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An Automated System for the Segmentation of Dynamic Scintigraphic Images

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Abstract
This paper presents a novel system for the automatic segmentation of Dynamic Scintigraphic Images (DSI). DSI allow a functional exploration of the studied structure and therefore a good understanding of the pathological phenomenon. The proposed system aims at achieving high accuracy of the segmentation process for a precise calculation of the renal functions and the ventricular ejection fraction, thus speeding up the clinical diagnosis and decision-making. The proposed method combines the Fast Marching Method (FMM) and HOG3D spatiotemporal descriptor with the supervision of a Multi Agent System (MAS). Our MAS is composed of a set of supervisor and explorer agents able to detect the regions of interest from a video sequence of scintigraphic images captured over time. The behavior of communicating supervising and exploring agentsis inspired from the Active contour technique. This automatic segmentation system is expected to assist physicians in both clinical diagnosis and educational training. The results of the application of our method on several dynamic images are presented and discussed.

Keywords: Dynamic scintigraphic images; Automated system; Segmentation; Multi-Agent System; Fast Marching Method; Hog3D.

Introduction

Scintigraphy is a nuclear imaging technique that uses the radioactive sources to study the organs functioning. This is what makes it different from radiography which analyzes their morphology only. This technique has been used by several application fields such as cardiopulmonary, endocrine, osseous and renal affections. The scintigraphic images are particularly difficult to function automatically because they do not possess all the qualities of a planar image. This is particularly lower signal and higher noise. The DSI face other problems like the interpatient variation and absence of anatomical benchmarks that helps the physician define easily the Regions Of Interests (ROI). The spatio-temporal aspect of DSI, requires different ROI for N images. In a manual mode, the reproducibility is not guaranteed and causes a big problem.

For all these reasons our study focused on a novel method to define the ROI of DSI without any intervention of the user.

Our system can be very beneficial for the DSI processing and analysis of as far as quantification is concerned in particular.

Indeed quantification in nuclear medicine remains one of the key points of this imaging technique. It is based on the determination of the ROI including all the pixels contained in a studied structure in order to determine the activity to its level.

The goal of cardiac scintigraphy is to evaluate myocardial perfusion and/or function to detect physiological and anatomical abnormalities of the heart and determine the prognosis.

In this study we presented a comparative study of many scintigraphic image segmentation methods. Then our automated system of DSI segmentation was introduced with the obtained results.

In literature, a limited number of studies have used a system of automatic segmentation of ROI in the dynamic scintigraphy,Hannequin et al. have developed an automated system based on cluster analysis to define the ROIS in dynamic scintigraphy [1]. In 2011, Ståhl et al. also proposed an automatic analysis of dynamic renal scintigraphy [2].

A segmentation method, specific to the renal scintigraphy, was proposed in [3]. An automatic thresholding algorithm was used to segment each kidney images. To avoid any preprocessing, pixels in the area around the initial boundary are classified as kidney pixels or background. However this method does, not consider the fact that diseased kidneys may show lower uptake in wedge-shaped areas around their boundaries.

The active contour is a frequently used segmentation technique. It consists in initializing a curve (closed or not, in fixed extremities or not) in the circle of acquaintances of the border of an object to be detected. The active contour was used by Kaur et al. in [4] for the segmentation of thyroid scintigraphyimages. The same technique was employed byHraiech et al. in [5] for the detection of the left ventricle in scintigraphicimages.

Many mathematical techniques were used to treat and analyze scintigraphic images. In this context, N.Gribaa et al. have developed a system of restoration of scintigraphic images based on the transformation of the Fourier and Wavelet domains [6]. Khlifaet al. have treated the noise existing in the scintigraphic images using another mathematical method called Fisz Transformation [7].

Based on the Bayesian method, Šmídl et al. proposed a probability model for the functional analysis with the evaluation of ROI [8].

The region growing segmentation technique is conceptually simple and fast. This method was used in [16] for the detection of renal ROI on scintigraphic images.

In the aim of the current study was to automate the segmentation phase using MAS with the collaboration of two other techniques FMM and HOG3D.

The remaining of this paper was organized as follows: section II presented a detailed description of the proposed system, section III was devoted to the experimental results and.We present concluding remarks in section IV.

Overview of the Proposed System

Scintigraphic Images

Scintigraphic images are often characterized by much noise and low contrast and resolution, which makes the perception of regions of interest very difficult [19].

