Survey on segmentation of medical images based on low level features

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Abstract- Medical imaging is a method and process used to create images of the human body for clinical purposes. The amount of medical digital images that are produced in hospitals is increasing incredibly. The need for systems that can provide efficient segmentation and retrieval of images of particular interest is becoming very high. Image segmentation is the basic unit process for image retrieval. In this paper, the process of segmentation of medical digital images is discussed using low level features such as color and texture features by LS-SVM and LBP methods.

Keywords – LBP, LS-SVM, Medical imaging, Segmentation.

I. Introduction

Medical imaging is a technique which is used to create images of the human body for clinical and medical purposes such as medical procedures seeking to reveal, diagnose, or examine disease [11]. The processing of medical image data is playing an increasingly important role. With medical imaging techniques such as X-Ray, computer tomography (CT scan), magnetic resonance imaging (MRI), and ultrasound, the amount of digital images that are produced in hospitals is increasing incredibly. So the need for systems that can provide efficient retrieval of images of particular interest is becoming very high. Unfortunately, only very few medical image retrieval systems are currently used in clinical routine. Image segmentation process is very necessary to perform before image retrieval so it can be easily stored in and retrieved from the database.

Image segmentation is often required as a preliminary and indispensable stage in the computer aided medical image process, object localization, data compression etc [13]. The goal of image segmentation is to cluster pixels into salient image regions, i.e., regions corresponding to individual surfaces, objects, or natural parts of objects. Segmentation could be used for object recognition, occlusion boundary estimation within motion or stereo systems, image compression, image editing, or image database look-up. We consider bottom-up image segmentation. That is, we ignore (top down) contributions from object recognition in the segmentation process. For input we primarily consider image brightness, although similar techniques can be used with color, motion, and/or stereo disparity information. This is typically used to identify objects or other relevant information in digital images.

II. Related Work

In this section, we first briefly review previous works which are directly related to our work. These related works include various methods used for image segmentation. Image segmentation is a process of dividing an image into different regions such that each region is nearly homogeneous, whereas the union of any two regions is not [1]. There are various methods which are used in segmentation for medical digital images:

2.1 Histogram thresholding-based methods such as Otsu's method: In histogram thresholding method [14-15] operation of converting a multilevel image into a binary image is performed, where it assigns the value of 0 (background) or 1 (objects or foreground) to each pixel of a medical digital image based on a comparison with some threshold value T (intensity or color value). If the T is constant, the approach is called global thresholding otherwise, it is called local thresholding. Global thresholding methods can fail when the background illumination is uneven so to compensate for this uneven illumination we can use multiple thresholds and the threshold selection is typically done interactively. These methods are popular due to their simplicity and efficiency. However problems in this method are that traditional histogram-based thresholding algorithms cannot process images whose histograms are nearly unimodal, especially when the target region is much smaller than the background area.

2.2 Edge detection-based methods: Edge detection [16] method is widely used to the problems of medical image segmentation. These methods locate the pixels in the image that correspond to the edges of the objects seen in the image and the result is a binary image with the detected edge pixels. Common algorithms used are Sobel, Prewitt and Laplacian operators. These algorithms are suitable for images that are simple and noise-free. But it does not work well when images have many edges and noise, and unable to easily identify a closed curve or boundary

2.3 Clustering methods, such as K-means: Clustering method [17-18] is a process in which a data set or say pixels are replaced by cluster; pixels may belong together because of the same color, texture etc. There are two natural algorithms for clustering: divisive clustering and agglomerative clustering.

Using these two methods directly is that there are lots of pixels in an image which is difficult. An alternative approach can be used is to first write an objective function and then build an algorithm. The K means and fuzzy c-means algorithms are the iterative techniques that are used to partition an image into K clusters, where each pixel in the image is assigned to the cluster that minimizes the variance between the pixel and the cluster center and is based on pixel color, intensity, texture, and location, or a weighted combination of these factors. These algorithms may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K. Over-segmentation and feature extraction are the problems in clustering methods.

2.4 Graph-based methods: Graph based methods [20] uses a graph in which the nodes represent the image pixels and arcs represent the neighboring pixels. The segmentation is achieved by minimizing the weight that cut a graph into sub-graphs. Generally it suffers from high computationally complexity.

2.5 Region-based methods: In region-based segmentation [21] it uses image characteristics to map individual pixels in an input image and change with the sets of pixels called regions that might correspond to an object or a meaningful part. The various techniques are: Local techniques, Global techniques and Splitting and merging techniques. If the image is sufficiently simple, simple local techniques can be effective. Over-stringent criteria create fragmentation lenient ones overlook blurred boundaries and over-merge.

These algorithms are not generally applicable to all images and particular applications require different algorithms so, different techniques can be used for segmentation like LS-SVM, LBP etc. These techniques are used for medical digital image segmentation using low level features such as color and texture features are discussed in this paper by using LSSVM and LBP. Both are used for segmentation purposes in medical imaging.

