ARG: A Semi-automatic system for ROI detection on Renal Scintigraphic images

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Abstract— **In this paper, we propose, a semi-automatic approach for the identification of Regions Of Interest (ROI) of the kidneys (healthy and diseased) on dynamic scintigraphic images. The triggering of the method depend on the intervention of an expert, such as a specialist in nuclear medicine. Our contribution is made obvious here through referring to the adaptive threshold relying on the calculation of the gradients histogram and thus accurately detecting the places of the region of interest. The adaptive threshold will be the average of the histogram of the matrix of the calculated gradients. This approach was tested on dynamic scintigraphic images acquired clinically and satisfactory results are obtained.**

Keywords-ARG; ROI detection; adaptive threshold; scintigraphic images;

I. INTRODUCTION

Nuclear medicine is a subspecialty of radiology that uses radioactive substances to create anatomical and functional images of the human body.
Images are formed following the detection of the energy emitted by the radioactive substance administered to the patient. The generated images are called scintigraphic images which are particularly difficult to treat automatically because they have a somewhat weak signal and high noise [1].
Certainly the software tool facilitates many tasks for the processing and analysis of scintigraphic images.
Indeed, quantification in nuclear medicine relies on identifying regions of interest "Regions Of Interest" (ROI) containing all the pixels in an existing structure studied and calculating activity at its level. The activity of a radioactive source is the number of disintegrations per second inside this source measured in becquerels. The problem addressed in

this thesis deals with the automatic definition of ROIs on scintigraphic images.
Our work focuses on the analysis of scintigraphic images in order to detect regions of interest. The treatment of scintigraphic images is complex and we aim to suggest a robust method to detect regions of interest on scintigraphic images.
The objective quantification of the Dynamic renal scintigraphy, is to determine the functional division between the two kidneys. This is based on the identification of the regions of interest defining each kidney from which are obtained in function of time, curves counting the activity of the tracer. The acquisition of the dynamic image is a primary phase which immediately preceeds the segmentation phase of the kidney's regions of interest.
The final step will be the evaluation of renal function.

Determining automatically the number of regions is considered as a major problem. Taking into account this definition, we began our research in the field of segmentation of the dynamic scintigraphic image. Indeed the segmentation of scintigraphic images is a low level processing which precedes the stage of measure, understanding and decision. Its objective consists in subdividing the image into homogeneous and related regions following a homogeneity criterion of to be especially difficult to define in the case of textured regions. In our case, it is a question of segmenting the regions of interest to facilitate the decision of the nuclear doctor for the evaluation of the functioning of the target organ. Generally, the scintigraphic images offer bad resolution because of the noise which makes the perception of the regions of interest difficult.
This paper is structured as follows. In section (2), a summary of the main approaches in the literature of image

segmentation is presented and attempts to compare the works to our contribution.

In section (3), two semi-automatic approaches for identification of regions of interest on a scintigraphic image sequence is presented.

Conclusions and future work are discussed in Section (4).

II. LITTERATURE REVIEW

In this section, an analysis of the existing image segmentation methods is proposed. First, we give a brief overview of the segmentation of images followed by a description of the main surrounding areas of segmentation. Having presented the characteristics of the dynamic scintigraphic images, we would refer to all the systems proposed in the literature that tried to segment this type of images. We finish by a balance assessment presenting the performances and the problems of the existing segmentation systems for the ROI detection.

The use of digital images is now very widespread in our modern world. In fact, enormous quantities of images are produced every year in various fields, particularly in the medical and industrial applications.

These images are not only visually used in the rough but often undergo an analytical process that usually requires a low level treatment, called image segmentation, in order to extract objects of interest in the image .

Segmenting an image comprises dividing the image into several regions so that all regions covering the whole image and the interactions between two different regions are blank.

In medical imaging, the regions of interest are simply regions that correspond to different anatomical structures [2].

The reliable and accurate segmentation of anatomical volumes (normal or pathological) from imaging systems remains an important goal in the treatment of medical information because it is the first link in the analysis chain leading to the study of the morphology internal structures, and the detection and quantification of lesions.

Many segmentation methods have been proposed for such images in the previous years. Synthesis methods of segmentation of medical images are numerous as shown in the literature [3].

The segmentation of images strongly depends on its application. That is why there is no general solution to this problem but rather a set of mathematical algorithmic tools which can be used to solve specific problems. These segmentation tools or methods are at present classified in two main categories [4]: the approaches outlines and the approaches regions. Numerous works were dedicated to these techniques. For more details, it is recommended to consult the papers of Haralick [5] and Pale [6], which summarize the existing segmentation techniques and their classification.

