Available online at www.sciencedirect.com
ScienceDirect
Procedia Computer Science 90 (2016) 68 – 73
Procedia Computer Science

International Conference On Medical Imaging Understanding and Analysis 2016, MIUA 2016, 6-8 July 2016, Loughborough, UK

An Automated Computer-Aided Diagnosis System for Abdominal CT Liver Images

Gehad Ismail Sayed[a,*], Aboul Ella Hassanien[a], Gerald Schaefer[b]

[a]*Faculty of Computers and Information, Cairo University, Cairo, Egypt*
[b]*Department of Computer Science, Loughborough University, Loughborough, U.K.*

Abstract

In this paper, we present a computer-aided diagnosis (CAD) system for abdominal Computed Tomography liver images that comprises four main phases: liver segmentation, lesion candidate segmentation, feature extraction from each candidate lesion, and liver disease classification. A hybrid approach based on fuzzy clustering and grey wolf optimisation is employed for automatic liver segmentation. Fast fuzzy *c*-means clustering is used for lesion candidates extraction, and a variety of features are extracted from each candidate. Finally, these features are used in a classification stage using a support vector machine. Experimental results confirm the efficacy of the proposed CAD system, which is shown to yield an overall accuracy of almost 96% in terms of healthy liver extraction and 97% for liver disease classification.

Peer-review under responsibility of the Organizing Committee of MIUA 2016
Keywords: Liver segmentation, grey-wolf optimisation, fuzzy c-means, support vector machine

1. Introduction

The liver plays an important role in the human body and is one of the most essential organs, while liver cancer is one of the leading death causes. Early detection and accurate staging of liver cancer is hence a critical task in practical radiology. Liver lesions can be identified in abnormal tissues found in the liver by considering intensity pixel differences in the CT image. Manual segmentation of these are tedious and time-consuming. However, automatic segmentation is a very challenging task, due to various issues including the indefinite shape of lesions and intensity similarities between lesions and other nearby tissues. Tumours can be classified as benign or malignant[11]. Benign tumours are not cancerous, and do not spread to other parts of the body, unlike malignant tumours which indicate presence of cancer. Malignant tumour cells can invade nearby tissues and spread to other parts of the body.

Image segmentation is an essential step in medical imaging[1]. Clustering is one of the most common techniques used for image segmentation, with clustering approaches typically being grouped into hierarchical and partitioning-based techniques[4,5].

* Corresponding author.
E-mail address: gehad.ismail@egyptscience.net

Peer-review under responsibility of the Organizing Committee of MIUA 2016
doi:10.1016/j.procs.2016.07.012

Several approaches for liver segmentation have been proposed in the literature. These can be categorised based on their degree of automation into fully automatic, semi-automatic and interactive methods.. Some are based on traditional image segmentation methods such as edge detection, region based segmentation or watershed algorithms, however these methods have drawbacks and often fail to obtain accurate results. For example, approaches based on region growing are dependent on the initial seed points such as in[7] where a human expert intervention to select the suspected region is required, while other approaches rely on contour detection methods like[3] which requires prior knowledge of the image, such as location and shape of the liver.

Several approaches have been presented for tumour segmentation, feature extraction and classification. For example, in[2], various image processing techniques for automatic detection of tumours in human liver have been proposed. The approach in[9] is based on using spatial fuzzy c-means segmentation, flood filling and morphological operators.

In this paper, we present a fully automatic segmentation and diagnosis CAD system for abdominal CT liver images. Our approach comprises four main phases: liver segmentation, lesion candidate segmentation, feature extraction from each candidate lesion, and liver disease classification. We develop a hybrid approach based on fuzzy clustering and grey wolf optimisation for automatic liver segmentation, while a fast fuzzy c-means clustering technique is used for lesion candidate extraction. A variety of features are extracted from each candidate, and are used in a classification stage using a support vector machine classifier. Experimental results confirm the efficacy of the proposed CAD system, which is shown to yield an overall accuracy of almost 96% in terms of healthy liver extraction and 97% for liver disease classification.