Each digital image is a set of values a_{ij}" corresponding to the number of counts in a set of pixels identified by (i, j), represented in matrix form by $\{(i, j, a_{ij})\}$. Defining ROI and counting the activity on all the validated pixels for N recorded images, not only allow the tracking over time but also the evolution of the activity of the structure corresponding to the selected pixels. Thus, the access to a dynamic study of the functioning of the studied organ is achieved (renal or cardiac studies) that is to say a study incorporating the evolution over time. Data is then expressed in a matrix by inserting the time parameter t_k which indicates the progress of images: $\{(i, j , a_{ij}), t_k\}$.

- i and j are the geometric coordinates of the pixel,
- a_{ij} is the measure in counts per minute,

- t_k locates the k^{th} image acquisition.

It will then be relatively simple to draw the curves evolution of the activity in time by representing the digital measured values (a_{ij}) of each ROIon a graph [21].

Figure 1 illustrates an example of a visualization of functional images from a dynamic renal scintigraphy.

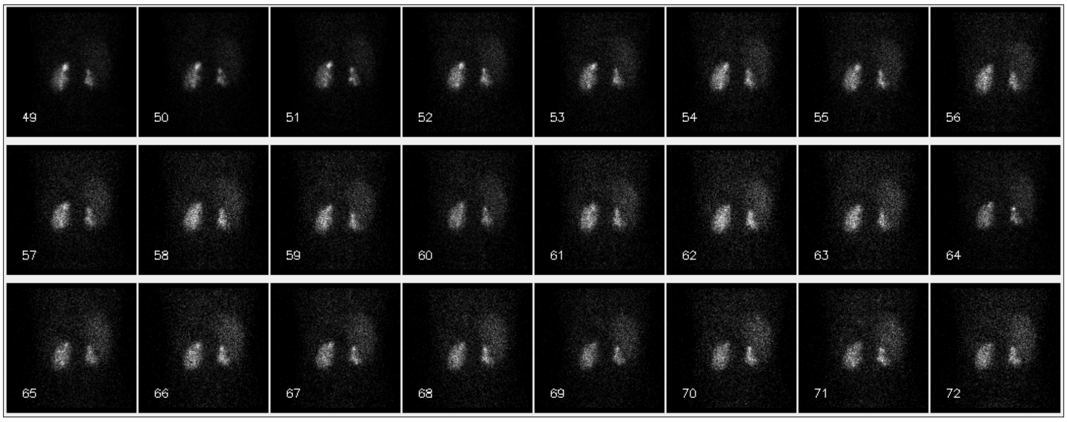

Figure 1. Example of a renal DSI

In Figure 2 an example of a visualization of functional images from a dynamic cardiac scintigraphy is illustrated.

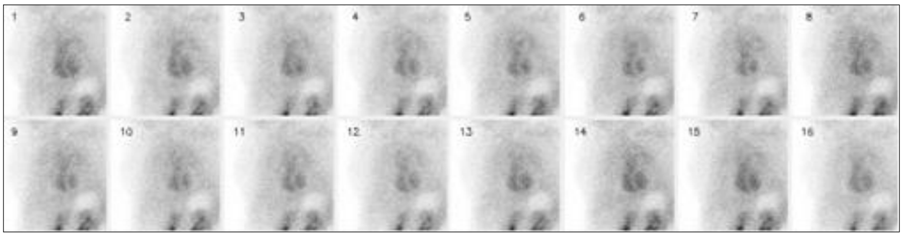

Figure 2. Example of a cardiac DSI

For these two types of studies we applied the same method to automatically define the ROI on the images. The flowchart of our method is shown in Figure. 3. The diagram shows the specific module of our system, the video decomposition of cardiac or renal DSI, and the segmentation phase.