The dynamic renal scintigraphy is a medical diagnosis technique of nuclear imaging which allows the exploration of the loins functionning loins by watching the exit of the radioactive product injected into a patient. The tracking is achieved by measuring the movement of the bright product in time. In the literature, very few works present a system of automatic segmentation of the ROI on scintigraphiqc images. Kaur and al in [7] implemented an automated system by definition of the regions of interest in dynamic scintigraphy. Their algorithm suggests selecting regions of interest on the dynamic scintigraphies.

This algorithm is based on the factorial and cluster analyses. Consisting first in extracting the images of orthogonal factors of the series by using the factorial analysis of the correspondences. These images will then be automatically segmented using a hierarchical ascending classification procedure.

Other works also proposed an automatic analysis of the dynamic renal scintigraphy. Siogkas in [8] proposed a new method for the automatic renal detection of the ROI based on the neurons networks RBF.

The system consists of four modules: preprocessing of the images, the initial estimation of the renal zone, the estimation of the renal regions and the automatic elimination of the pond zone and finally the characteristic and the neuron classification extraction module.

To identify ROIS renal from a dynamic acquisition, Jose [9] proposed an original method for the identification of ROIS using a combination(overall) of the dynamic information, the intensity multilayer segmentation and the neurons network segments identification associated with loins to generate renal ROIS. Ståhl and al. [10] proposed another method of segmentation, specific in the renal scintigraphy.

They used an automatic thresholding algorithm to segment every kidney. This method, however, does not consider the disease of loins. An algorithm of image processing "AUTOROI" was developed by Garcia et al. [Garcia, 2010] allowing to detect the outlines of loins and produce the renal regions of interest for the extraction of the quantitative measures.

In 2014 Rahmatpour et al. [11] presented a study which aims at obtaining an automatic method to determine ROI of the kidney based on the method of seuillage in order to reduce the operator's manual method errors.

In [12] a novel method for automatic detection of the renals ROI is presented using RBF neural networks.

Another segmentation method, specific to renal scintigraphy, is proposed in [13]. An automatic thresholding algorithm is used to segment each kidney. To avoid under segmentation, pixels in an area around the initial boundary are classified as kidney pixels or background. This method does, however, not consider the fact that diseased kidneys may show lower uptake in wedge-shaped areas around its boundary. An intelligent system for segmentation of renal regions of interest kidney based on the combination of fast marching method and HOG3D was developed in [14].

We presented in this section several segmentation techniques which can intervene in the field of the medical imaging and specifically in the scintigraphy.

Several existing systems in the literature use various segmentation techniques, but rare are the systems which rely on an automatic segmentation. According to our bibliographical study we were able to discover the algorithms which can be effective for the segmentation of the scintigraphic images.

III. THE PROPOSED SEMI-AUTOMATIC SYSTEMS

The automatic determination of the number of regions is a crucial topic.

Bearing in mind the above definition, we set up our research in the area of scintigraphic images segmentation.

Indeed the segmentation of the renal scintigraphic images is an essential step in any image analysis process. This is a low level treatment preceding the measuring, analysis and decision steps.

Its objective is to partition the image into homogeneous regions, related to the meaning of a difficult criterion to define, especially in the case of textured regions homogeneity. In our case, it is to segment the kidney regions of interest in order to facilitate the decision of nuclear medicine for the evaluation of renal function. Scintigraphic images are often marred by noise, bad contrast and poor resolution which make it difficult to extract regions of interest. In the remainder of this chapter we present two systems in which we used different techniques for the identification of the kidney regions of interest.

The performance of the proposed systems is compared with other traditional approaches to segmentation.