2. Preliminaries: Grey Wolf Optimisation

Grey Wolf Optimisation (GWO) is an optimisation techniques developed by Mirjalili in[6]. Here, grey wolves are considered as apex predators who have a strict social dominant hierarchy. Four types of grey wolves – alpha, beta, delta, and omega – are employed to simulate this leadership hierarchy. Alphas are leaders, and are mostly responsible for making decisions about hunting, identifying the sleeping place, time to wake, etc. Betas represent the second level in the hierarchy. They are subordinate wolves that help the alpha in decision-making or other pack activities. A beta wolf is probably the best candidate to make an alpha in case one of the alphas dies or becomes very old. Omegas are the lowest ranking wolves, and thus have to submit to all other dominant wolves. Deltas comprise the fourth group.

Let α be the best solution, β the second best solution, δ the third solution and ω the remainder of all candidate solutions. In GWO, hunting is guided by α, β and δ, while ω solutions follow these three wolves.

During the hunt, grey wolves encircle the prey. This encircling behaviour is modelled as

$$\vec{X}(t+1) = \vec{X_p}(t) - \vec{A} \cdot \vec{D}\ , \text{ with } \quad \vec{D} = |\vec{C} \cdot \vec{X_p}(t) - \vec{A} \cdot \vec{X}(t)|, \tag{1}$$

where t is the iteration number, $\vec{X_p}$ is the prey position and $\vec{X}$ indicates the position of the grey wolf. $\vec{A}$ and $\vec{C}$ are coefficient vectors and calculated as

$$\vec{A} = 2\vec{a} \cdot \vec{r_1} - \vec{a}, \text{ and } \quad \vec{C} = 2 \cdot \vec{r_2}, \tag{2}$$

where the components of $\vec{a}$ are linearly decreased from 2 to 0 over time, and $\vec{r_1}$, $\vec{r_2}$ are random vectors in $[0, 1]$.

α is usually guiding the hunt, while β and δ might participate in hunting occasionally. In order to simulate the hunting behaviour of grey wolves, α (the best candidate solution), β and δ are assumed to have better knowledge about the potential location of prey. The first three best solutions obtained so far and ω (the other search agents) update their positions according to the position of the best search agents according to

$$\vec{D_\alpha} = |\vec{C}_1.\vec{X_\alpha} - \vec{X}|, \quad \vec{D_\beta} = |\vec{C_2}.\vec{X_\beta} - \vec{X}|, \quad \vec{D_\delta} = |\vec{C_3}.\vec{X_\delta} - \vec{X}| \tag{3}$$

$$\vec{X_1} = \vec{X_\alpha} - \vec{A_1} \cdot (\vec{D_\alpha}), \quad \vec{X_2} = \vec{X_\beta} - \vec{A_2} \cdot (\vec{D_\beta}), \quad \vec{X_3} = \vec{X_\delta} - \vec{A_3} \cdot (\vec{D_\delta}), \tag{4}$$

and

$$\vec{X}(t+1) = \frac{\vec{X_1} + \vec{X_2} + \vec{X_3}}{3}, \tag{5}$$

A grey wolf end a hunt by attacking the prey. When $|A| < 1$, the wolves attack towards the prey, which represents an exploitation process. In contrast, in an exploration process, α, β and δ diverge from each other to search for prey and converge to attack it. This is modelled by using $\vec{A}$ with random values greater than 1 or less than -1, since with $|A| > 1$ the wolves move from the current prey to look for a fitter solution.

3. The Liver CAD System

The proposed abdominal CT Liver parenchyma segmentation and diagnosis CAD system comprises four phases: liver segmentation, lesion segmentation, feature extraction and classification. In the following, we describe each stage in detail along with the steps involved and the characteristic features for each phase.

3.1. Liver Segmentation

Image noise is a random variation of brightness or colour information in images[8] and can lead to serious degradation of image quality. Removing noise while preserving edges and image detail plays a vital role in image processing. The median filter is one of the simplest and most popular approaches for removing certain types of noise like salt and pepper noise. In our approach, we first resize the CT image to 256×256 pixels in order to reduce computation time, and then median filter the image with a filter of size 3×3.

Fuzzy c-means (FCM) is an iterative clustering algorithm. The goal of FCM is to find optimal cluster centroids that minimise a defined dissimilarity function. However, one of the main drawbacks of FCM is that it might converge to a local rather than the global minimum. In this paper, we therefore propose a hybrid approach that combines FCM with GWO for accurate liver segmentation.

GWO is used to find optimal threshold values and to enhance clustering results produced by FCM. In particular, the cluster centroids obtained using FCM are used as initial wolf positions of the GWO algorithm. Algorithm 1 details the proposed clustering algorithm. As parameters, we used the following in our implementation: number of fuzzy clusters = 3; number of search agents = 10; number of Iterations = 5; boundary of search space = $[0; 255]$)

Algorithm 1 FCM-GWO algorithm pseudo code.