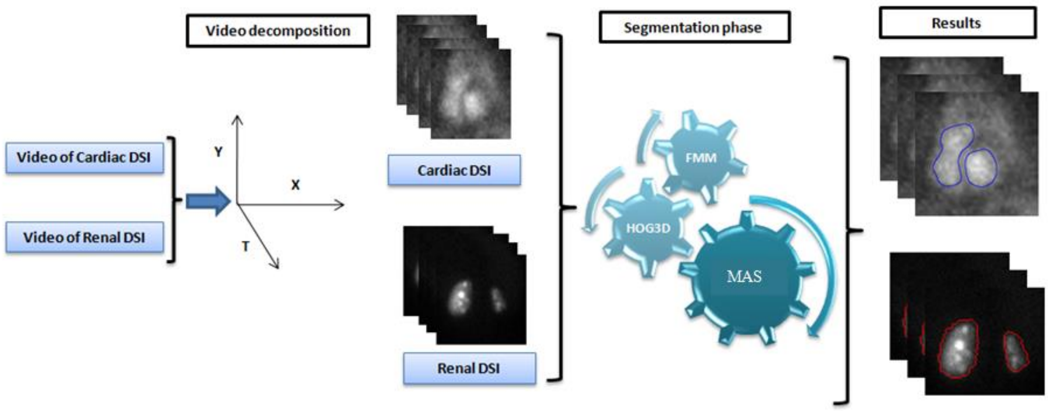

Figure 3. The flowchart of the proposed system

Segmentation Phase

In order to launch the segmentation phase, we have used the Multi-agent model in order to accelerate and automate the image-processing system. In fact the data is too large and also the resulting contours are inaccurate.

For Weiss [11], an agent is a computational entity; it can be considered as perceiving and acting independently from its environment. A Multi-agent system consists of a set of IT processes taking place simultaneously. Hence, the multiple agents interacting at the same moment share common resources and communicate with each other. In, the present study a multi-agent system to segment the dynamic scintigraphic images sequences was defined. The used agents are supervisor and explorer agents that communicate with each other and are inspired from Fast marching method in their behavior.

The proposed agent model consists of two types of explorer and supervisor agents.

The interaction between agents goes through communication and determines the organization of the system.

The explorer agents used in our system are initialized on the points of interest of the image detected by the spatio-temporal descriptors.

We use the Multi-agent system on the FMM to get the contour of the renal ROI during the cine presentation of scintigraphic images. Tracking is carried out relying on the HOG3D spatio-temporal descriptor. It is a 300-bin descriptor proposed by Kläser et al. [10]. It is based on the orientation of the histograms of 3D gradients.

The authors propose to define a grid *nx * ny *nt* in the surrounding space-time area and compute of the 3D grid gradients orientations for each cell.

The evolution of our model is based on cooperation among all the explorer agents of the images that have a limited capacity and a partially known environment yet able to communicate with the supervisor agent.

HOG3D. The HOG3D is a descriptor based on the spatio-temporal aspects; it is based on 3D gradient orientations histograms. The integral image representation is essential for the calculation of gradients. For a standard quantification of the orientation of the spatiotemporal gradients, we can use the regular polyhedra. The shape and movement descriptors are combined together simultaneously.

In Figure 4 we illustrate the representation of the differentconstruction stepsof the HOG3D descriptor.

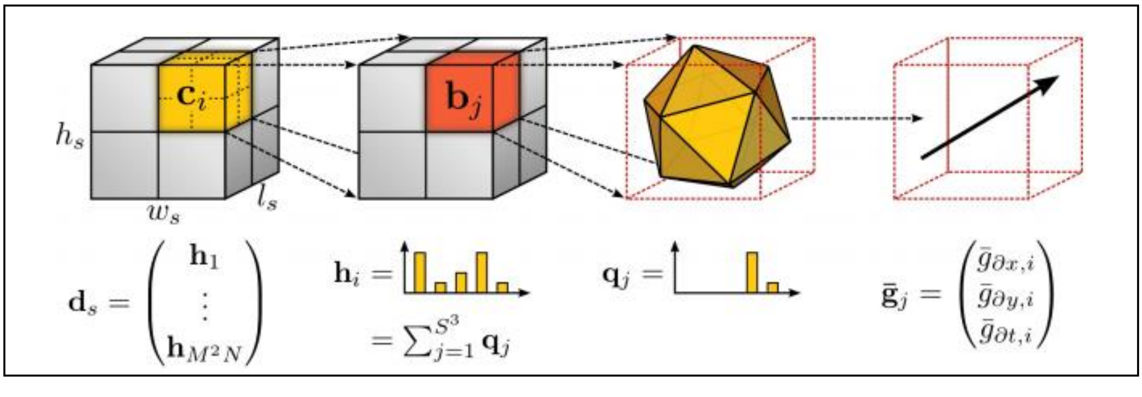

Figure 4. Overview of the HOG3D descriptor

In the first step the support region around a point of interest is divided into a grid of gradient orientation histograms. In the second step, each histogram is computed over a grid of mean gradients. Then in the third step each gradient orientation is quantized using regular polyhedrons. Finally each mean gradient is computed using integral videos.

