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ORIGINAL PAPER

Identifying Regions of Interest in Medical Images Using Self-Organizing Maps

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Abstract Advances in data acquisition, processing and visualization techniques have had a tremendous impact on medical imaging in recent years. However, the interpretation of medical images is still almost always performed by radiologists. Developments in artificial intelligence and image processing have shown the increasingly great potential of computer-aided diagnosis (CAD). Nevertheless, it has remained challenging to develop a general approach to process various commonly used types of medical images (e.g., X-ray, MRI, and ultrasound images). To facilitate diagnosis, we recommend the use of image segmentation to discover regions of interest (ROI) using self-organizing maps (SOM). We devise a two-stage SOM approach that can be used to precisely identify the dominant colors of a medical image and then segment it into several small regions. In addition, by appropriately conducting the recursive merging steps to merge smaller regions into larger ones, radiologists can usually identify one or more ROIs within a medical image.

Keywords Computer-aided diagnosis · Image segmentation · Region of interest · Self-organizing map

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Abbreviations

BMU	Best Matching Unit
CAD	Computer-Aided Diagnosis
CBIR	Content-Based Image Retrieval
ROI	Region of Interest
SOM	Self-Organizing Map

Introduction

With the remarkable advances that have occurred in computer technologies in recent years, the number of applications that utilize digital image processing techniques has greatly increased. For clinical use, images are now almost always collected and stored digitally. Common medical images include ultrasound images, images produced by magnetic resonance imaging (MRI), X-ray images, and images produced by computed tomography (CT) and digital mammography [1, 2]. With the aid of data acquisition, processing and visualization techniques, medical imaging can easily facilitate diagnosis.

However, radiologists must still interpret the details of medical images. Suspicious regions of an image, as indicated by abnormal colors or shapes, must be manually identified by radiologists for further clinical examination. Nevertheless, with the development of computer-aided diagnosis (CAD), methods of interpretation have begun to improve; radiologists can use computerized medical images for input in making diagnostic decisions [3]. In addition, analogous to the role of CAD algorithms in medical imaging to complement the opinion of a radiologist, CAD algorithms may also be used to complement the opinion of the pathologist for disease detection, diagnosis, and prognosis prediction [4]. Furthermore, content-based image retrieval (CBIR) techniques are becoming valuable to radiologists by identifying similar images in large archives that could assist with decision support [5].

Image segmentation is often an important part of image processing and computer vision [6]. Generally speaking, image segmentation entails partitioning a digital image into multiple regions—i.e., sets of pixels—according to a given criterion for further analysis. Segmentation techniques are essential in many contexts, including the discovery of regions of interest (ROIs) in medical imaging. To ensure that information that is invaluable for some applications is not lost, representative parts of the overall image should be preserved as much as possible.

The procedures used to perform image segmentation may vary from one type of medical application to the next [7]. For example, the focus of segmentation is different for brain MRIs, leg X-rays, and liver CT images. Thus, variations on the standard technique, including the region-based, edge-based, and thresholding methods, are usually incorporated into conventional approaches. Taking into account the known drawbacks of these approaches, this study focuses on adaptively segmenting various types of medical images. Specifically, we utilize self-organizing maps (SOMs) to perform color reduction; we choose SOMs because they are adaptive, self-organizing and error tolerant in handling input data. Furthermore, we carefully integrate additional steps into our system flows to satisfy additional requirements associated with the handling of medical images.

Note that extracting dominant colors from an image is a crucial step because color helps human beings to identify objects within an image and because visually indistinguishable color differences may be neglected to increase computation efficiency. A region with two similar colors and smooth contours may be an ROI. Our proposed two-stage SOM model and additional merging steps address these difficulties, making it easier to identify ROIs in medical images. Furthermore, the empirical results show that our segmentation techniques can be efficiently and effectively used with various types of medical images.

The remainder of this paper is organized as follows. In "Preliminaries", we briefly discuss background information on image segmentation and explore several related studies. Our approach to extending the applications of SOM to medical image segmentation is presented in "Exploiting the self-organizing map for medical image segmentation". Empirical studies evaluating both the effectiveness and the efficiency of our approach are conducted in "Empirical studies". The paper concludes with "Conclusions".