Read enhanced CT image $\bar{I}$ (after noise removal)
Get cluster centroids of $\bar{I}$ from FCM as C_j where $j = 1, 2, ...m$ and m is the number of clusters
Initialise grey wolf positions randomly P_i where $i = 1, 2, ...n$, number of search agents w and maximum number of iterations Max_{iter}
Assign C_j to P_j
Initialise α, β and δ
Initialise wolves positions P_α, P_β and P_δ
Set $iter = 0$
while $iter < Max_{iter}$ **do**
    for each search agent **do**
        Update current search agent position
        Calculate fitness function of each search agent
    end for
    Update P_α, P_β and P_δ
    Set $iter$ to $iter = iter + 1$
end while
Get the best solution P_α

In the segmentation phase, the best cluster image produced by the proposed FCM-GWO will be selected based on the maximum mean value. Then, morphological operations including open, close and hole filling are used to enhance the liver cluster image and to focus on the liver parenchyma. Finally, the largest region is taken as the final segmented liver region, since the liver is the largest area in middle cross sections of abdominal CT images[3].

3.2. Lesion Segmentation

Fast fuzzy *c*-means (FFCM) is a memory efficient implementation of the FCM clustering algorithm. In addition, it decreases the number of distance calculations of the FCM by computing distances between data points and the nearest cluster centers. In this paper, we use FFCM to extract lesions from the segmented liver. The extracted liver image is divided into three clusters, so that one cluster represents the background, the second captures lesion pixels and the third cluster represents the liver pixels. For post-processing, morphological operators including closing and opening are applied to enhance the extracted lesions.

3.3. Feature Extraction

Images contain large amounts of data but much of it is redundant. Hence, data reduction is often a major component in analysing images. This can be accomplished by gathering only useful information from the image in a feature extraction stage. In our system, several features are extracted from each candidate lesion. These describe texture and shape properties of the lesion and include: area, median, mean, skewness, standard deviation and kurtosis [12] and ten Haralick texture features extracted from the graylevel co-occurrence matrix [13].

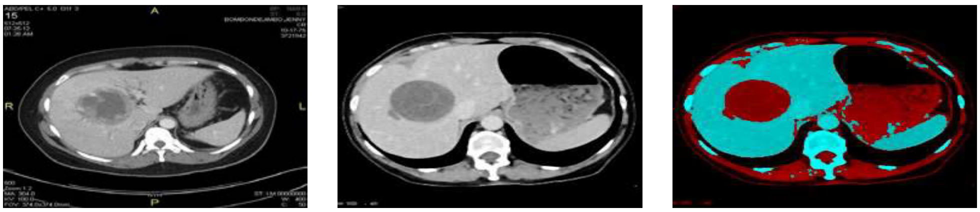
3.4. Classification

In the final stage, a support vector machine (SVM) classifier is employed. SVM is one of the most common classifiers, and is based on a training process to derive an optimal hyperplane, typically in a high-order space. We evaluated three different types of kernel functions, Gaussian (RBF), quadratic, and linear kernels and found the RBF kernel to give the best performance. The features extracted from each lesion are used as input for the SVM in order to arrive at a classification of benign or malignant.

4. Experimental Results

We performed a series of experiments based on CT scans from [10]. Our proposed approach was tested on 62 middle slice sections of abdominal CT images from different patients. The accuracy of proposed liver segmentation approach is measured using correlation, Dice coefficient, Jaccard index, accuracy, sensitivity, F-measure and precision [3,10].

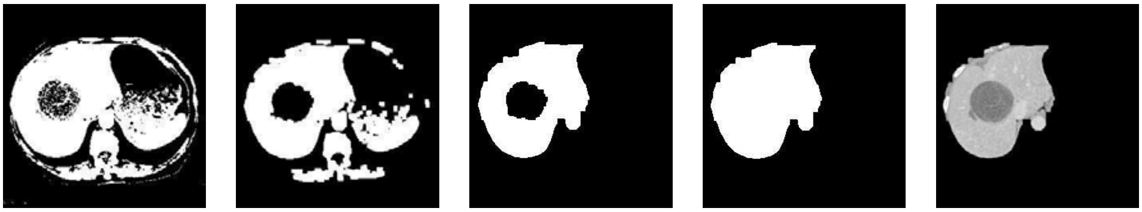
Fig. 1 gives an example of the obtained results from the liver segmentation pre-processing phase and FCM-GWO clustering stage.



