An Optimize Mechanism for Multifunction Diagnosis of Kidneys by using Genetic Algorithm

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Abstract— In existing system, it was take more time (in minute) to detect and the output was less accurate. The medical technicians laboratory adjust rules and parameters (stored as "templates") for the included "automatic recognition framework" to achieve results which are closest to those of the clinicians. These parameters can later be used by non experts to achieve increased automation in the identification process. The system's performance was tested on MRI datasets, while the "automatic 3-D models" created were this research presents a multifunctional platform focusing on the clinical diagnosis of kidneys and their pathology (tumors, stones and cysts), using a "genetic algorithm". This research presents the automatic tumor detection (ATD) platform: a new system to support a method for increased automation of kidney detection as well as their abnormalities (tumors, stones and cysts). As a first step, specialist clinicians guide the system by accurately annotating validated against the "3-D golden standard models." Results are promising to give the average accuracy of 97.2% in successfully identifying kidneys and 96.1% of their abnormalities thus outperforming existing methods both in accuracy and in processing time needed. In this paper, the proposed design will define the "genetic algorithm" which will generate the output within a second and more accurate than the existing system.

Keywords—Detect, clinicians, Automatic , genetic algorithm ,Abnormalities, Accurate.

1. Introduction

Medical imaging is the technique and process used to create images of the human body (or parts and function there) for clinical purposes (medical procedures seeking to reveal diagnose or examine disease) or medical science (including the study of normal anatomy and physiology). Although imaging of removed organs and tissues can be performed for medical reasons, such procedures are not usually referred to as medical imaging, but rather are a part of pathology [1]. A kidney is a bean-shaped organ located toward the back of the body, beneath the rib cage. A person is usually born with two kidneys, located on either side of our spine. The primary function of the kidney is to act as a filter to cleanse the blood of waste products and to make hormones to support blood pressure and blood cell production. The kidneys are composed of microscopic tubules that function as filtering units. As they filter the blood, the waste products accumulate in fluid, now called urine, which exits the kidneys via long tubes, the ureters, which pass into the bladder where it is stored and, eventually, expelled from the body.

The study has focused on the kidney image segmentation and diagnosis for stone, tumor, cysts detection. The rapid evolution of advanced medical image modalities such as the modern MRI scanners and the large amount of data provided have brought about the need for more automatic processes in computer aided diagnosis. Clinicians need to examine large numbers of complex medical images to detect abnormalities; a difficult and time consuming task. Hence, there is a need for

systems that will automatically detect organs and their possible abnormalities and provide useful metrics [2].

The problem is in existing system, it was take more time (in minute) to detect and the output was less accurate. In this paper, the proposed design will define the "genetic algorithm" which will generate the output within a second and more accurate than the existing system. This automatic kidney detection system has a number of advantages over the existing systems given as follows:

1) Automatic Tumor Detection (ATD) is not only a method, but a multifunctional platform supporting real-time processing;
2) It simultaneously detects organs as well as their pathology (tumors, stones and cysts) with increased accuracy.
3) Processing time is faster than the existing methods, as the main algorithms and additional controls run "on the fly." The processing time about in second;
4) The system achieves more accurate results for the recognition of kidneys compared with the existing methods by implementing "genetic algorithm".

Image mining:

Image mining deals with the extraction of knowledge, image data relationship, or other patterns not explicitly stored in the images. It uses methods from computer vision, image processing, image retrieval, data mining, machine learning, database, and artificial intelligence. Rule mining has been applied to large image databases. There are two main approaches. The first approach is to mine from large collections of images alone and the second approach is to mine from the combined collections of images and associated alphanumeric data.