2.6 LS-SVM: It stands for least square support vector machine The LS-SVM considers equality type constraints instead of inequalities as in the classic SVM approach. This reformulation greatly simplifies a problem such that the LS-SVM solution follows directly from solving a set of linear equations rather than from a convex quadratic program. In this pixel level color feature and image pixels are extracted and inputted to LS-SVM, which results in segmentation of an image.

2.7 LBP: It stands for local binary pattern. It is a type of feature used for classification in computer vision. LBP was first described in 1994. It has since been found to be a powerful feature for texture classification; it has further been determined that when LBP is combined with the Histogram of oriented gradients (HOG) classifier, it improves the detection performance considerably on some datasets. The LBP feature vector, in its simplest form, is created in the following manner: Divide the examined window to cells (e.g. 16x16 pixels for each cell).For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise where the center pixel's value is greater than the neighbor, write "1". Otherwise, write "0". This gives an 8-digit binary number (which is usually converted to decimal for convenience).Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center).Optionally normalize the histogram. Concatenate normalized histograms of all cells. This gives the feature vector for the window.

III. Detailed Comparison of Ls-svm And Lbp

In this section, we first present the details of both the techniques and then its algorithms.

3.1 LS-SVM: It is an effective color image segmentation approach based on pixel classification with least square support vector machine. In this approach following steps [1] are involved as explained in the figure1 given below.

Firstly, the pixel-level color feature, Homogeneity, is extracted in consideration of local human visual sensitivity for color pattern variation in HSV color space.

Secondly, the image pixel's texture features, Maximum local energy, Maximum gradient, and Maximum second moment matrix, are represented via Gabor filter.

Then, both the pixel level color feature and texture feature are used as input of LS-SVM model (classifier) and the LS-SVM model (classifier) is trained by selecting the training samples with Arimoto entropy thresholding.
Finally, the color image is segmented with the trained LS-SVM model (classifier). This image segmentation not only can fully take advantage of the local information of color image, but also the ability of LS-SVM classifier.

LS-SVM solution follows directly from solving a set of linear equations rather than from a convex quadratic program. The pixel level color feature extraction includes each pixel of an image is identified as belonging to a homogenous region corresponding to an object or part of an object. The problem of image segmentation is regarded as a classification task, and the goal of segmentation is to assign a label to individual pixel or a region. So, it is very important to extract the effective pixel-level image feature. It includes color space is selected and Compute the pixel level color feature where discontinuity and standard deviation are computed.

Then, Image pixel texture feature representation is done where color space transformation is selected and Gabor filter is applied and Local energy, local gradient and second energy moment are extracted and computed.

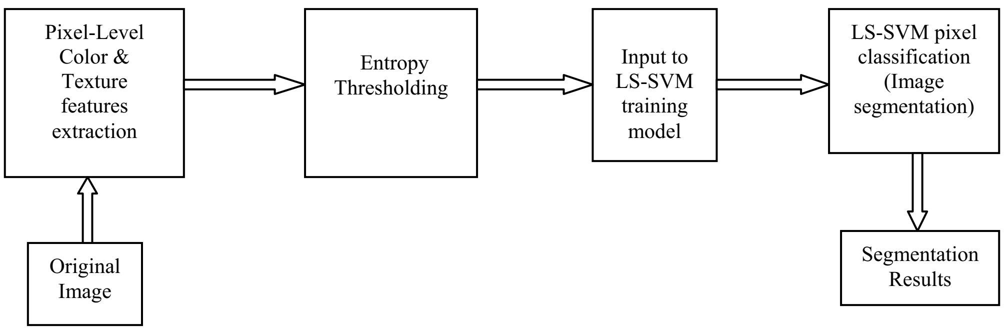

Figure 1: LS-SVM technique using color and texture features

3.1.1 Algorithm for LS-SVM is presented as:

1) Input image for segmentation
2) Process the pixel level color and texture feature extraction
3) Applying the entropy thresholding
4) Inputs the parameter for Modified LS-SVM as a training
5) Classification with LS-SVM and obtain Segmented Results
6) Segmentation results are compared and matched
7) Retrieved.

3.2 LBP: The local binary pattern operator [12] is an image operator which transforms an image into an array or image of integer labels describing small-scale appearance of the image. These labels or their statistics, most commonly the histogram, are then used for further image analysis.
Basic LBP: The basic local binary pattern operator, introduced by Ojala, was based on the assumption that texture has locally two complementary aspects, a pattern and its strength.
There are different versions of the actual LBP operator. LBP using 8 pixels in a 3 × 3 pixel block, this generic formulation of the operator puts no limitations to the size of the neighborhood or to the number of sampling points.
Mapping of LBP levels: An extension to the original operator called uniform patterns when a uniformity measure of a pattern is used: U (“pattern”) is the number of bitwise transitions from 0 to 1 or vice versa when the bit pattern is considered circular. A local binary pattern is called uniform if its uniformity measure is at most 2.
Many other versions like Rotational invariant LBP, multiscale LBP, center-symmetric LBP are also used. In this approach, follow steps are involved as firstly Divide the examined window to cells (e.g. 16x16 pixels for each cell).For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise where the center pixel's value is greater than the neighbor, write "1". Otherwise, write "0". This gives an 8-digit binary number. Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center).Optionally normalize the histogram. Concatenate normalized histograms of all cells. This gives the feature vector for the window.