We propose the semi-automatic system for processing and analysis of the scintigraphy images in order to determine the Differential Renal Function (DRF). Figure 1 shows our proposed system.
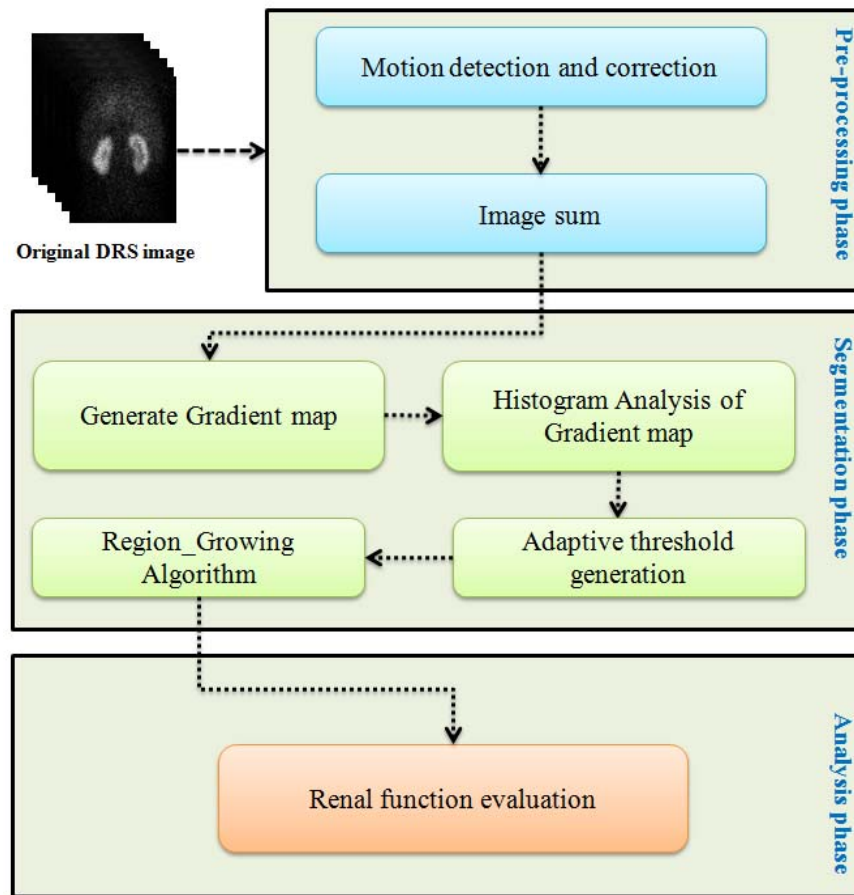

Figure 1. The overall structure of proposed system for renal function evaluation

A. Adaptive Region_Growing

The adaptive Region Growing (AGR) segmentation technique is proposed to segment dynamic scintigraphic images to assist in the medical diagnosis.

This process contains two procedures:

- Find the starting points of the regions.
- Enlarge the regions agglomerations of neighboring pixels.

The choice of the starting point is the critical part in our algorithm. Indeed, the growth step will use a similarity measure to select the pixels to be added. If the starting point

is located in a non-homogeneous area, the similarity measure will produce large variations and growth will stop early.

Therefore, it is necessary to choose the starting points in areas as homogeneous as possible.

Step growth aims to enlarge a region to include neighboring pixels. The pixels are selected to maintain the homogeneity of the region. To this end, we need a homogeneity indicator. The neighboring pixels are added to the region of homogeneity if this homogeneity exists.

Growth stops when you cannot add more pixels without breaking homogeneity.
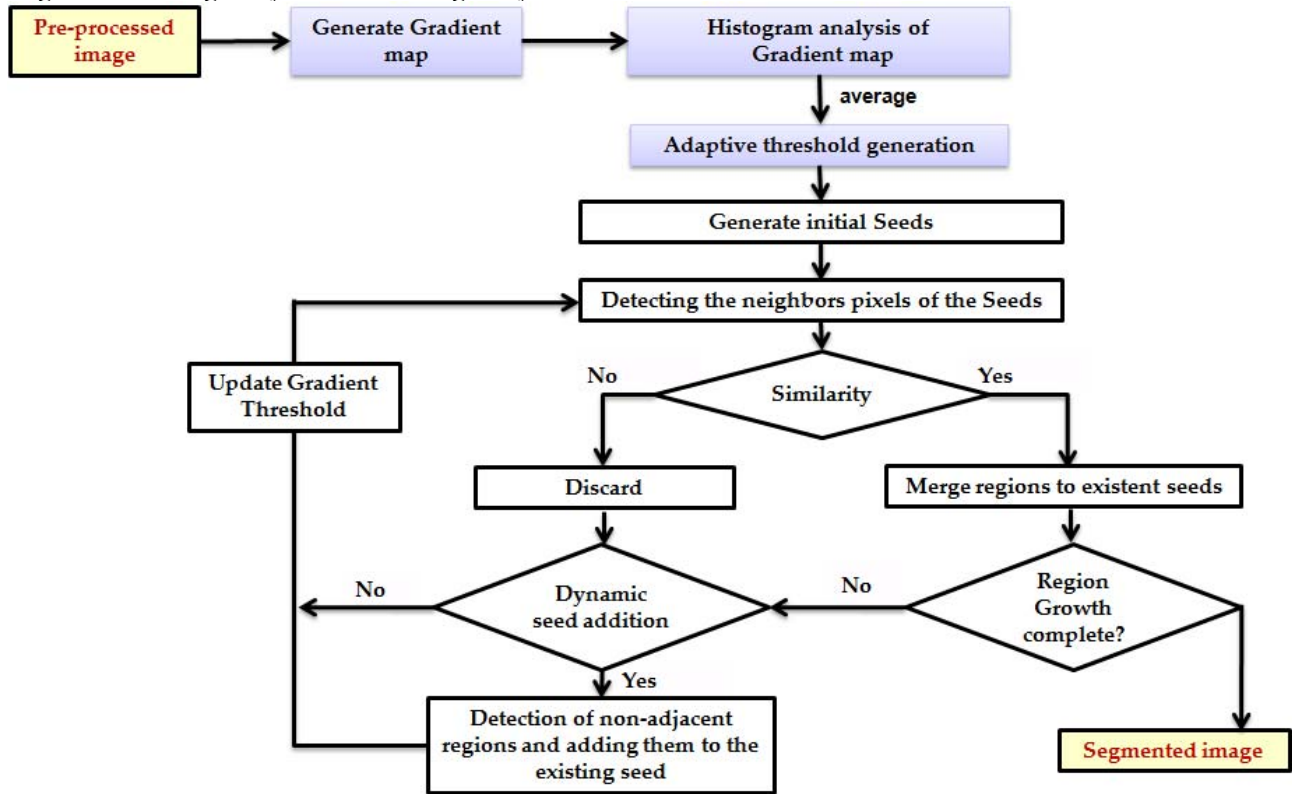

