TẠP CHÍ KHOA HỌC
TRƯỜNG ĐẠI HỌC QUY NHƠN

Một kỹ thuật xác định điểm bao phục vụ đánh giá sự thay đổi của vùng bất thường trên ảnh y tế

Lê Thị Kim Nga[1,*], Đoàn Thị Xương[2], Đoàn Thị Thu Cúc[3]

[1]Viện Nghiên cứu ứng dụng khoa học và công nghệ, Trường Đại học Quy Nhơn, Việt Nam
[2]Thư viện, Trường Đại học Quy Nhơn, Việt Nam
[3]Khoa Công nghệ thông tin, Trường Đại học Quy Nhơn, Việt Nam

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TÓM TẮT

Việc đánh giá sự tăng trưởng hay giảm thiểu của vùng bất thường trên ảnh y tế nói chung và ảnh chụp cắt lớp nói riêng là một vấn đề quan trọng được quan tâm nghiên cứu nhiều trong những năm gần đây tại Việt Nam. Bài báo trình bày một kỹ thuật xác định điểm trên đường bao vùng bất thường để làm cơ sở sau này có thể đánh giá sự phát triển của vùng bất thường trên ảnh y tế. Kỹ thuật dựa trên việc phân tích kết cấu cục bộ tại lân cận đường bao vùng bất thường kết hợp với sử dụng mạng nơ ron tích chập và đã được cài đặt thử nghiệm và đánh giá dựa trên bộ dữ liệu mẫu 3D-IRCADb-01 với các vùng u gan.

Từ khóa: *Khối u, vùng bất thường, chất liệu.*

[*]Tác giả liên hệ chính.
Email: kimnle@arist.edu.vn

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A technique of identifying the contour point to assess the change of abnormal areas on medical imaging

Le Thi Kim Nga[1,*], Doan Thi Xuong[2], Doan Thi Thu Cuc[3]

[1]Research Institute for Applied Science and Technology, Quy Nhon Universiy, Vietnam
[2]Library, Quy Nhon University, Vietnam
[3]Faculty of Information Technology, Quy Nhon University, Vietnam

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ABSTRACT

Assessing the growth or reduction of abnormal areas in medical imaging in general and tomography in particular is a greatly concerned and important research issue in recent years in Vietnam. The article presents a technique of identifying contour points of an abnormal area as a basis for later assessment of the development of abnormal area on medical imaging. The technique is based on the analysis of local structures in the vicinity of abnormal area boundaries combined with the use of convolutional neural networks and has been tested and evaluated based on 3D-IRCADb-01 sample data set with liver tumors.

Keywords: *Tumor, abnormalities, texture.*

1. INTRODUCTION

Medical imaging plays a vital role in diagnosis job of the doctors. Modern medicine today diagnoses not only by clinical symptoms but also by subclinical symptoms or so-called subclinical diagnosis. In particular, the diagnosis on medical imaging is a subclinical diagnosis based on images obtained from specialized imaging equipment, such as ultrasound, endoscopes, CT scanners (Computed Tomography), MRI (Magnetic Resonance Imaging), PET (Positron Emission Tomography) or SPECT (Single Photon Emission Computed Tomography) machines, etc. Each medical imaging device has its own advantages and decisive meaning in many diagnostic cases.

Being an important part, medical imaging is also a critical data type for information technology research in health. An important issue with medical imaging is that abnormal areas, such as strange areas appearing in an image of organ, such as a lesion or tumor. In such cases, it is desirable not only to quickly and accurately detect that abnormal area, but also to track changes in that abnormal area over time. Being able to estimate changes in abnormal areas, whether growth or reduction, has an important implication for healthcare job of the doctors.

Normally, abnormal areas on medical imaging will not have a stable geometric structure. We can imagine with other objects, such as human face when looking straight and we can see that the geometric structure is quite stable and can be used as a basis for conducting research, but with areas of vegetation or unoccupied land appearing on remote sensing

[*]*Corresponding author.*
Email: kimnle@arist.edu.vn

images are completely different. It is often tough to make assumptions or think of a common geometric structure for them. The abnormal area on medical imaging is similar. They appear quite randomly and have unpredictable shapes. Often image processing problems for this object type are detected and segmented. If we want to track changes in abnormal area, we need to analyze the boundary of the abnormal area on the basis of correlation with itself in the previous time.

In studies on the demarcation of the subject on medical imaging, Mikkel Stegmann and Dorthe Pedersen[1] conducted a quantitative analysis on cardiac magnetic resonance imaging data. In this paper, the authors aim to estimate the ejection fraction in the left ventricle based on four-dimensional MRI data based on the Cootes algorithm expansion study of the Cootes group[2]. In the experiment, Mikkel Stegmann and Dorthe Pedersen used data of 12 patients with a model of 1560 points and achieved a deviation of -1.2 $\rightarrow$ - 3.3% when compared to the results of the observers.

