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Liver Segmentation on Computed Tomography Images

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Abstract: Background: Liver segmentation using computed tomography data is the first step for the diagnosis of liver diseases. Currently, the segmentation of structures and organs is far from the precision level achieved by modern 3D systems based on images performed in the country's hospitals, so it is necessary to search for viable alternatives using the PDI on a computer. Objective: From a computational point of view, to determine an effective variant for the segmentation of liver images for clinical purposes in routine hospital conditions. Methods: Two modern segmentation methods (Graph Cut and EM/MPM) were compared by applying them to liver tomography images. An evaluative and statistical analysis of the results obtained in the segmentation of the images from the Dice, Vinet and Jaccard coefficients was carried out. Results: With the Graph Cut method, the desired region was segmented in all cases, and even when the image quality was low, a high similarity was observed between the segmented image and the reference mask. The level of visual detail is good, and edge reproduction remains true to the reference image. Image segmentation using the EM/MPM method was not always satisfactory. Conclusions: The Graph Cut segmentation method achieved a higher precision for the segmentation of liver images.

Key words: computer-assisted image processing; X-ray computed tomography; liver

1. Introduction

Medical image segmentation provides quantitative analysis of gender characteristics present in specific organs or lesions. There are various segmentation methods have been described in the literature. Their use largely depends on the objects to be segmented and the collection technology. Many references provide abstract of the most commonly used methods and techniques. [1, 2] Given the difficulty of liver segmentation, many successful methods have been proposed with varying degrees of success. [3] However, some key issues remain unresolved. In recent years, the most accepted methods used by the scientific community are those that work in terms of energy minimization, [4] among which there is a preference for the method based on the level set and the method based on graph cuts. [1, 5]

Although modern CT scanners are equipped with software for image processing, research is constantly being carried out on processing methods to improve image quality, which in turn contributes to improved diagnostics. Structural and organ segmentation methods are part of these progressive improvements. The present study focuses on liver segmentation from CT images. This aspect is of both scientific and practical importance from a clinical point of view, since it is necessary to obtain a very precise segmentation of this organ, both for transplantation purposes and for the treatment of liver tumour. For these reasons, the objective of this research was to determine an effective and computationally efficient variant, for the segmentation of liver images of clinical purposes under routine hospital conditions.

2. Methods

Two modern segmentation methods (Graph Cut and EM/MPM) were compared by applying them on liver tomography images. An evaluative and statistical analysis of the results obtained in image segmentation was carried out by using Dice, Vinet and Jaccard coefficients.

The Graph Cut based segmentation method creates a graph of the image where each pixel is a node connected by weighted edges. The higher the probability that the pixels are related, the higher the weight. This algorithm cuts the image of interest along weak edges to achieve object segmentation in the image [6].

For this method, it is defined as:

- $X = (x_1,...., x_p,..., x_{|p|})$ as the set of pixels of the image to be segmented in greyscale.
- $P = (1,..., p,..., |P|)$ serves as the index set for image I.
- N is an unordered pair {p, q} in the 4-(8-) neighborhood system, where {p, q} are two adjacent pixels.
- $L = (L_1,..., L_P, ..., L_{|P|})$ is a binary vector whose components specify the mapping of image pixels. This value indicates whether it belongs to the background or foreground (the foreground will belong to the structure, and the background will belong to other parts of the image). That is to say, this vector defines image segmentation.
- The energy function to be minimized is:

$$E(L) = U(L) + \delta B(L) \quad (1)$$

Where *U(L)* is the unary term, *Up* is the penalty given to *p*, background or foreground.

$$U(L) = \sum_{p \in P} U_p(L_p) \quad (2)$$

Among them, *B(L)* is the boundary term, and due to the discontinuity between *p* and *q*, it will receive greater punishment.

$$B(L) = \sum_{\{p,q\} \in N} B_{\{p,q\}} \varphi(L_p, L_q) \quad \varphi(L_p, L_q) \begin{cases} 1, L_p = L_q \\ 0, en\ otro\ caso \end{cases} \quad (3)$$

Finally, the coefficient δ specifies the importance of *U(L)* with respect to *B(L).*

The objective of Graph Cut is to find the segmentation that globally minimizes the energy of all possible segmentation while satisfying some constraints.