Figure 2.   Segmentation process with ARG

The flowchart of the proposed system describes our approach to the selection and generation of an adaptive threshold. Indeed, starting from a pre-processed image, the Region Growing method proposed by Zucker in 1976 relyed on the idea of starting an initial pixel called "seed" to define a neighborhood of growth that must meet the same characteristics, is applied intensity as the seed. The system evolves by changing the seed to increase the growing segmented region. The major problem with the conventional method of Region_Growing is that the threshold of similarity measure between a seed and its neighborhood is fixed in advance.

Our contribution intervenes at this level to make the choice of an adaptive threshold based on the calculation of the histogram of gradients at the end to detect the corners of the region of interest.

The adaptive threshold is the average of the histogram of the calculated matrix gradients.

B.   Results and discussion

Our system was developed on a multi-core i5 machine based on the "Interactive Data Language" IDL which is an ideal software for data analysis, visualization, and the development of cross-platform applications. IDL is an interactive software processing solar data ANA developed by the Solar Physics Group at NASA in the early 1980s for the treatment of data from the satellite Solar Maximum Mission (Goddard Space Flight Center, Washington). Figure 3 shows the final result of the segmentation of both kidneys of a patient applying our "ARG" approach.
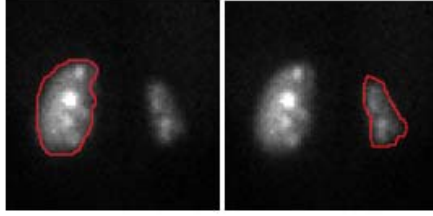
Figure 3.   Final segmentation result of both kidneys based on ARG

Experiments and tests were developed on a database including 3600 images from 30 patients selected to obtain a variety of images. Patient data taken for the purpose of system verification come from the department of nuclear medicine in CHU BOURGUIBA Sfax, Tunisia, and were chosen by the renal examination field experts in order to be representative sample of a broader population of medical cases. The results of the application of our method are presented and discussed in this section below. Fig. 4 shows exemplary sequence of images taken from one dynamic renal examination showing the evolution of segmented regions for both kidneys. Images presented on the figure reflect the most important part of the study, i.e. the period, while the kidneys reveal their different performance during the examination. Hence this is the period crucial for calculation of renal function parameters.
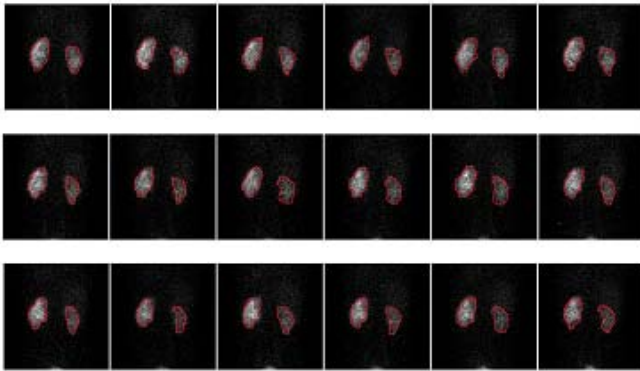

Figure 4.   Part of the examination sequence illustrating the evolution of ROI segmentations in renal scintigraphy images over time.