Preliminaries

Several techniques that are relevant for image segmentation are explored in "Image segmentation techniques". In addition, the foundational information on self-organizing maps is introduced in "Utilizing SOM for image segmentation" as a theoretical basis for this work.

Image segmentation techniques

Image segmentation usually involves identifying discontinuities and similarities in an image. Well-known approaches include edge detection, region growing methods, and histogram thresholding [8]. These conventional approaches have proved to be effective in utilizing either global or local information [9]. Specifically, both edge detection and histogram thresholding utilize global information on color distribution to segment images into regions with similar colors. These techniques work well with grayscale images that only include a single color component. However, when these two techniques are used to process color images, the segmentation results may be poor. This is because to determine a specific threshold so as to define edges or background pixels is not trivial, not to mention an appropriate set of threshold values for multiple color components. On the other hand, because region growing techniques merely use local information for growing regions into larger ones, the resulting segmentation results may also be limited. Specifically, regions are iteratively grown by comparing all unallocated neighboring pixels to the regions. One may thus easily understand that noise in the image can mislead such a growth process.

In recent years, data clustering techniques have been introduced for use with several digital imaging applications. Hierarchical clustering methods and neural networks [10–12] are used for image segmentation because these techniques can be used to group image pixels together according to their color components and spatial coordinates. Nevertheless, a major problem with using these techniques for image segmentation is that the appropriate number of clusters (or segments) should usually be determined in advance. Otherwise, unsatisfactory results may be obtained due to the problem of over-segmentation or under-segmentation (i.e., the image is split into too many or too few regions). Thus, the feasibility of utilizing clustering techniques directly tends to be low in practice.

Although many image segmentation approaches have been developed in prior studies to segment images of various forms is non-trivial [9]. Generally speaking, there is no single segmentation method that can be used with all types of image contents. In this paper, we focus on developing and applying an appropriate approach for medical images. The specific purpose of medical image segmentation is to delimit the image areas representing different objects, including organs, bones, different tissue types, and vasculature [1]. In prior studies, preliminary attempts have been successful in conducting this procedure with specific types of medical images [7, 13].

Utilizing SOMs for image segmentation

Self-organizing maps (SOMs) are commonly used for dimensionality reduction [14]. In a typical SOM, n-dimensional input vectors can be mapped to a few neurons of one or two dimensions. When the aim is to segment color images, a typical option is to use all color components of each pixel as input vectors. This process reveals the corresponding two-layer structure of the SOM, which will contain input vectors and output neurons, as shown in Fig. 1. Without loss of generality, the RGB color model is used in Fig. 1. Other color models, including Lab, Luv, HSV and YCbCr, can also be utilized in a similar way. During the iterative learning process, the output neurons usually converge on the dominant colors of the original image. The goal of color reduction can thus be achieved by discarding insignificant colors.

The weight vectors associated with the neurons in the output layer are denoted by $W_i = [w_{i1}, w_{i2}, w_{i3}]^T$; their initial values are randomly determined, where $0 \leq i \leq M \times N$ (i.e., $M \times N$ is the size of the output layer). Note that the SOM procedure works iteratively to form an unsupervised learning process. In each iteration, the most similar neuron or the best matching unit (BMU) can be designated as an input vector. In addition, a training process begins in which neighboring units of the BMU are identified according to an exponential decay function at time t as follows.

$$\sigma(t) = \sigma_0 \exp\left(-\frac{t}{\eta}\right) \tag{1}$$

where η is a time constant and σ_0 is the initial value of the neighboring length. Furthermore, as can be represented by a Gaussian function $\delta(t)$, the effect of learning gradually decreases in magnitude from the BMU to the edge of the neighborhood. On the other hand, the learning rate $L(t)$ also decreases over time as the learning process converges. Consequently, every neuron within the neighborhood of BMU has its weight vector adjusted according to the following equation.

$$W_i(t+1) = W_i(t) + \delta_i(t)L(t)(V(t) - W_i(t)) \tag{2}$$

if $\|i - BMU\| \leq \sigma(t)$ where $\delta_i(t) = \exp\left(-\frac{\|i-BMU\|^2}{2\sigma^2(t)}\right)$ and $L(t) = L_0 \exp\left(-\frac{t}{\eta}\right)$.