The expectation maximization of the posterior marginal (EM/MPM) algorithm aims to minimize the expected value of the number of misclassified pixels. The EM/MPM algorithm is based on the MPM algorithm for segmentation and the EM algorithm for estimation of the algorithm can be summarized in two steps. For this, it is considered that the element of a random field X at spatial location $s \in S$, is denoted as X_s. The label field is denoted as X and the observed image as Y. Then, θ is a nonrandom vector whose elements are the unknown parameters of the conditional probability density function of Y given by X. The samples of the random fields are denoted as x and their images as y. (EM/MPM)

Then, in the first step, the MPM algorithm is used to obtain approximations of the marginal conditional probability mass functions of X, using the estimates of θ. That is, $p_{X_s|Y}(k|Y, \hat{\theta}^{(p-1)}) \, \forall\, s \in S \text{ y } k = 1, \ldots L$ is estimated using a Gibbs sample (German, 1984 # 12), and the following equation:

$$p_{X_s|Y}(k|Y, \theta) \approx \frac{1}{n} \sum_{i=1}^{n} \left[1 - i(x_s^{(i)}, k)\right] \quad (4)$$

Where

- k is the set of values that the random variable X can take; $k \in \{1, 2,..., L\}$, and L is the number of different classes or objects in the image.
- n is the number of iterations performed for the Gibbs sample.

In the second step, the EM algorithm is used to update the estimation of θ by using the results of the MPM algorithm. That is to say, through using the $p_{X_s|Y}(k|Y,\hat{\theta}^{(p-1)})$ estimation obtained in the first step, the approximate value estimations MPM of X and θ are obtained using the following equations, denoted as $\hat{x}_{MPM}^{(p)}$ and $\text{y}\ \hat{\theta}^{(p)}$, respectively.

$$\mu_k^{(p+1)} = \frac{1}{N_k^{(p+1)}} \sum_{S=1}^{N} y_S p_{X_s|Y}(k|Y,\theta^p) \quad (5)$$

$$\sigma_k^{2(p+1)} = \frac{1}{N_k^{(p+1)}} \sum_{S=1}^{N} \left(y_S - \mu_k^{(p+1)}\right)^2 p_{X_s|Y}(k|Y,\theta^p) \quad (6)$$

$$N_k^{(p+1)} = \frac{1}{N_k^{(p+1)}} \sum_{S=1}^{N} p_{X_s|Y}(k|Y,\theta^p) \quad (7)$$

- Where p is the interaction parameter space.
- N is the total number of pixels in the image.
- μ and σ are the mean and variance respectively.
- $\theta^{(p)}$ is the estimate of θ in the pth iteration.

The images used were obtained from the CHAOS_Train_Sets abdominal computed tomography database of Combined Healthy Abdominal Organ Segmentation (CHAOS). Each dataset in this database corresponds to a series of DICOM images belonging to a single patient. The datasets are collected retrospectively and randomly from the Picture Archiving and Communication System (PACS) of the DEU Hospital.

The database contains CT images of 40 different patients. These patients are potential liver donors, as they have a healthy liver (without tumors, lesions or any other disease).

Images acquired with three different scanners were used: a Philips SECURA CT with 16 detectors, a Philips M×8000 CT with 64 detectors and a Toshiba Aquilion ONE with 320 detectors (all equipped with the spiral CT option). Patient orientation and alignment is the same for all data sets. Each dataset consists of 16-bit DICOM images, with a resolution of 512 × 512 pixels, slice thickness between 0.7 - 0.8 mm and an inter-slice distance between 3 - 3.2 mm. This corresponds to an average of 90 slices per dataset (i.e. minimum 77, maximum 105 slices). In total, there are 1367 tomographic slices (2D images).

The evaluation of the results was carried out by comparison with reference or groundtruth images. Among the various measures for the supervised evaluation, the Jaccard coefficient, the Dice coefficient and the Vinet distance were selected for application in this work.

3. Results

The segmentation methods used have produced different results, from which analysis will determine which segmentation method has been proven to be the most effective in the experiments conducted.

Figure 1 shows visually the effectiveness of the Graph Cut method for one of the images in the database. The results obtained from the segmentation process can be considered satisfactory for the CT images used, since in all cases the desired region was segmented, and even when the quality of the images is low, a high similarity is observed between the segmented image and the reference mask, as shown in the figure. The level of visual detail is good and the edge production remains faithful to the reference mask (Fig. 1).