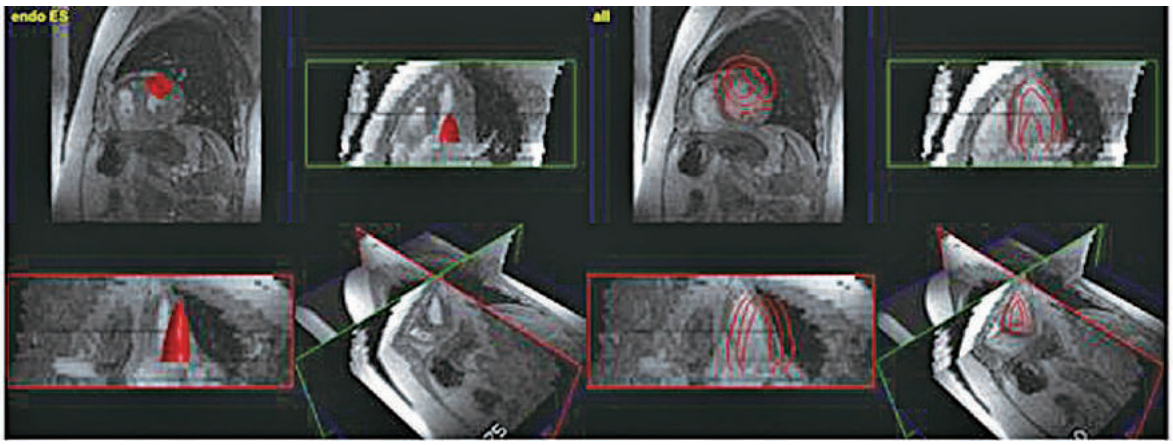

Figure 1. Some images of research results[1]

Zhao's team[2] again has a study of improved dynamic contour models with the combined use of local and global intensity data. In the study, the effect of Gaussian scroll image data with the original image will replace the original image and the authors built a gradient flow model based on Euler-Lagrange equation. Accordingly, the research results are presented on both composite image data and medical imaging data.

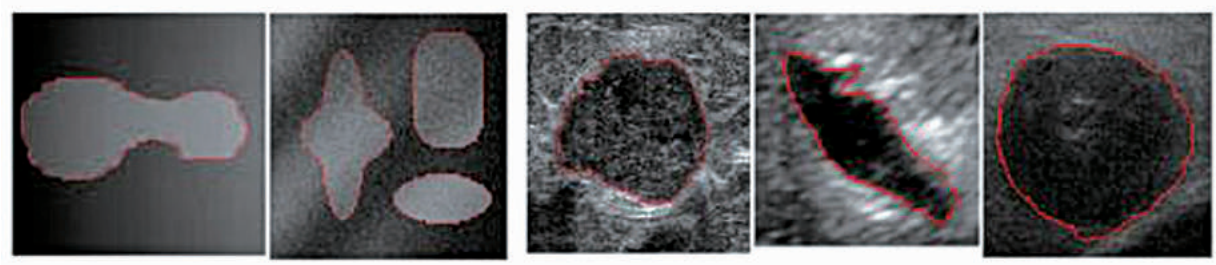

Figure 2. Results of Zhao team[3]: composite image (left) and medical image (right)

In a recent study, the Guha team[4] built a function to map a pair of input images into a deformed field using machine learning. The group performed functional parameterization via a convolutional neural network and performed network learning on an image data set. The team performed a test on a set of 3731 brain MRI data from eight different published data sets, where each scan was sampled to a 256 x 256 x 256 and 1mm grid on voxel.

In this article, we present a technique of determining the points on a contour to assess the change of abnormal area based on the change of the abnormal area contour nearby, in other words,

transform from an adjacent boundary. The problem is about estimating the displacement of a set of boundary points sampled on the contour to find a new location for it. Section 2 will detail the proposed technical content while Section 3 will present experimental results and final conclusions.

2. IDENTIFYING THE CHANGE OF ABNORMAL AREA ON MEDICAL IMAGING

2.1. Abnormal area on medical imaging

On medical imaging, an abnormal area is an image area corresponding to the location of anomalies of the object in the image. For example, with CT scans of the liver region, tumor areas, lesions, etc., these can be considered abnormal areas. In this case, the paper assumes an abnormal area without holes. That is, any sub-region in the abnormal area is also an abnormal area. Thus an abnormal region may be represented by its boundary.