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2 Related Work

Several algorithms detect kidney abnormalities, addressing the challenge of increased difficulty in their delineation due to their intensity variation. Prevost *et al.* [3] had automatically localized the kidney with a novel ellipsoid detector, and then applied deformation of this ellipsoid with a model-based approach in the segmentation process. Using the Dice Similarity Coefficient (DSC) as a metric [4], this system achieved a DSC of 87.5%. Similar to this platform, they calculated the accuracy of automatic segmentation outcome by comparing it with the result of the semiautomatic segmentation method coming from the radiologist's work (golden standard). Lin *et al.*'s [5] model-based approach for kidney Segmentation achieved an average correlation coefficient of 88%, while [6] used Bayesian concepts for a probability map generation to achieve an automatic kidney Parenchyma volume try with a DSC of 90.3%. [7] used an automated graph-cuts segmentation technique for dynamic contrast-enhanced 3-D MR renography achieving a DSC of 96% for the kidney and 90% for the cortex and the medulla. Their method was very fast (approximately 20 min) compared with the time needed for a manual segmentation of about 2.5 h, In [8], the authors presented a combination of texture features and a statistical matching of geometrical shapes of kidneys for an automatic segmentation in 3-D MRI images with a mean DSC of 90.6%.

Concerning abnormality detection, [7] presented a finite-element method based on 3-D tumor growth prediction for kidney tumors, with an average true positive fraction of 91.4% on all tumors. Tamilselvi and Thangaraj [8] used an improved seeded region growing method and classification of kidney images with stones and focused on the kidney image segmentation and diagnosis for stone detection. In [9] the authors achieved a DSC of 95%. In [10] three neural network algorithms for diagnosis of kidney stones diseases were tested. They claim that the multilayer perception with two hidden layers and the back propagation algorithm produced the best model for the diagnosis of kidney stone disease with an accuracy of 92%. In [11], an automatic segmentation algorithm for segmenting liver and tumor based on threshold and region growing techniques was used. The tumor was segmented with an alternative FCM clustering algorithm and the DSC for liver and tumor was 95.8% and 89.8%, respectively. The methodology of [12] was closer to the one presented here as their automatic segmentation method was based on association rule-mining to enhance the diagnosis and classification of kidney images. They used conditions and communication to hide the confidential information from unauthorized user or the third party. In this process if the feature is visible, the point of attack is evident thus the goal here is always to give chances to the very existence of embedded data. The security issues and top priority to an organization dealing with confidential data the method is used for security purpose as the burning concern is the degree of security. The security system is categorized into criteria to adjust their system, thus achieving results with an average accuracy of 92%.

In a survey of systems focusing on identifying pathologies in transplanted kidneys with most of those methods suffering from low accuracy, or the need for extended involvement of clinicians to identify organs and abnormalities was presented. In the field of transplant kidney rejection, [13] and [14] presented a related system based on dynamically enhancing the contrast of 2-D MRI images with achieve organ identification. The first part of their method is related to our own system and achieved an average accuracy of 97.02% (although our system focuses on tumor detection as well as generic abnormalities).

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3. Methodology

This method combines the low level features automatically extracted from images with high level knowledge given by the specialist in order to suggest the diagnosis of a new kidney image. This is to implement a computer-aided decision support system for an automated diagnosis and classification of kidney images.

The proposed system is divided into mainly,
i) the training phase and
ii) the test phase.

Algorithm:
Input - training images and a test image
Output - kidney category classification
1. Input image is preprocessed.
2. Extract the required features.
3. Relevant features are extracted through feature selection process.
4. Execute PreSAGe algorithm.
5. Generate association rules.
6. Classify the image based on generated association rules.

The propose work will divide into the following model:-

1. Image segmentation:
In this module the input image will be segmented to find the most probable portion where kidney disorder might exit. For this various techniques like double thresholding, fuzzy, means segmentation can be used to detect tumor stones, cyst.

2. Feature Evaluation:
In this module the feature of segmented image will be found and store into database with the type of deformative.

3. Database creation:
In this module the input image will be segmented and features will be evaluated along with the deformative types and this will be stored to database.

4. Application of genetic Algorithm:
In this module the genetic algorithm will be developed and various features will be evaluated which will help in proper classification of the input image.

5. Database evaluation or diseases detection:
In this module the given input image will be segmented and feature will be evaluated with the help of genetic algorithm and with the help of classification Techniques .we will get the type of diseases all with its localization.