The experimental results are visually promising. However, for clinical validation, we need comparative segmentation between an expert and experimental results measures. We used two standard measures for the validation of segmentation and morphological measurements. Traditional measures of comparison of contour and regions are able to Vinet and the distance to the nearest point (Hamming distance). Vinet measuring comprises counting the number of pixels in the common segmented part by the expert and the software by the segmented object. Then calculate the ratio:

$$\frac{R_i - R_i \cap V_j}{R_i}$$

where R_i is the number of pixels of the renal region and V_j for those of the calculated area. For our database of over 800 images, we got an average of 0.17 for the Vinet distance.

TABLE I.   A SUMMARY OF THE PERFORMED MEASURMENT

Mesure	Average	Lag type
Vinet	0.17	0.03
Hamming	1.4	0.36

These first results are very satisfactory; so we will continue to analysis our method.

Table 2 depicts a comparative analysis that highlights the segmentation accuracy of the proposed ARG algorithm for the examined renal scintigraphic image samples, respectively.

The considred metrics to estimate the performance are TPR, FPR, precision, and accuracy. The metrics are obtained using the following equations:

$$TPR = \frac{TP}{TP+FN}$$

$$Precision = \frac{TP}{TP+FP}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Here, TP (True Positive) represents the number of pixels correctly detected as ROI. FP (False Positive) represents the number of non-ROI pixels detected as ROI. TN (True Negative) represents the number of pixels correctly detected as non-ROI. FN (False Negative) represents the number of skin pixels detected as non-ROI.

As presented in Table 2 for the examined renal dynamic scintigraphic image samples for 5 patients, the average accuracy of the segmented ROI using the proposed ARG approach was 92.8%.

TABLE II. ACCURACY OF THE PROPOSED ARG

Performance Metrics(%)	Proposed ARG			
	TPR	FPR	Precision	Accuracy
Patient 1	90.1	15.9	71.3	89.6
Patient 2	91.3	16.3	72.6	94.2
Patient 3	92.4	17.2	73.4	95.4
Patient 4	91.4	16.5	72.8	94.4
Patient 5	90.3	15.9	70.9	90.4

Figure 5 shows a comparative analysis that highlights segmentation evaluation measures for the proposed system, and two other systems accuracy results.
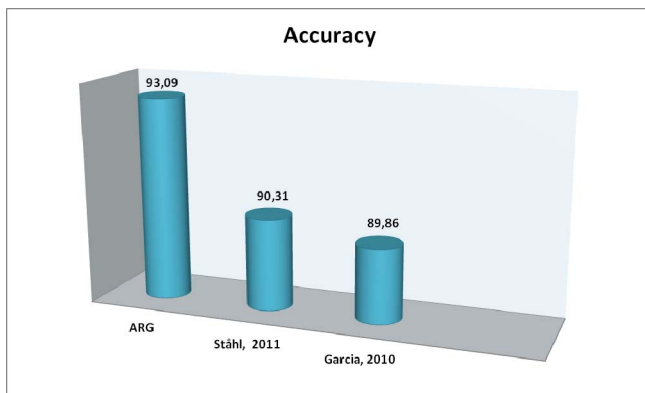

Figure 5. Classification accuracy of the proposed ARG against two other automated systems

From figure 5 one can conclude that proposed system out performs the other methods in terms of accuracy being of 3% to 4% closer to a referral values.

IV. CONCLUSION

In this paper we presented a semi-automatic method for the definition of ROI in scintigraphics images. The proposed methods ARG is tested on real images and they give a good results in term of accuracy.

So through ARG systems, we have a good strategy for the semi-automatic 2D segmentation in a set of scintigraphic images.

This strategy can be used as a preliminary to the implementation of an automatic method for the segmentation of a sequence of scintigraphic images.

Nevertheless, there are still some questions that need to be answered. In fact it would be interesting to know wether the selected contour detector is relevant, if we can refine the segmentation using richer Region Growing variant found in the litterature, and if we could simplify the model overcome the maximum constraints posed settings and ultimately if we can add others units to other modules in our system to automate segmentation and improve accuracy.

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