The boundary of an abnormal area is a border points list of this area. So, we can describe the boundary of abnormal area A on image I as follows:

$$A = \{P_i\}_{i=0}^{n-1}, P_i \in [0, I_{width} - 1] \times [0, I_{height} - 1]$$

Each point P_i is a point on the contour; two points in a row $P_i P_{i+1}$ is an edge on the contour.

2.2. Regression problem at each point

The problem here is that we need to identify the abnormal area on the input image based on a state of the irregular region that has been assumed to be adjacent. That is, we need to define a new set of contour points based on a set of contour points that have been instantiated close enough. Because the abnormal area is an unstructured material object, the points on the contour all have the same role, whether they are P_i points or a certain point in the middle of any $P_i P_{i+1}$ segment.

Considering that the abnormal area and the normal area both have certain material characteristics, and the boundary of the abnormal area is the boundary between the two material areas, thus assuming a straight line intersects the boundary once, then points on that line will have two different characteristics. We use this statement to construct a regression problem at each point. Specifically, at any point near the boundary, we can evaluate the characteristics of surrounding materials to draw conclusions about the ability to move that point to the boundary. The regression performance at any point on the contour is the same. In order to increase the similarity between characteristics at points in different locations, we assume additional parameter of the point's direction. We expect that when the point stops at the boundary, the direction of the point will coincide with the normal of the contour at that point.

Algorithm of characteristics in points.

Function: sampling

Input: image, P, N, angles, times, step

Ouput: sample

Process:

1. *sample* = ∅
2. *for each :* α ∈ *angles:*
3. *D = rotate(N,* α*)*
4. *for each t* ∈ [1, time]:
5. *S = P + D*t*step*
6. *sample = sample* ∪ {*image. at(S)*}

The algorithm performs specificity at the input point *P* on the *image*. The characteristic is calculated by sampling the pixel values in different directions in the list of *angles* sampling directions which are relative and depend on the current *N* direction of point P. In each direction, sampling was performed in *times*; each time was *step* apart. Initially, *sample* output characteristic is set to empty. For each angle *α* in the set of *angles*, we calculate the *D* sampling direction by rotating the current *N* angle by the angle *α*. With the calculated *D* sampling direction, we measure the sampling position *S* with each sampling and then integrate the pixel value at point *S* of the

image into the *sample* output characteristic. At the end of the process, a characteristic at point *P* can be obtained in *N* direction of the *image*.

With the characteristic at a point calculated according to the above rule, a regression model is needed to estimate the displacement parameter for a position on the contour. Thus, with a medical imaging data set labeled abnormal areas, we can build an input sample set to learn regression model. Supposing for an image that has been labeled an abnormal area, a data set can be generated based on it. Rules can be envisioned at each sampling as follows:

- Taking random point P on the contour and calculate N direction of P.

- Generating random points P_1 adjacent to P and N_1 of P_1.

- Using the characteristics of P_1 and N_1 with parameters that change from P_1, N_1 to P, N as input samples for learning. Variable parameters include a rotation value and a step length.

- Variable parameters are normalized to paragraph [0, 1].

After several sampling iterations over a set of labeled medical images, we will build a specific learning data set. Note that the regression is performed for each point on the boundary, so to get the result boundary we need a postprocessing step that includes removing points that are too close together, inserting point when two consecutive points too far and handle cases where the updated points deviate to create an intersection.

2.3. Building regression network

With the point-to-point regression problem described along with how to build the learning data set from a set of medical images that have been labeled with an abnormal area, the next step is to design a machine learning model to solve the regression problem at each point. The machine learning model used is a convolutional neural network structured as shown below.

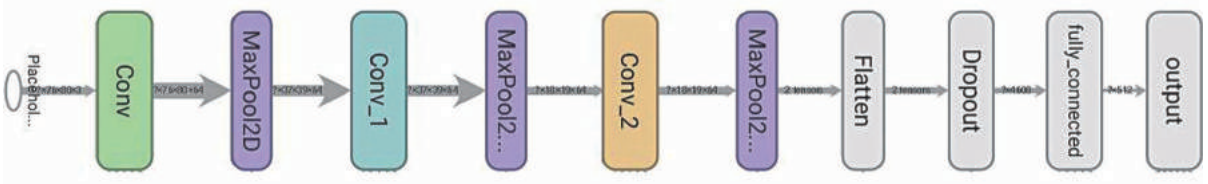

Figure 3. Structure of convolutional neural network

The deviation on the output per sample is calculated as the average of the deflections of each output value from the actually established value. Network training will be done through this deviation.