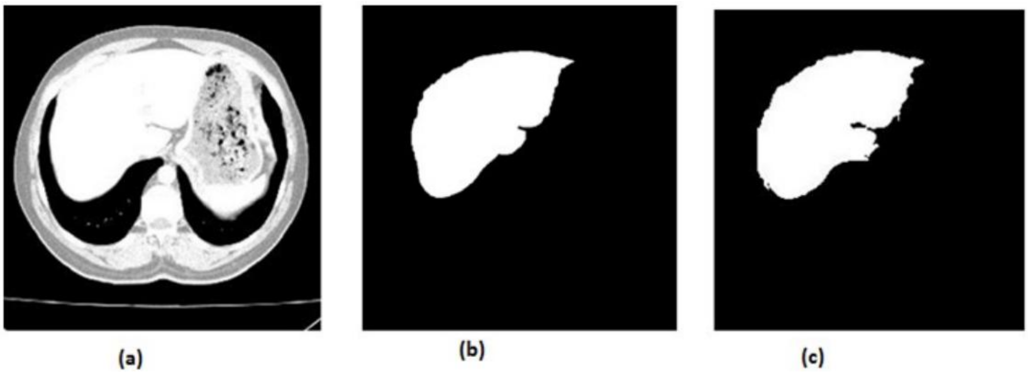

Figure 1. (a) Original image. (b) Reference mask. (c) Segmented image using the Graph Cut method.

The results of segmenting CT images using EM/MPM methods are not always satisfactory. As shown in Figure 2, most of the selected images have been correctly segmented, and good similarity can be seen between the segmented image and the reference mask. The reproducibility of the edges is good, and the level of detail is also good. However, some images were not properly segmented as shown in Figure 3, mainly when the liver in the image to be segmented has a more complex morphology or there are very low contrast differences in the image. This result questions the effectiveness of this method for this specific task. (Fig. 2 and Fig. 3).

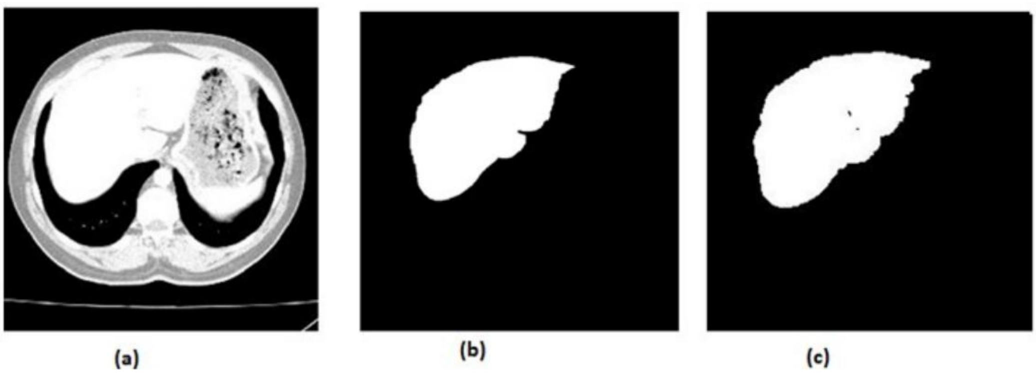

Figure 2. (a) Original image. (b) Reference mask. (c) Segmented image using the EM/MPM method.

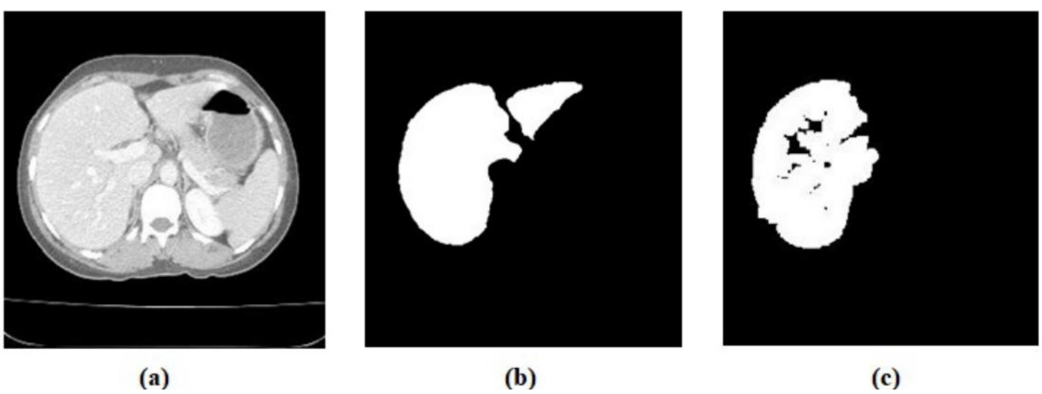

Figure 3. (a) Original image. (b) Reference mask. (c) Segmented image using the EM/MPM method.