Note that $V(t)$ denotes the input vector, $\|i - BMU\|$ stands for the distance between the neuron i and the BMU, and L_0 is the initial learning rate.

The learning process converges after a number of iterations, and the output neurons can be regarded as representatives of all input vectors. In image segmentation, this typical use of the SOM procedure can help to reduce a wide range of colors to a few representative ones and to identify corresponding segments. Nevertheless, there are usually many noise pixels embedded in medical images, and radical over-segmentation may result if the noise is mistakenly selected to form output neurons. Consequently, the direct use of the SOM technique for color segmentation may not work well in all cases, especially those with inherent noise.

Exploiting the self-organizing map for medical image segmentation

To effectively segment medical images so as to identify ROIs for further diagnosis, we propose an extensive approach based on the SOM technique. The utilized two-stage procedure is presented in "Two-stage SOM structure". Furthermore, additional steps that can be used to enhance the feasibility of our approach are explored in "Featured steps of our approach".

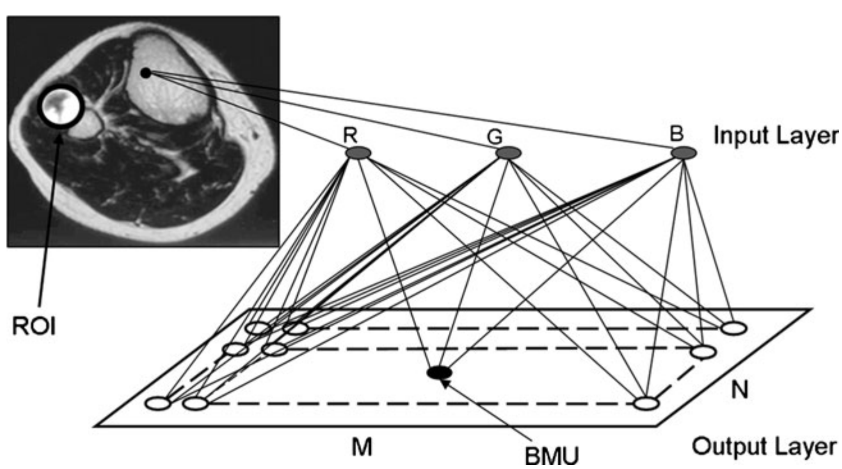

Fig. 1 Two-layer structure of the self-organizing map for image segmentation

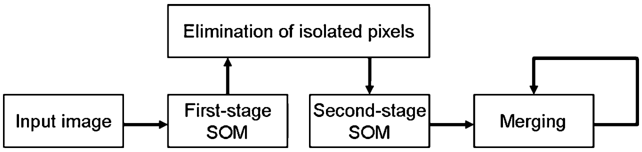

Fig. 2 The flow of our approach, which involves the use of a two-stage SOM technique and additional steps to achieve image segmentation

Two-stage SOM structure

A two-stage SOM structure is used in this work for color reduction and color clustering. Specifically, the complete flow of our approach is shown in Fig. 2. In the first stage, the SOM helps to roughly identify a number of representative colors. The color components of all pixels in the original image are used in the training process for the first-stage SOM. Thus, similar colors tend to be clustered together, and colors that appear frequently are usually identified as the representative ones. The original image is then represented by using these representative colors so that parts of the noise appearing in the image can be depressed.

In the second stage, the SOM indicates the final dominant colors based on the image with the representative colors. The overall process is analogous to that developed in prior studies [12] to segment images containing only a few concrete objects. The advantage of utilizing this type of two-stage SOM rather than a typical one-stage SOM is that the segmentation results can be significantly refined, with the proper set of color segments precisely identified. Furthermore, the most important difference between our approach and earlier methods is that we devise to remove isolated pixels, i.e., noises, between the execution of the two stages. Specifically, this additional step dramatically improves the segmentation results by eliminating the negative effect of noise deriving from the selection of dominant colors. The effectiveness of this two-stage SOM approach is empirically evaluated in later sections of this paper.