3.2.1 Algorithm for LBP is presented as:

1) Divide the examined window into cells.

2) Compare the pixels with its neighbors.
3) Follow the pixels along a circle (clockwise or anti clockwise, if center pixel's value is greater than neighbor write "1".
4) Compute and normalize the histogram.
5) Segment and retrieve.

IV. CONCLUSIONS

In this paper, we discuss and presented the segmentation of medical digital images using low- level features by LS-SVM and LBP. Both techniques are used primarily for medical image segmentation but in LS-SVM a classifier and a training model is used to segment the medical images. But in LBP, patterns are made for the segmentation process so that basic LBP. Histogram is also used in LBP technique to segment the images. Both techniques can yield better performance as compared to basic algorithm techniques for medical image segmentation.

REFERENCES

[1] Hong Ying Yang, Xiang Yang Wang, Qin Yan Wang and Xian Jin Zhang, "LS-SVM based image segmentation using color and texture information," J.Vis.Commun.Image, 23(7): 1095-1112,2012.
[2] Thi Nhat Anh Nguyen, Jianfei Cai, Juyong Zhang and Jianmin Zheng, "Image processing," IEEE Transactions, 21(8):3734-3743, Aug. 2012.
[3] Yu Sun and Bir Bhanu, "Reflection symmetry-integrated image segmentation," IEEE Trans. Pattern Anal. Mach. Intell, 34(9):1827-1841, 2012.
[4] Yi Yang, Sam Hallman, Deva Ramanan, and Charless C. Fowlkes, "Layered object models for image segmentation," IEEE Trans. Pattern Anal. Mach. Intell, 34(9):1731-1743, 2012.
[5] Chang Cheng, Andreas Koschan, Chung-Hao Chen, David L. Page, and Mongi A. Abidi, "Image segmentation based on background recognition and perceptual organization," IEEE Trans On Image Processing, 21(3):1007-1019,2012.
[6] J. Shi and J. Malik, "Normalized cuts and image segmentation," IEEE Trans. Pattern Anal. And Machine Intell, 22(8):888–905, 2000.
[7] G.N.Srinivasan and Dr. Shobha G, "Segmentation Techniques for Target Recognition," International journals, 27(3):59-67, 2007.
[8] Manojkumar.S.Kathane and Vilas Thakare, "Brain Segmentation using Support Vector Machine: Diagnostic Intelligence Approach," IEEE trans. Based on image processing, 20(4):127-132, 2012.
[9] J. Wang, L.L. Ju and X.Q. Wang, "An edge-weighted centroidal voronoi tessellation model for image segmentation," IEEE Transaction on Image Processing, 18(8): 1844–1858, 2009.
[10] Yu Yuan-Hui and Chin-Chen Chang, "Scenery image segmentation using support vector machines," Fundamental Informaticae, 6(3): 379–388, 2004.
[11] http://en.wikipedia.org/wiki/Medical_imaging.
[12] Ahonen and Pietikäinen, "Soft histograms for local binary patterns," In: Proc. Finnish Signal Processing Symposium, 17(4):278-291, 2007.
[13] R. Unnikrishnan, C.E. Pantofaru and M. Hebert, "Toward objective evaluation of image segmentation algorithms," IEEE Transaction on Pattern Analysis and Machine Intelligence, 29(6): 929–943, 2007.
[14] M.E. Yuksel and M. Borlu, "Accurate segmentation of dermoscopic images by image thresholding based on type-2 fuzzy logic," IEEE Transaction on Fuzzy Systems, 17(4): 976–982, 2009.
[15] K.S. Tan and N.A.M. Isa, "Color image segmentation using histogram thresholding fuzzy C-means hybrid approach," Pattern Recognition, 44(1): 1–15, 2011.
[16] B. Sowmya and B.S. Rani, "Color image segmentation using fuzzy clustering techniques and competitive neural network," Applied Soft Computing, 11(3): 3170–3178, 2011.
[17] E. Dana and F. Paul, "Image segmentation based on the integration of color-texture descriptors: a review," Pattern Recognition, 44(10–11): 2479–2501, 2011.
[18] D. Comaniciu and P. Meer, "Mean shift: a robust approach toward feature space analysis," IEEE Transaction on Pattern Analysis and Machine Intelligence, 24(5): 603–619,2005.
[19] X.Y. Wang, J. Bu, "A fast and robust image segmentation using FCM with spatial information," Digital Signal Processing, 20(4): 1173–1182, 2010.
[20] M.B. Salah, A. Mitiche and I.B. Ayed, "Multi region image segmentation by parametric kernel graph cuts," IEEE Transaction on Image Processing, 20(2): 545–557, 2011.
[21] J.F. Ning, L. Zhang and D. Zhang, "Interactive image segmentation by maximal similarity based region merging," Pattern Recognition, 43(2): 445–456, 2010.