Fast Marching method. The segmentation approaches based on active contours have proven their effectiveness and robustness facing the noise. But the major disadvantage of these methods is that they have a high cost in time and usually exclude all propagation on a large scale. The Fast Marching Method can solve this problem.

The FMM method is a numerical method introduced by Sethian in [9] and Tsitsiklis in [17] to effectively solve the Eikonal equation isotropic on a regular grid.

FMM works only if the speed never changes its sign, if the front always moves towards the inside or towards outside (the gain in computation time much higher than that of the Narrow Band method).

FMM allows us to solve the boundary value problems of the eikonal equation:

$$|\nabla u| f(x,y) = 1 \text{ Subjectto } u\,|_{S} = g(x,y) \tag{1}$$

For f(x,y)=1 and g(x,y) = 0, the solution gives the covered distance of the surface S [20].
This method computes the transit time T (x, y) of the front at each point (x, y) (each point is examined only once). It can shown that T evolves according to

$$|\nabla T| . F = 1 \tag{2}$$

this means that the transit time is inversely related to the front speed.

Segmentation steps. The description of our system is as follows:

- Initially, the video is divided into images.
- We define the points of interest in the first image using the descriptor HOG3D.
- The supervisor agent is activated, then the explorer agents are scattered in the image which is being processed.
- The explorer agents must form a closed contour. They are initially placed on the points of interest of the image.
- Each explorer agent perceives 8 surrounding pixels (the number of agents was originally defined). There is only one supervisor agent in the system.
- Each explorer agent evolves in the image by means of migrating from one pixel to another while respecting the rules of the Fast Marching algorithm.

These steps are repeated until all the agents can no longer evolve (stop condition).

If a given pixel towards which an agent is about to evolve is not occupied by any other agent, the original position of the agent is modified to the pixel having the nearest value to the initial pixel. Then, the position associated with the original pixel is modified with the nearest pixel value of the ancient pixel. In the opposite case, the supervisor agent deals with the conflict and decides whether such a pixel belongs to an agent. At this stage the initial contour is subdivided. The end of the algorithm is conditioned by the stabilization of all the agents.
Figure 5 shows the segmentation phase.

The interaction between agents goes through communication and determines the organization of the system.

- Communication type 1: it achieves the communication between the supervisor and the explorer agents. The role of this communication type is to manage the situations of conflict between the agents, for example the case of superposition of two or more agents on the same pixel. Through this communication, the supervisor agent decides whether a contour is divided into two regions or not. This type of communication can be regarded as cooperation.
- Communication type 2: it ensures the communication between explorer agents. This communication type aims to manage the evolution of each explorer agent according to the information received from other agents. Each explorer agent receives the values and the positions of other agents in the image to be able to determine the evolution direction. This type of communication can be regarded as coordination.

Figure 6 illustrates the communication between the different types of agents.