Later on, from the results of network construction, the assessment of abnormal area change can be carried out according to the following steps: to have the boundary of abnormal area at a given time, to figure the boundary of abnormal area at the moment and to assess the change. Having an abnormal area at the previous scan of the patient, we want to determine the change of that known abnormal area. The initial position is taken on the earlier boundary area. We need to identify the contour of the abnormal area on the current image through the regression of the sampled locations as described above. For each position, the regression model will give parameters to change the new position. After some steps, the new location will converge and the results will be located on the current contour. We can evaluate to increase or decrease accordingly depending on the density of positions on the contour. With the new contour, it is easy to assess the change of abnormal area compared to the previous time.

3. EXPERIMENT

The technology was tested and installed with the support of open source libraries OpenCV, VTK and Tensorflow. The data set selected for testing is 3D-IRCADb-01[5] and it consists of a number

of anonymous medical image sets of patients and manually marked internal organs by medical professionals. The data set included CT scans of 10 women and 10 men; each patient's data was stored in a folder. Medical imaging data and the mask data are stored in DICOM format.

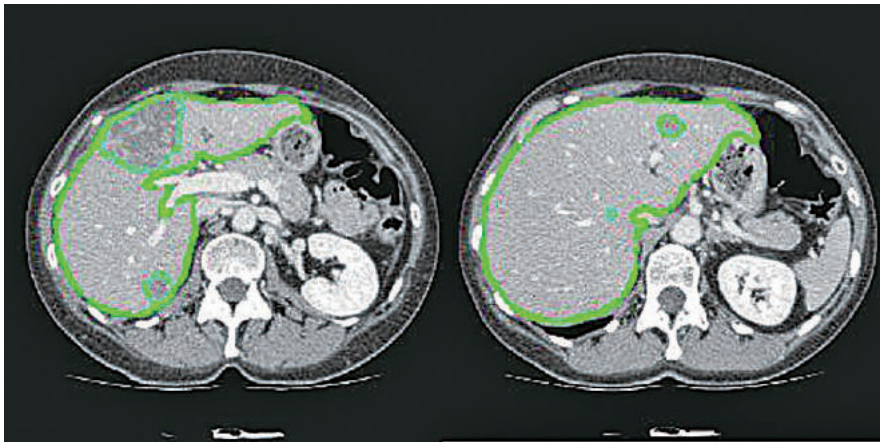

Figure 4. Illustrative data of 3D-IRCADb-01 set with liver area and abnormal area on liver

With slices with abnormal data, especially areas marked with liver tumors, we randomly generate data around the contours. The number of generated points is taken randomly and depends on the circumference of the abnormal area. In the test to generate data, the number of surrounding sampling locations corresponding to an abnormal area is calculated by the circumference of the abnormal area multiplied by a random value in the segment [0.5, 2].

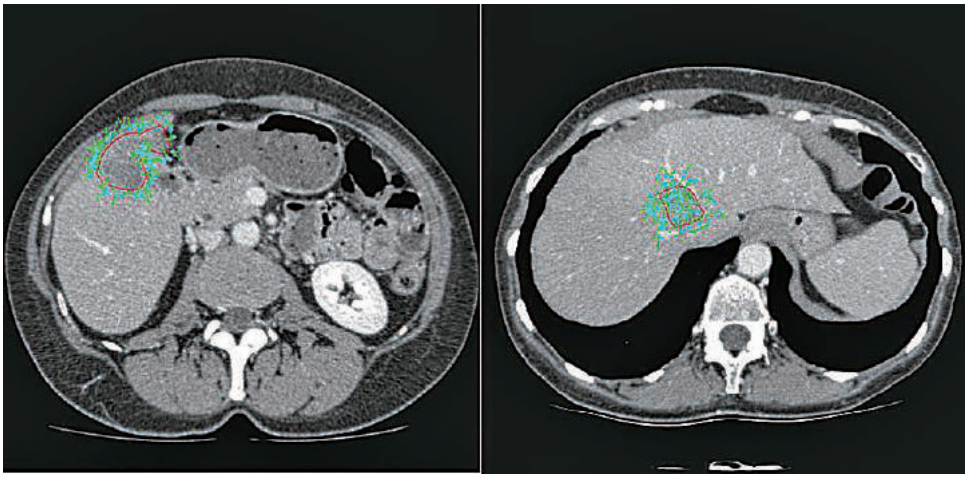

Figure 5. Illustration of random generation data around the boundary of the abnormal area: the abnormal area boundary is in red while the generated data samples consist of a position (in cylan) and the direction at that location (green arrow).