Figure 4 shows the evaluation of the segmentation quality with Graph Cut and EM/MPM methods from the Dice coefficient for the 36 images selected for testing. In the figure, the images are named in the form ia_00b, where a is the patient number and b is the selected cut. It can be seen that there is a greater fluctuation between patients for the EM/MPM method than for Graph Cut method. In other words, the Graph Cut method is more accurate in obtaining the the liver contour of each patient and therefore more effective for the task at hand (Fig. 4).

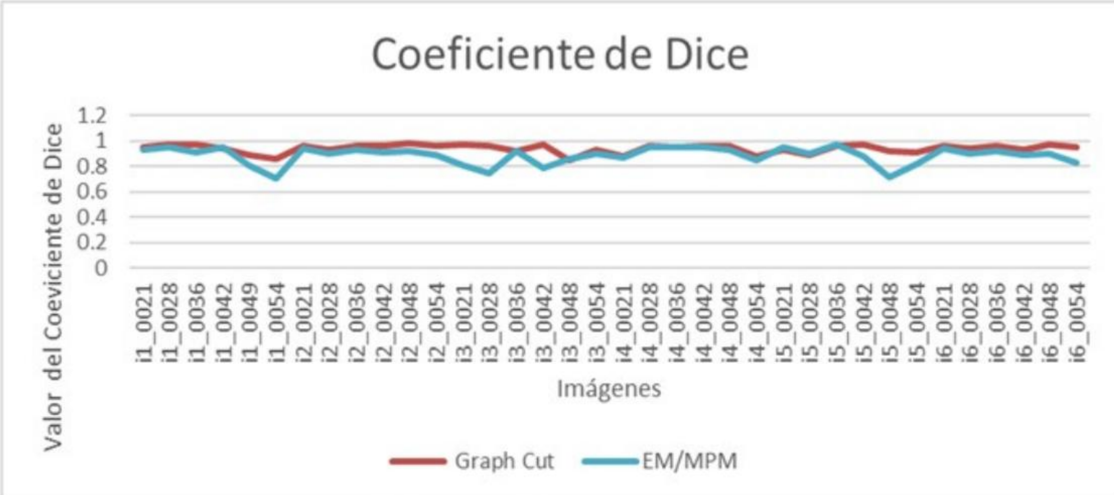

Figure 4. Dice coefficient behavior for each of the images.

Tables 1 and 2 show the mean of Dice coefficient calculation per patient for the Graph Cut and EM/MPM methods, respectively. The mean of Dice coefficient reveals that in the Graph Cut method the segmentation was good, since in all patients it exceeds the value of 0.90. In the case of the EM/MPM method, a low value can be observed in patient 5. It was in this case where undesired structures were segmented together with the liver. A visual evaluation of the data obtained, with the calculation of the Dice coefficients (without having performed the statistical analysis), it can be said that the segmentation method that offered the best results in this experiment was Graph Cut. In each of the patients, the mean of Dice coefficient for this method was higher than in the EM/MPM method (Table 1 and Table 2).

Table 1. Mean for the six images of each patient of the Dice coefficient (Graph Cut).

Pacientes	Valor Mínimo	Valor Máximo	Media	Desviación típica
1	0,862	0,977	0,933	± 0,047
2	0,929	0,980	0,959	± 0,016
3	0,846	0,978	0,935	± 0,050
4	0,877	0,967	0,933	± 0,042
5	0,886	0,975	0,931	± 0,033
6	0,934	0,969	0,954	± 0,014
Total			**0,941**	**± 0,036**

Table 2. Mean for the six images of each patient of the Dice coefficient (EM/MPM).

Pacientes	Valor Mínimo	Valor Máximo	Media	Desviación típica
1	0,706	0,955	0,893	± 0,094
2	0,889	0,944	0,917	± 0,019
3	0,746	0,918	0,837	± 0,067
4	0,846	0,955	0,918	± 0,047
5	0,721	0,973	0,877	± 0,093
6	0,824	0,939	0,897	± 0,040
Total			**0.887**	**± 0,069**

Figure 5 shows the evaluation of the segmentation quality with Graph Cut and EM/MPM methods from the Jaccard coefficient for each image. It can also be seen that there is a greater fluctuation per patient for the EM/MPM method than for Graph Cut and that, in general, the latter shows greater precision and therefore greater efficacy for the intended task (Fig. 5).