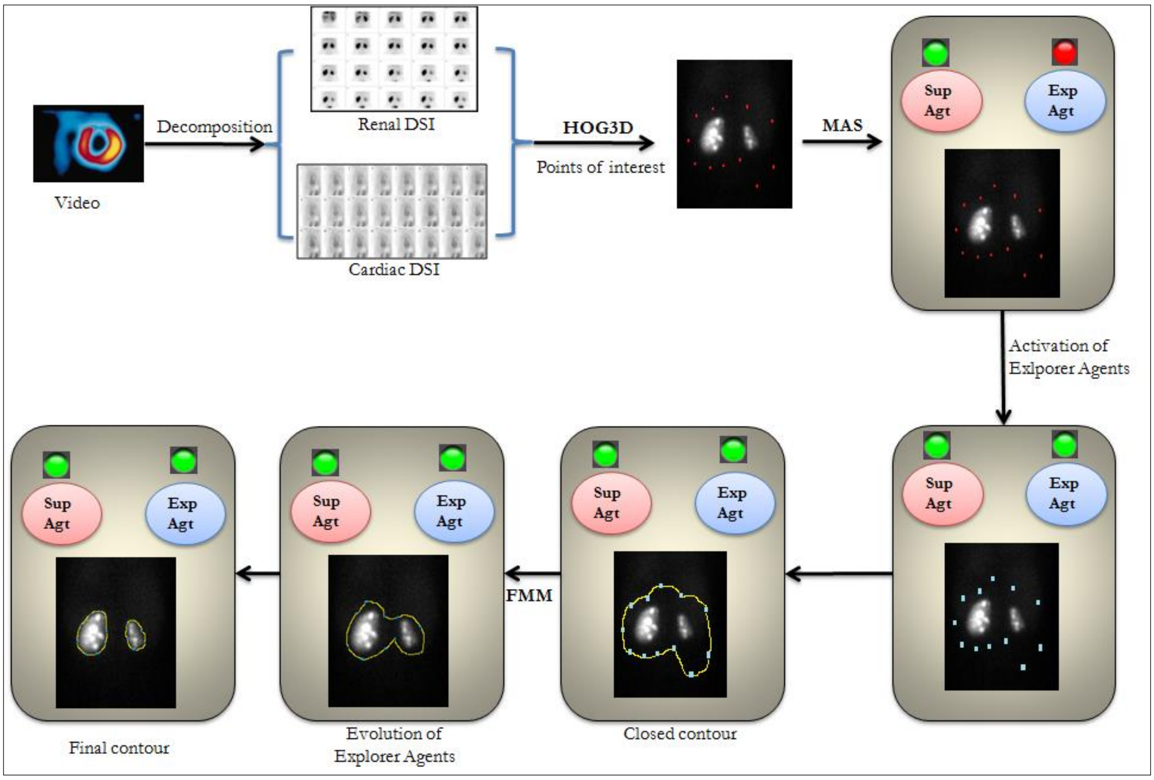

Figure 5. The segmentation process

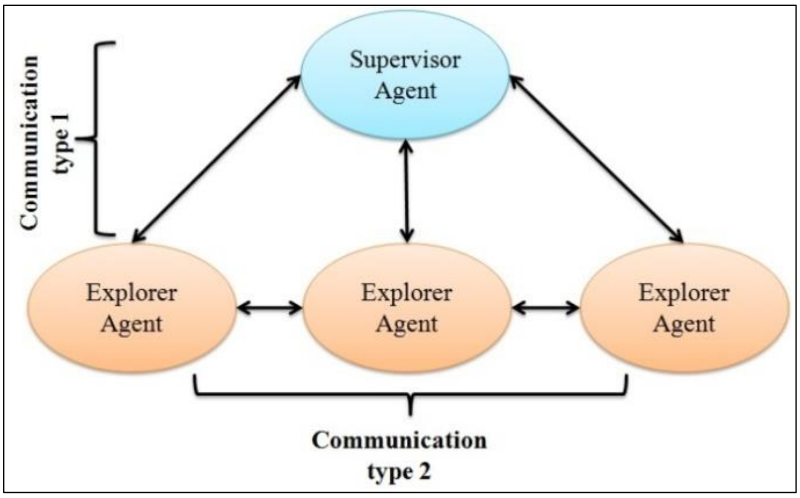

Figure 6. Communication mode between agents

Experimental Results and Analysis

The nuclear imagery is distinguished from the other imagery methods by the fact that it allows a functional exploration of the considered organ and thus allows a good understanding of the patalogical phenomenon [13]. The acquisition of the image sequences allows more learning about the explored organ function. The Visual analysis of these images can provide the physician with some information such as the presence or absence of abnormalities [14] but such an examination remains very limited.

Segmentation Results and Analysis of Vardiac DSI

In this section, we are particularly interested in cardiac DSI scintigraphy also called gamma-angio-cardiography which is performed after vascular pool marking (marking cells red technetium Tc-99m). It provides information on the kinetics of the walls and parameter values for filling and ventricular ejection [12]. To evaluate these parameters, we should first delimit the ventricles of a patient in a sequence of 16 images.