(a) (b) (c)

Fig. 1. Results of pre-processing and clustering: (a) original image, (b) image after enhancement, (c) results of FCM-GWO segmentation.

Fig 2 shows results of the liver segmentation post-processing and final segmentation. As can be seen, an accurate definition of the liver area is achieved.



(a) (b) (c) (d) (e)

Fig. 2. Results of post-processing and segmentation: (a) clustered image after binarisation, (b) image after morphological opening, (c) image after selecting largest object and applying morphological closing, (d) image after hole filling, (e) final extracted liver region.

Fig. 3, one the left, compares the segmentation results obtained from traditional methods like region growing, active contour and global thresholding with morphological operators with the results obtained from our proposed segmentation approach. As can be seen, our approach provides very competitive performance. The right side of Fig. 3 compares the results achieved using our FCM-GWO approach compared to those obtained by just employed standard FCM, confirming improved performance due to the employment of the GWO stage.

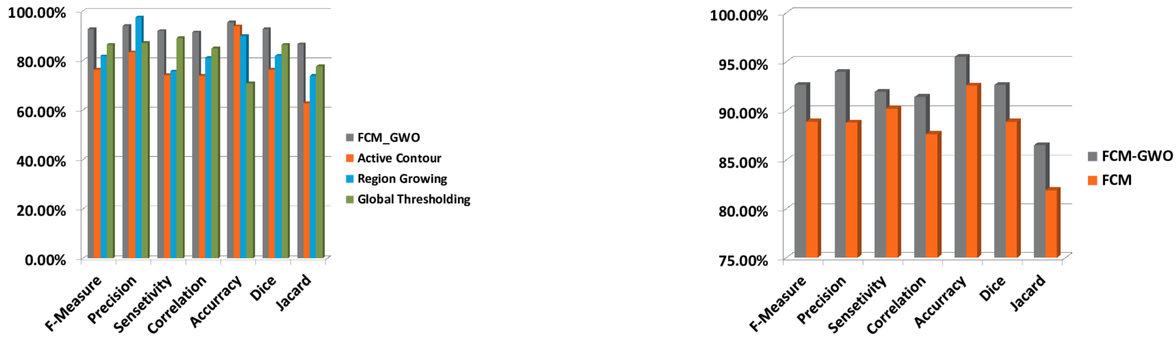
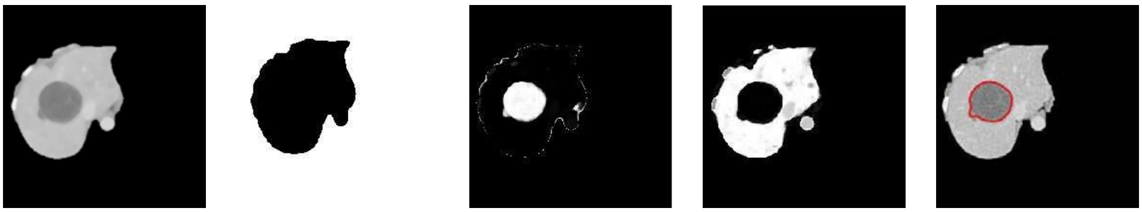


Fig. 3. Left: comparison between traditional methods and the proposed segmentation approach in terms of Correlation, Dice Coefficient, Jaccard Index, Accuracy, Sensitivity, F-measure and Precision. Right: comparison between FCM-GWO and standard FCM approaches.

Fig. 4 shows the result obtained from the lesion segmentation phase. As can be observed, the tumour that is present in the slice is accurately separated.



(a) (b) (c) (d) (e)

Fig. 4. Results of lesion segmentation phase: (a) extracted liver image, (b) background cluster, (c) lesion cluster, (d) liver cluster, (e) final extracted tumour results.

Table 1 compares the results of our proposed CAD approach with other existing works on liver disease identification from abdominal CT in terms of accuracy. It is clear that the presented approach yields excellent performance in comparison with other methods from the literature.

Table 1. Comparison between the proposed approach and other, existing approaches.