6. Result evaluation and optimization:

In this module result will be evaluated and compare with the paper to get an analysis of the implemented technique.
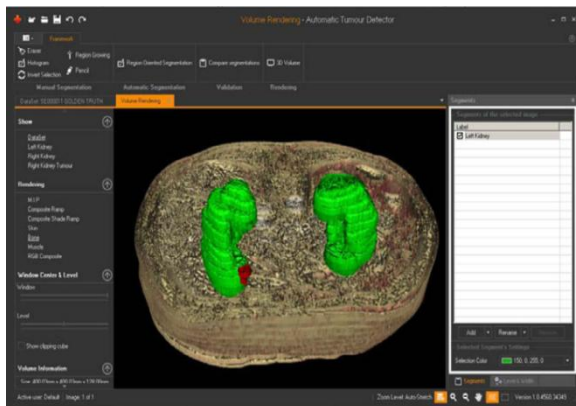

Fig.1.3-D model of the body integrating the previously delineated areas. Green represents the kidneys, while red identifies the tumour [15].

Fig. 3. Defining parameters and rules ("Templates") for the automatic segmentation process [15].

4. Segmentation Algorithms

The "segmentation framework" is responsible for the training of the systems as well as the creation of the "templates." The basic steps of this framework are as follows.

1) A clinician opens an MRI dataset (i.e., abdominal).
2) An edge-preserving anisotropic diffusion filter (Perona Malik) removes the noise of the images [20].
3) The clinician selects the RoI, the organ, and the abnormalities and saves these choices.
4) Later, a medical technician defines the working area thus reducing the amount of data to be processed.
5) A modified version of a region-oriented segmentation algorithm is introduced to recognize the organs [15].The histogram values are normalized to get better results: the user interactively defines the parameters to smooth the histogram (the up/down values to recognize more or less compact internal areas and the area parameter to avoid selecting tiny objects during the organ's recognition process).
6) The value of the seed pixel and the sensitivity are defined and used for the recognition of abnormalities.

7) The medical technician records the best results and then stores the generated values into a "template."
8) Another user can now get a dataset of the same type (e.g., abdominal) and select a template to identify specific organs (e.g., kidneys). The framework will automatically define the organ in the dataset and detect the potential abnormalities.

5. Genetic Algorithm

The genetic algorithm is a method for solving both constrained and unconstrained optimization problems that is based on natural selection, the process that drives biological evolution. The genetic algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution. You can apply the genetic algorithm to solve a variety of optimization problems that are not well suited for standard optimization. algorithms, including problems in which the objective function is discontinuous, non differentiable, stochastic, or highly nonlinear. The genetic algorithm can address problems of *mixed integer programming*, where some components are restricted to be integer-valued.

The genetic algorithm uses three main types of rules at each step to create the next generation from the current population:

- Selection rules select the individuals, called *parents*, that contribute to the population at the next generation.
- Crossover rules combine two parents to form children for the next generation.
- Mutation rules apply random changes to individual parents to form children.
-

The Algorithms

1. Randomly initialize population (t)
2. Determine fitness of population (t)
3. Repeat
    1. Select parents from population (t)
    2. Perform crossover on parents creating populn(t+1)
    3. Perform mutation of population (t+1)
    4. Determine fitness of population (t+1)
5. Until best individual is good enough [1].

The genetic algorithm differs from a classical, derivative-based, optimization algorithm in two main ways, as summarized in the following table [1].

Classical Algorithm	Genetic Algorithm
Generates a single point at each iteration. The sequence of points approaches an optimal solution.	Generates a population of points at each iteration. The best point in the population approaches an optimal solution.
Selects the next point in the sequence by a deterministic computation.	Selects the next population by computation which uses RNG.

5. Conclusion

This research presents a new MRI diagnosis-assistive platform that, after initial creation of a "template," is capable of providing a more automatic 3-D identification of kidneys and their abnormalities (tumors, stones, and cysts). The segmentation process is carried out with improved SRG for identifying the intensity threshold variation. The texture extracted from the segmented portions is mapped to the size of the pixel squares with its size magnitude.

Our approach is divided into four major steps: pre-processing, feature extraction and selection, association rule generation, and generation of diagnosis suggestions from classifier. The results are applied to real databases and the proposed system achieves high sensitivity and accuracy for diagnosing. This brings more confidence to the diagnosing process.

The feature extraction step can be improved to obtain more representative features for the future works. Since feature extraction is the first step for diagnosing the medical images. It will also be interesting to investigate the applicability of our proposed method for other medical images. It is required to analyze different sizes of the kidney detection and based on these numerical values of features it is highly feasible to develop a universal reference for kidney detection categories.

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