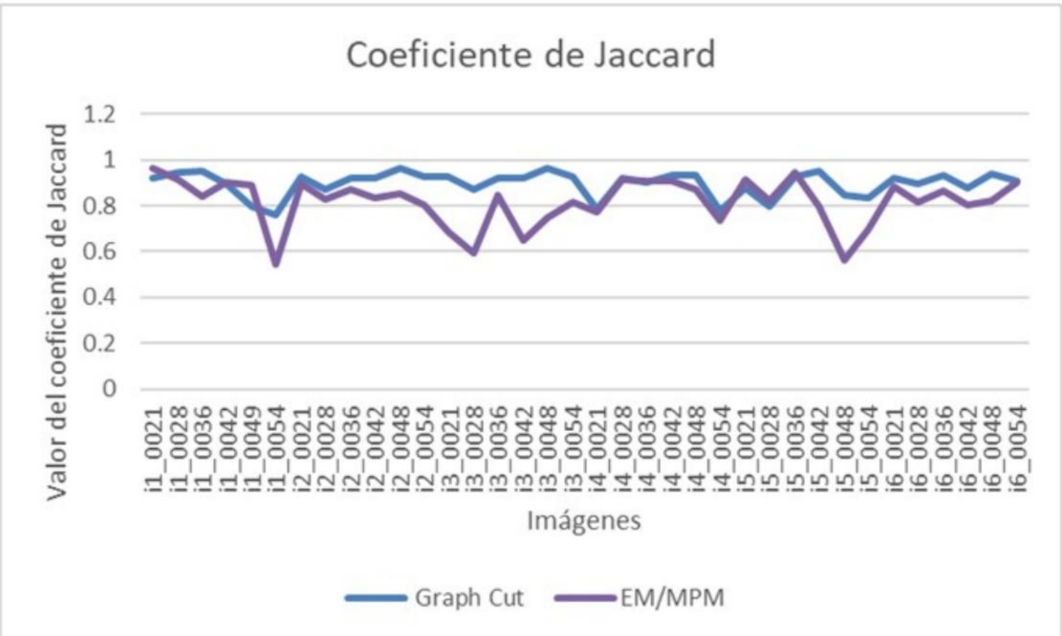

Figure 5. Jaccard coefficient behavior for each image.

Tables 3 and 4 show the mean values per patient of the Jaccard coefficient calculation for the Graph Cut and EM/MPM methods, respectively. A visual evaluation of the data obtained with the calculation of the Jaccard coefficients, as with the Dice coefficient, shows low values for patient 5 in the EM/MPM method, while the values for the Graph Cut method always exceed the mean of 0.85 (Table 3 and Table 4).

Table 3. Mean values for the six images of each patient of the Jaccard coefficient (Graph Cut).

Paciente	Valor Mínimo	Valor Máximo	Media	Desviación típica
1	0,757	0,954	0,878	± 0,,081
2	0,868	0,961	0,921	± 0,030
3	0,796	0,951	0,872	± 0,,058
4	0,781	0,936	0,876	± 0,073
5	0,796	0,951	0,872	± 0,058
6	0,868	0,961	0,921	± 0,030
Total			**0,897**	**± 0,055**

Table 4. Mean values for the six images of each patient of the Jaccard coefficient (EM/MPM).

Pacientes	Valor Mínimo	Valor Máximo	Media	Desviación estándar
1	0,545	0,964	0,832	± 0,150
2	0,801	0,894	0,847	± 0,,033
3	0,594	0,849	0,724	± 0,099
4	0,733	0,915	0,851	± 0,078
5	0,563	0,947	0,791	± 0,142
6	0,803	0,904	0,850	± 0,040
Total			**0,887**	**± 0,69**

Figure 6 shows the evaluation of segmentation quality with Graph Cut and EM/MPM methods from the Vinet coefficient. In general, this coefficient was more sensitive to the variability of the livers in the sample studied than the Dice and Jaccard coefficients. Nevertheless, the fluctuation is smaller for Graph Cut than for EM/MPM (Fig. 6).

