It makes sense of how to describe input data as showed by their social affair in input space and neighboring neuron get neighboring in input space [6]. Subsequently SOM learns both the scattering and the topology of data. By the day's end, the framework layout topological associations in wellsprings of data and neighbor inputs mapped to neighbor neuron in outline. It involves two layers. The primary layer is the data layer and the amount of neurons in this layer is identical to estimation of data. The second layer is the forceful layer and each neuron in this layer identifies with one class (plan). The amount of neurons in this layer depends to the amount of bundles. The neurons in centered layer are coordinated in predictable geometric structure like work. A weight vector is doled out to each relationship from input layer to a neuron in forceful layer [7]. In learning stage champ neuron, neuron in forceful layer with least complexity from input data, is found then victor neuron in its neighborhood neurons changed towards input data. Neighborhood assess lessens in each accentuation. The SOM has two essential advances. All things considered, the heaviness of the triumphant neuron and its neighbor pixels are changed towards the data.

Watershed

Watershed is a point based division technique. Different point regards are considered as different statures. Impacting a hole in each close-by minimum and splash in water, the water to will climb until neighborhood maximums. Exactly when two conduits meet, a dam is worked between them. The water rises until the point that all concentrations in the guide are splashed. The photo is separated by the dams. The dams are called watersheds and the divided regions are called catchments bowls. The over division issue till exists in this strategy. The ordinary diminish level of each zone is seen as the diminish level of pixels in the locale [8].

Fluffy C Means

Fluffy c-mean division is one of unsupervised gathering estimations that is comprehensively used as a piece of image getting ready and PC vision since it easy to execute and gathering execution [9]. It's used to divide a photo by social event pixels that have similar or relatively practically identical regards into a pack, where each get-together of pixel's regards that have a place with one gathering resemble each other and not the same as pixel's regards that have a place with various bundles, and after that these gatherings address the segments of the divided picture. The customary fluffy c-mean encounters a couple of obstacles; it's not correct in the division of noisy picture and monotonous in light of the way that it's iterative nature.

Comparative analysis presents the optimization in terms of various parameters as given in Table 1

Table 1: Comparative techniques for brain disease detection

Algorithm	Basis	Parameters	Advantages	Disadvantages
FCM (fuzzy C-Means) [10]	based on minimizing an object function	Cluster center Vector value	▪ Computational burden rate improved ▪ Coverage rate improved	▪ Time consuming
Gauss mixture vector [11]	Based on estimate distribution in each class	Mean Gaussian component	▪ Less sensitive to noise	▪ Does not preserve edges
LVQ [12]	defines class boundaries prototypes, a nearest-neighbor rule and a winner-takes-it-all paradigm	Weight Euclidean distance	▪ High accuracy and less time consuming	▪ Can be defined for more colors
Self-organizing maps (SOM) [2]	organizes input data into several patterns according to a similarity factor like Euclidean distance	Plasticity Learning rate	▪ Better interpretation of image	
Watersheds [1]	gradient-based segmentation technique			
Multi region based active control [13]	Based on level set	Region Energy	▪ Interpret better tumor effected region	▪ Noise reduction is not done properly
Atlas-based segmentation [7]	Uses atlas as a prior information	Standard deviation Pixel intensity value	▪ Better extraction rate	▪ More time consumption
Markov random field (MRF)	Based on spatial relation of neighboring pixels	Hyper parameter	▪ Accurate and robust segmentation	▪ Costly

3. Parametric evaluation of literature conducted

Conducted literature presents the parameters which are critically used within the existing literature and can be considered for future enhancement.

3.1 Cluster center and vector values

This is critical parameter in the analysis of MRI image in case clustering mechanism is used. Cluster center identifies the distance of each point form the center and also identify which pixel must be a part of cluster. Amount of deviation of point from given cluster center is identified by the use of vector. In case of Kmeans clustering following formula is used to identifying member of clusters.

$$centeroid = \arg\_\min(\, dist(c_i, x)^2)$$

C is the cluster center and x is the distance of point from the cluster center. This distance from cluster center must be minimum in order for the point to lie within the cluster

3.2 MSE and PSNR

MSE indicates mean square error. This is the actual deviation of predicted result from actual result. For accurate prediction this distance or MSE must be minimum. PSNR indicates peak signal to noise ratio. PSNR must be high for prediction. These parameters are evaluated using the following equations.

$$MSE = \sum_{i,j=1}^{m,n} \frac{(x_i - x_j)^2}{m * n}$$

$$PSNR = 10 * \frac{\log(R^2)}{MSE}$$

Where R is the maximum fluctuation of, signal within the image.