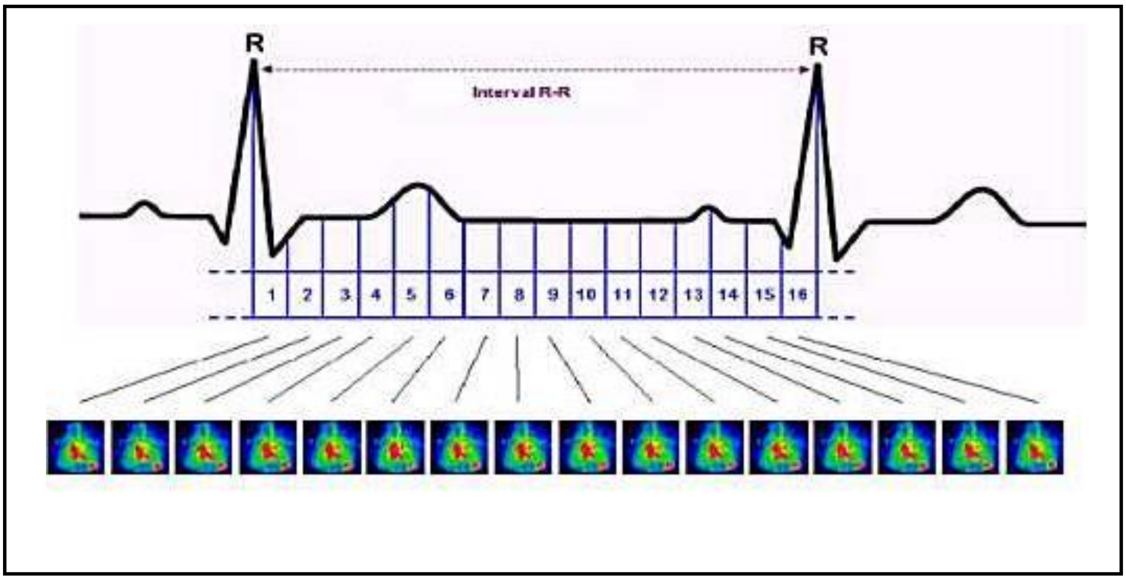

Figure 7. Sequence of 16 images

The ventricular Ejection Fraction (VEF) is a parameter which informs about the ability of blood ejection by the ventricle. It is defined by the following formula [13]:

$$VEF = (VTD - VTS)/\ VTD \quad (3)$$

where VTD and VTS indicate the diastolic volume (maximum filling of the heart) and systolic volume (minimum filling of the heart) respectively. We have applied our automated system on ten sequences of images coming from healthy and sick subjects. Table 1 presents the results of a VEF compared to those obtained by the physician.

These results were shown to specialists who expressed their satisfaction. Figure 8 shows some results in the evolution of ROI segmentations in cardiac DSI over time.

Table 1. Results of Ventricule Ejection Fraction

Sequence	Physician result	Our result	Difference
1	66	68.5	2.5
2	62	66	4
3	34	37.5	3.5
4	48	42	6
5	52	54	2
6	71	70	1
7	38	35.5	2.5
8	59	53.5	5.5
9	61	67	6
10	53	56	3

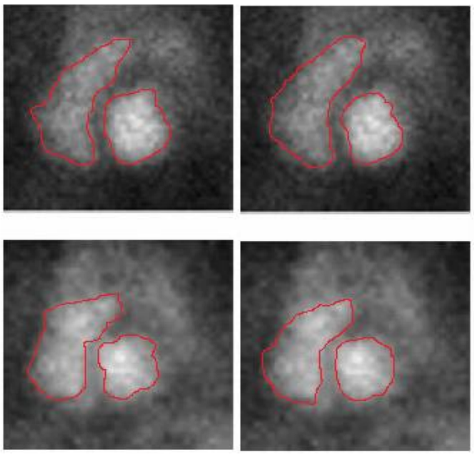

Figure 8. Results of segmentation of the image of the heart

Segmentation Results and Analysis of Renal DSI

Experiments and tests were developed on two databases of dynamic renal scintigraphy. The first, called "Database of dynamic renal scintigraphy" [14], involves images from 107 selected adult patients to obtain a variety of images. The second database includes 1800 images from 15 patients taken for the purpose of system verification and is taken from the department of nuclear medicine in the CHU BOURGUIBA Sfax, Tunisia. These images were chosen by the renal examination field experts in order to get a representative sample of a broader population of medical cases.

Most patients suffered from various stages of chronic renal diseases. Image data are available in DICOM [15] and INTERFILE formats.

Images in both posterior and anterior projections were recorded in 128x128 matrix in 10s frame intervals for 30 minutes. For each patient the Differential Renal Function (DRF) is calculated from the curves of renal activity of each kidney after the definition of renal ROI in all images. DRF is a comparative examination performed with simultaneous measurements for functional parameters of one kidney compared with the contralateral kidney. In the case of scintigraphy modality of measurements, the DRF can be calculated from both renal activity functions. Full renal activity function is calculated for the whole sequence of 120 images for each patient.

For the determination of the DRF value, we have used the integral method which is the mean value of the area under the background subtracted renogram curves during an early defined period of time. This method was extensively described in [18].

Although the differential function is usually calculated between 1 and 2 min, a quality control measure is performed to calculate the differential function for each frame separately during this time interval. If the differential function is constant (+/- 5%) from frame to frame this indicates the stability of this technique.