Authors	Features	Classifier	Year	Accuracy (%)
Mala et al. [12]	6 features from GLCM	Learning Vector Quantisation	2006	92
Mala et al. [13]	Biorthogonal wavelet-based and statistical texture feature	Probabilistic Neural Network	2010	96
Kumar et al. [14]	Fast Discrete Curvelet Transform	Feed Forward Neural Network	2010	93.3
Gunasundari et al. [15]	GLCM and Fast discrete Curvelet transform	Back Propagation Network	2012	96
Proposed Approach	Statistical Features and GLCM Features	SVM	2016	97

5. Conclusions

In this paper, a fully automatic CAD system for liver and lesion segmentation and liver diagnosis is proposed. The proposed liver segmentation approach is based on a hybrid approach of fuzzy clustering and grey wolf optimisation, while a fast fuzzy *c*-means technique is employed for lesion segmentation. Shape and texture features are extracted from lesions and employed in a classification stage using a support vector machine classifier. Experimental results obtained on a varied dataset show that our approach gives excellent performance and compares well to other approaches from the literature. We achieve an overall accuracy almost of 96% for healthy liver extraction and 97% for liver disease classification.

References

1. Aly A. , Deris S. , Zaki N. "Research Review for Digital Image Segmentation Techniques", *International Journal of Computer Science and Information Technology*, Vol. 3, No. 5, pp. 99-106, 2011.
2. Dixit V., Pruthi J. "Review of Image Processing Techniques for Automatic Detection of tumour in Human Liver", *International Journal of Computer Science and Mobile Computing*, Vol. 3, No. 3, pp. 371-378, 2014
3. Zayane O., Jouini B., Mahjoub M. A. "Automatic liver segmentation method in CT images", *Canadian Journal on Image Processing and Computer Vision*, Vol. 2, No. 8, pp. 92-95, 2011
4. Leung Y., Zhang J., Z. Xu. "Clustering by Space-Space Filtering", *IEEE Transactionson Pattern Analysis and Machine Intelligence*, Vol.22, No.12, pp. 1396-1410, 2000.
5. Frigui H., Krishnapuram R. "A Robust Competitive Clustering Algorithm with Applications in Computer Vision", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol.21, No.5, pp.450-465, 1999.
6. Mirjalili S., Mirjalili S.M., Lewis A. "Grey Wolf Optimizer", *Advances in Engineering Software*, Vol. 69, PP. 46-61, 2014.
7. Abdalla Z., Neveen I. G., Aboul Ella H., Hesham A. H. "Level set-based CT liver image segmentation with watershed and artificial neural networks",*12th International Conference on Hybrid Intelligent System*, pp. 96-102, 2012.
8. Sakthive N. Prabhu L. "Mean Median Filtering For Impulsive Noise Removal", *International Journal of Basics and Applied Science*, Vol. 2, No. 4, pp. 47-57, 2014.
9. Kole D. K., Bhattacharya S. , Mala S., Mandal S. , Sinha A., Sinha S., Mukhopadhyay D. "Automatic Detection and Size Measurement of Hepatic Lesions", *International Journal of Wisdom Based Computing*, Vol. 1, No. 3, 2011.
10. Abdalla M. , Hesham H., Neven I.G., Aboul Ella H., Gerald S. "Evaluating the Effects of Image Filters in CT Liver CAD System", *International Conference on Biomedical and Health Informatics*,, pp. 448-451, 2012.
11. Mala K. and Sadasivam V."Wavelet based texture analysis of Liver tumor from Computed Tomography images for characterization using Linear Vector Quantization Neural Network", *International Conference on Advanced Computing and Communication*, pp. 267-270, 2006.
12. Mala K., Sadasivam V. "Wavelet based texture analysis of Liver tumour from Computed Tomography images for characterization using Linear Vector Quantization Neural Network", *International Conference of Advanced Computing and Communication*, pp. 267-270, 2006.
13. Mala K., Sadasivam S. "Classification of Fatty and Cirrhosis Liver Using Wavelet-Based Statistical Texture Features and Neural Network Classifier", *International Journal of Software Informatics*, Vol. 4, No. 2, pp. 151-163, 2010.
14. Kumar S.S., Moni R.S. "Diagnosis of Liver Tumor from CT Images using Curvelet Transform", *International Journal of Computer Application*, Vol. 1, pp. 1-6, 2010.
15. Gunasundari S., Ananthi M. S. "Comparison and Evaluation of Methods for Liver Tumor Classification from CT Datasets", *International Journal of Computer Applications*, Vol. 39, No. 18, pp. 46 -51, 2012.