3.3 Euclidean distance

Euclidean distance is another critical parameter used to observe the deviation of result from actual result. It generally used within the clustering mechanism such as K-nearest neighbor. Euclidean distance is calculated using the following equation

$$Euclidean_{distance} = \sqrt{(x - x_i)^2 + (y - y_i)^2}$$

Higher the value of Euclidean distance more deviation is observed within the result.

3.4 Standard Deviation

This parameter is used to observe deviation of actual result and hence directly impact the classification accuracy. This feature is extracted when training and testing phase within supervised learning mechanisms are used. The formula to evaluate this parameter is given as under

$$\sigma = \sqrt{\frac{(x_i - x^-)^2}{\mathrm{N} - 1}}$$

X is the actual value and x- is the average value. N is the total number of observations.
The use of each parameter in observed 13 literature is summed up as follows

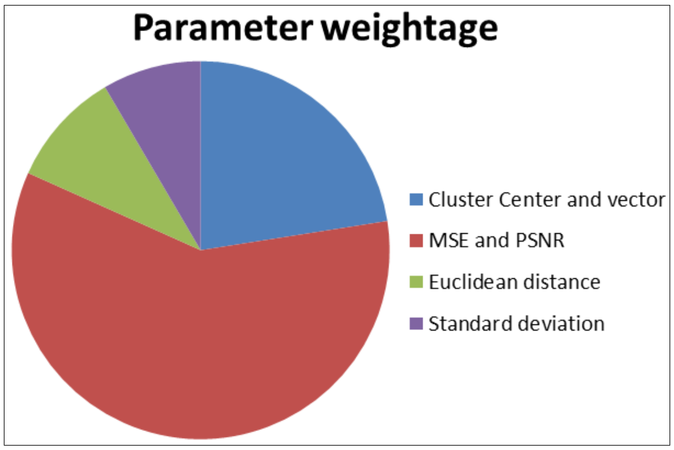

Fig 1: Parameter weightage used in existing literature

4. Conclusion

This paperbriefly review a study of different strategies relevant to brain image segmentation. These methods computerize the procedure of segmentation and consequently are quicker and less demanding than the manual techniques. The techniques used to investigate the problems present within the Brain can be further improved by enhancing classification accuracy by enhancing image through pre-processing stage.
In future preprocessing mechanism with enhanced segmentation can be used to achieve better classification accuracy.

5. References

1. Tirpude N, Welekar RR. A Study of Brain Magnetic Resonance Image Segmentation Techniques, 2013; 2(1).
2. Yeo NC, Lee KH, Venkatesh YV, Ong SH. Colour image segmentation using the self-organizing map and adaptive resonance theory, 2005; 23:1060-1079.
3. Salman N. Image Segmentation Based on Watershed and Edge Detection Techniques, 2006; 3(2):104-110.
4. Soille P. W a tersheds in Digital Spaces : An Efficient Algorithm Based on Immersion Simulations, 1991.
5. Pujara H. Image Segmentation using Learning Vector Quantization of Artificial Neural Network, 2013; 2(7):51-55.
6. IDT Goossens B, Philips W. MRI Segmentation of the Human Brain: Challenges, Methods, Applications, 2015.
7. Bhima K, Jagan A. Analysis of MRI based Brain Tumor Identification using Segmentation Technique, 2016, 2109-2113.
8. Lal AM, Aju D. Abnormality Extraction of MRI Brain Images Using Region Growing Segmentation Techniques, 2014; 3(8):76-82.
9. Deshmukh RD. Study of Different Brain Tumor MRI Image Segmentation Techniques, 2014; 4(4):133-136.
10. Mohammed HR, Alnoamani HH. Improved Fuzzy C-Mean Algorithm for Image Segmentation, 2016; 5(6):7-10.
11. Manju D, Seetha M, Rao KV. Comparison Study of Segmentation Techniques for Brain Tumour Detection, 2013; 2:261-269.
12. Yang M, Lin KC, Liu H, Lirng J. Magnetic resonance imaging segmentation techniques using batch-type learning vector quantization algorithms, 2007; 25:P265-277.
13. Engineering C. Region of Interest Based Medical Image Compression, 2014; pp.1-12.