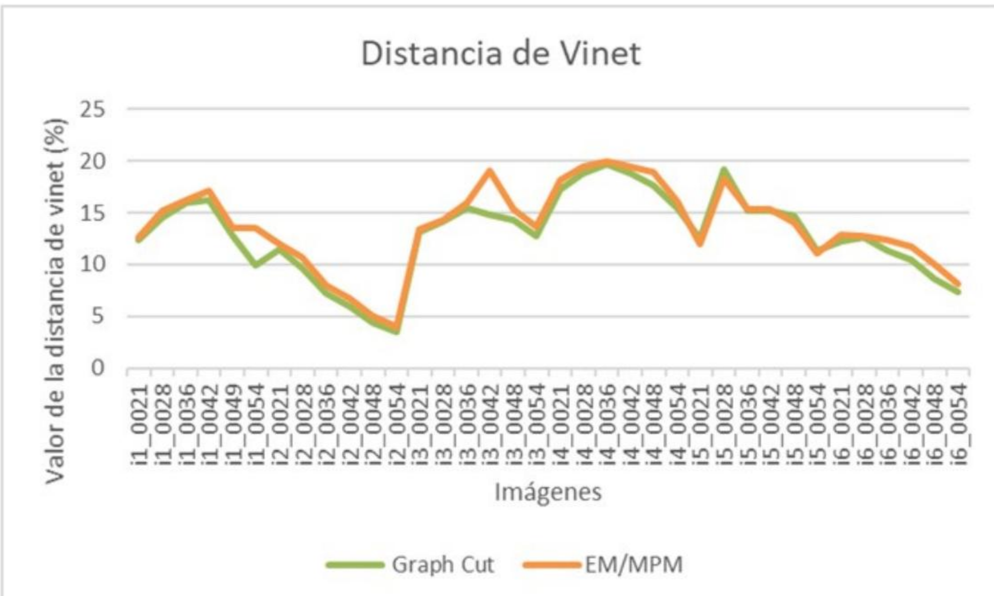

Figure 6. Vinet distance behavior for each of the images.

Tables 5 and 6 show the averages per patient of the Vinet distance calculation for the Graph Cut and EM/MPM methods, respectively. The results obtained in the Vinet distance calculation are interpreted differently from those obtained with the Dice and Jaccard coefficients. Here, the smaller the distance, the more accurate the segmentation of the images will be, because there is less difference between reference and segmentation. Therefore, making a visual assessment of the data, it can be said that the Graph Cut segmentation method provides smaller distances and confirms its greater efficiency for segmenting liver (Table 5 and Table 6).

Table 5. Average for the six images of each patient of the Vinet coefficient (Graph Cut).

Pacientes	Valor Mínimo	Valor Máximo	Media	Desviación estándar
1	9,907	16,227	13,614	± 2,418
2	3,426	11,443	7,027	± 3,082
3	12,812	15,505	14,118	± 1,014
4	15,411	19,656	17,914	± 1,499
5	11,293	19,239	14,664	± 2,745
6	7,342	12,634	10,438	± 2,078
Total			**12,962**	**± 4,060**

Table 6. Average for the six images of each patient of the Vinet coefficient (EM/MPM).

Pacientes	Valor Mínimo	Valor Máximo	Media	Desviación estándar
1	12,567	17,110	14,710	± 1,779
2	3,988	11,952	7,733	± 3,149
3	13,334	19,060	15,286	± 2,103
4	16,032	19,916	18,664	± 1,417
5	11,086	18,313	14,327	± 2,597
6	8,161	12,833	11,303	± 1,855
Total			**13,669**	**± 4,028**

The SPSS-22 software was used to perform the statistical analysis of the results. The method that presented the best ranges for all the coefficients was Graph Cut (higher for Dice and Jaccard and lower for Vinet).

4. Discussion

Among the segmentation methods selected and implemented with MATLAB in the present study, Graph Cut and EM/MPM, the one that showed the highest accuracy in the segmentation of liver CT images was Graph Cut.

According to the Dice and Jaccard coefficients and the Vinet distance, significant differences were found in the quality of segmentation with both methods, being superior in Graph Cut.

Graph Cut method shows great potential in achieving the advantages of obtaining global optima and for their practical efficiency (using good processors). When it comes to liver segmentation, other authors [8, 9, 10] have appreciated that sometimes the standard Graph Cut model fails, under the circumstance of seriously blurred ties and similar intensities between the liver and its neighboring organs. In addition, the model is sensitive to energy function parameters that are only of interactive information or empirical estimation. The aforementioned type of inaccuracies was not observed during the implementation of Graph Cut in the present investigation from the described variant, which outperforms the standard method.

Masuda et al. [11] proposed the method based on adaptive contrast enhancement and EM/MPM to detect tumors in CT images. The proposed method proved to be suitable for low contrast images. The results obtained were good, which coincides with the results obtained in this research.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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