The evaluation the segmentation algorithms was achieved by comparing the results of the automatically segmented images against those of a manual segmentation, which is also often referred to as a gold standard. The results based on the manual segmentation were derived on the basis of field expert physicians working at the CHU BOURGUIBA, Sfax. The degree of similarity between the manual segmented and machine segmented images reflects the accuracy of the segmented image. The segmented results were evaluated using performance indices such as accuracy and statistical parameters. Suppose that an image contains N object types. The accuracy measure is computed using Eq. (4):

$$\text{Accuracy} = \sum_{i=1}^{n} \mathrm{CSP(i)/TNP(i)} \qquad (4)$$

where CSP is the number of correctly segmented pixels in the ith object and TNP is the total number of pixels in ith object. The accuracy measure indicates the difference between the automatically segmented image and a region that was manually segmented by an expert.

Figure 9 shows exemplary sequence of images taken from one examination showing the evolution of the segmented regions for both kidneys. Images presented on figure 8 reflect the most important part of the study, i.e. the period, while the kidneys reveal their different performances during the examination. Hence this is the crucial period for the calculation of the DRF parameters.

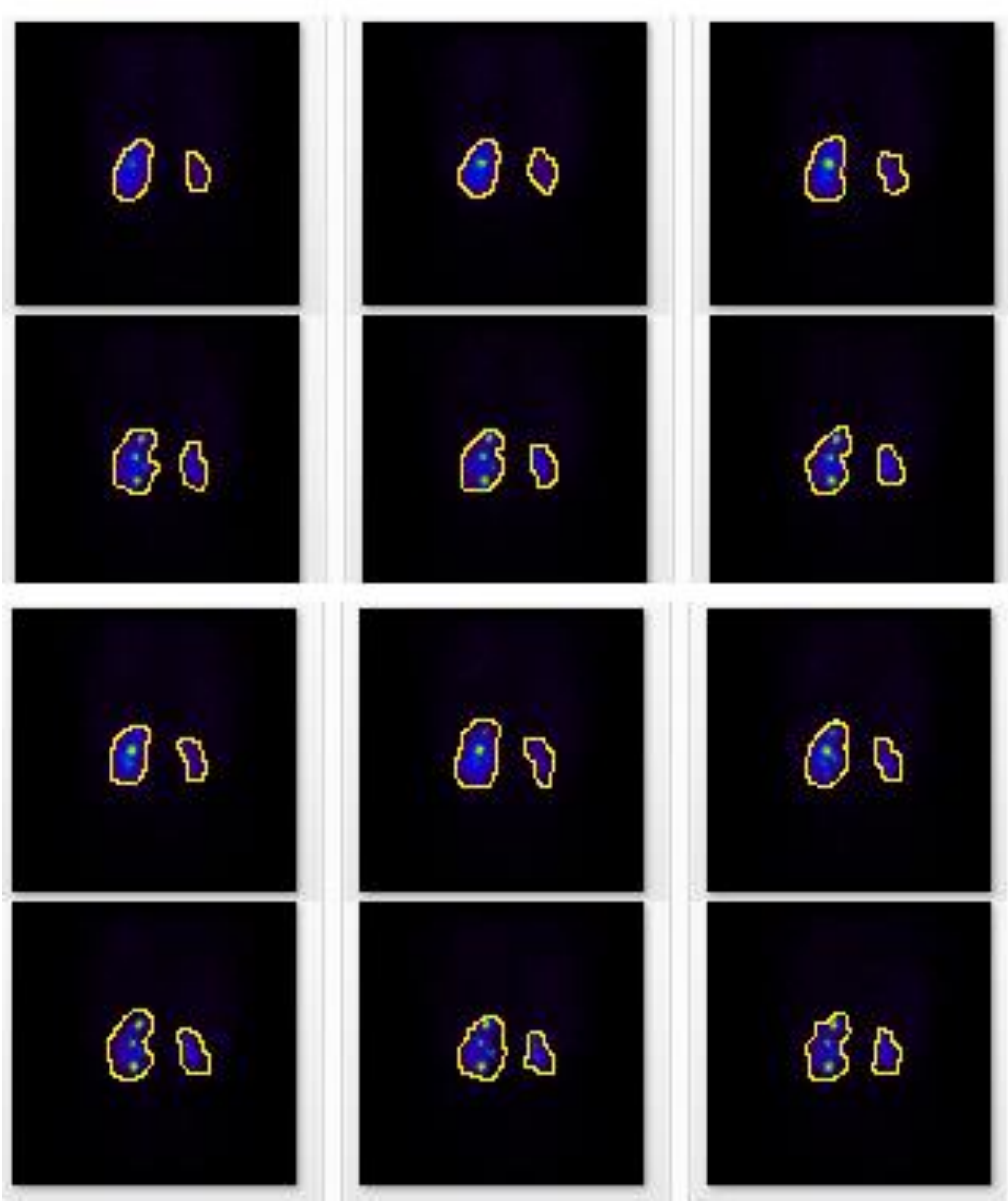

Figure 9. Results of segmentation using the proposed method

The evaluation of the segmentation algorithms, that are core part of the proposed system, was performed by the comparison of the obtained results with the other systems reported in the literature in terms of accuracy and time of execution.

As shown in both distinct results for separate images and the overall average, the results obtained by the proposed method are closer to the referral values calculated on the basis of experts' manual segmentation with an average of 90% conformity with the standard, while the other systems are around 83%.

Table 2. Comparative results (120 images/patient)

		Patient 1	Patient 2	Patient 3	Patient 4	Patient 5
Physician	Execution time (s)	389	406	318	415	502
	Average Accuracy (%)	90.6	89	91.2	92	88
Our system	Execution time (s)	6	5	6	6	5