From the sampling around the contours of the abnormal areas, we get data sets for learning and evaluation of results. In the experiment with 3D-IRCADb-01 data, the number of data samples was taken as 161351, half of which will be for network learning and half will be used to assess model results during network learning. The training program is installed and tested on the Google Colab platform; among them data has been pre-sampled. The deviation function is constructed by squaring the deviations from the regression value from included label value. This deviation function will be minimized during the training process.

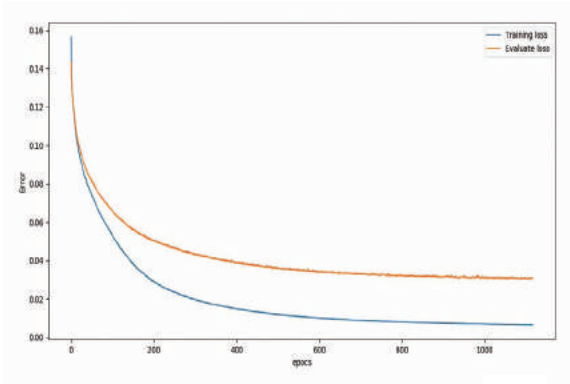

Figure 6. Chart updating training deviations in both training and evaluation

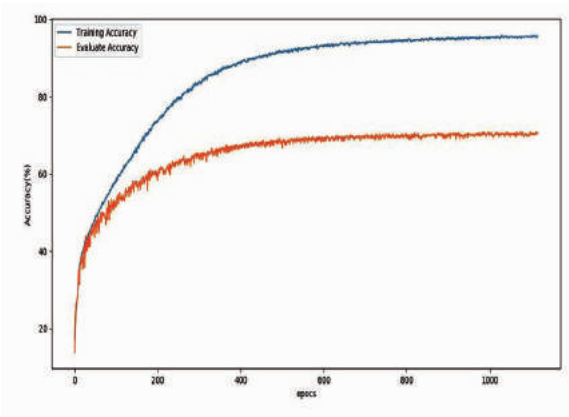

Figure 7. Chart updating training accuracy for both training and evaluation

In addition, to facilitate evaluation, the article sets up the accuracy value. For each sample, it is considered true if each result value is less than 0.1 deviation from the corresponding value in the input label. On that basis, the article also calculates accuracy on training and assessment exercises during network learning.

On the basis of trained network, we apply it to build the function of updating the coordinates of points on the boundary of the abnormal area. This is the basic function to estimate the change of abnormal area compared to the previous state.

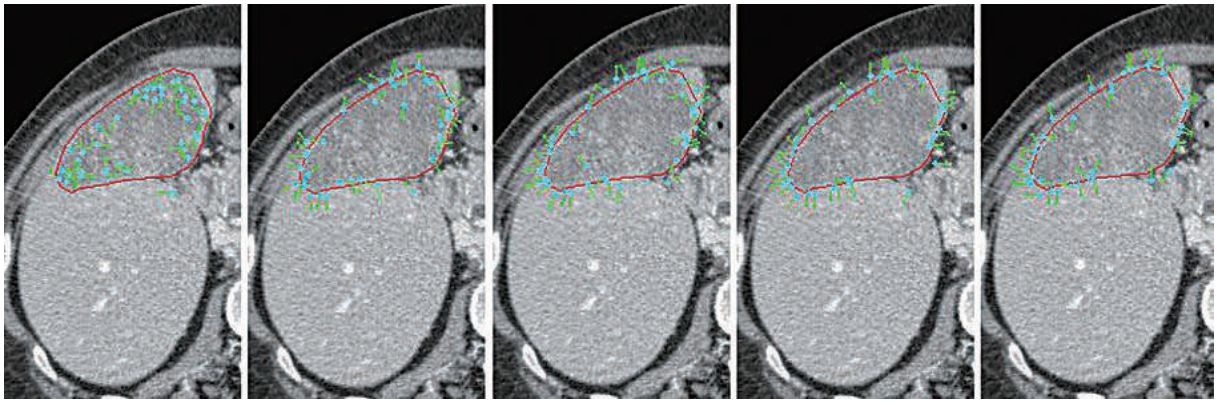

Figure 8. Process of updating the position of points on the contour of abnormal area

4. CONCLUSION

Identifying and assessing abnormal areas in medical imaging is generally an important issue, based on the application of research findings on machine vision and machine learning in practical problems. The article presents the technique of identifying points on the contour of abnormal area based on the analysis of local structures in the vicinity of the contour, in combination with machine learning regression. The technique has been tested on 3D-IRCADb-01 database and gained primary success. The outcomes demonstrate the effectiveness of the proposed approach and technique. This is an essential basis for further improvement studies and more large-scale testing.

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