	Average Accuracy (%)	91.4	90	89.6	91	90.4
Ståhl et al. [2]	Execution time (s)	25	26	23	24	24
	Average Accuracy (%)	82.5	83	85	83	89
Marcuzzo et al. [3]	Execution time (s)	30	32	31	30	31
	Average Accuracy (%)	84.7	88	80.8	78.4	84
Šmídl et al. [8]	Execution time (s)	15	13	14	14	14
	Average Accuracy (%)	82.6	88	81.7	87	78.1

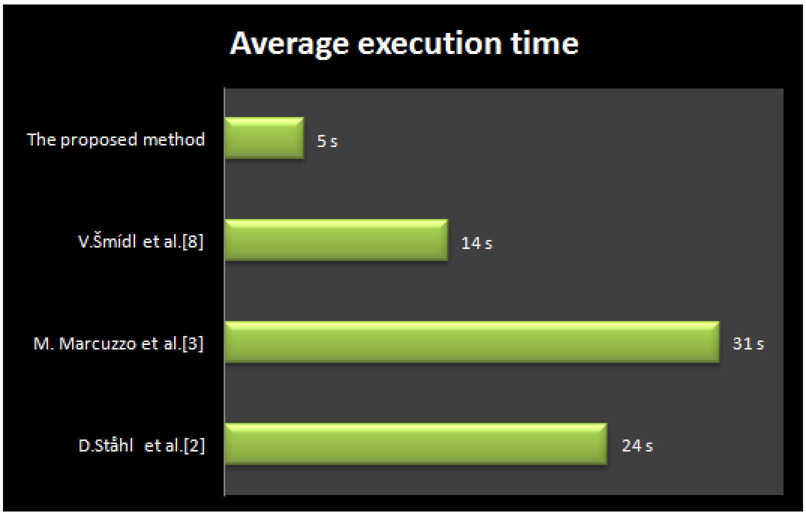

Figure 10. Classification execution time of the proposed method against three other automated systems

The comparison of execution time was recorded for a PC with Dual core, Pentium i5 3GHz and 4GB RAM. The speed of the image processing algorithm derives from the simple architecture multi-agent system coupled with a parallel agents move. Good accuracy of segmentation is, in our opinion, an effect of the application of a spatiotemporal descriptor coupled with the Fast Marching Method.

The proposed system was designed, developed and checked for renal and cardiac scintigraphy imaging diagnostics purposes. However, the obtained methodology can be easily suited and applied to other similar medical applications or adapted in the future to other image processing applications such as video indexing, motion recognition, video surveillance, video communication and compression, human-computer interaction or traffic control.

Conclusions and Future Works

Through this work, has become possible to make an automated system for the segmentation of renal and cardiac DSI. The proposed system is based on a multi-agent system, HOG3D descriptor and the fast marching method. The comparative study results with the classical methods show a good compliance with referential images and the advantage of the proposed method in terms of accuracy and execution time over other methods. The paper described the environment of our system, including image processing procedure, the type and attributes of the agents used and the tasks they perform. Results are discussed in the context of both a significant set of patients' data and the carefully chosen cases difficult to be assessed.

The proposed method remains open to other areas of research including different dynamic medical diagnosis imaging techniques and other applications.

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