Featured steps of our approach

Although a first-stage SOM can diminish a great deal of noise, isolated pixels may remain. These isolated pixels may impair the effectiveness of color clustering in the second-stage SOM. Therefore, our scheme involves an additional step: isolated pixels are eliminated between the two SOM stages. In our study, we replace all single isolated pixels with their dominant neighbors.

After all dominant colors in a medical image have been identified, the corresponding image segments can be formed. Additional merging steps are required for identify-

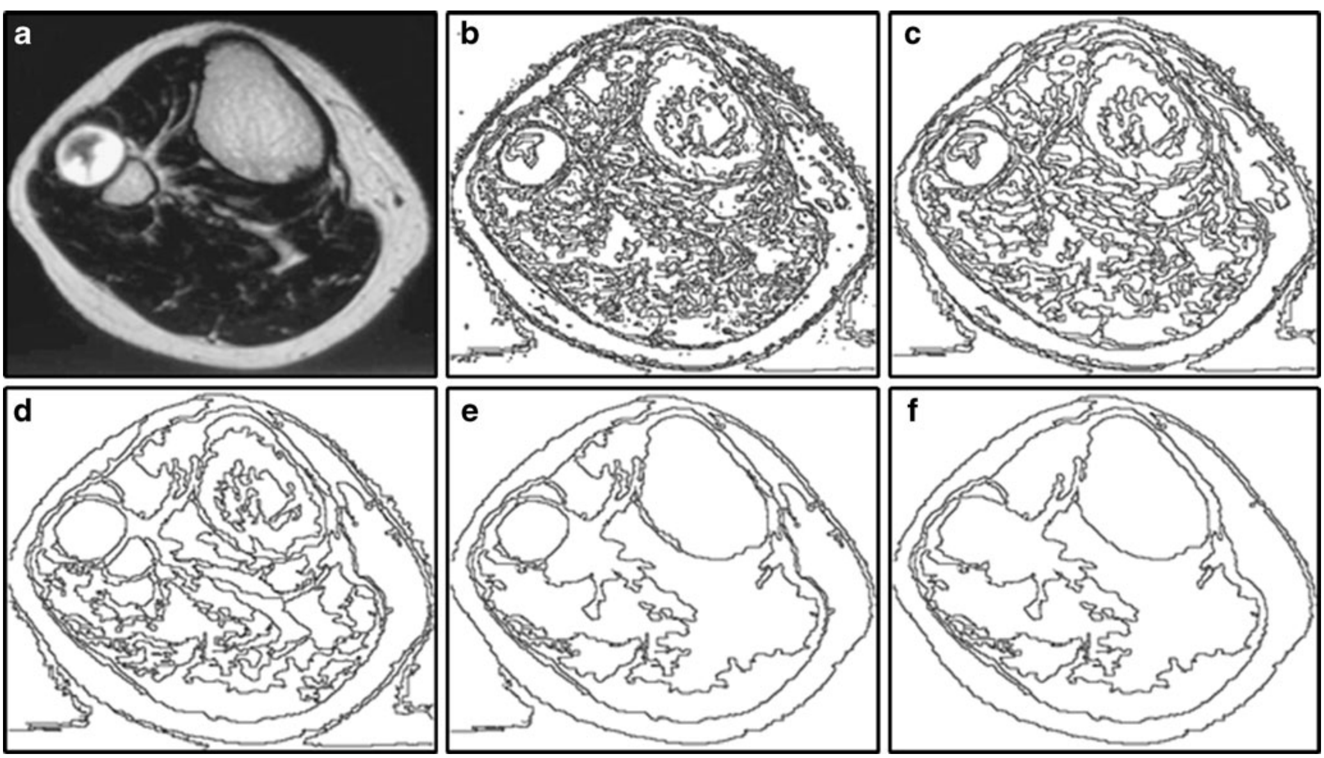

Fig. 3 Conducting the merging step recursively to reduce the number of image segments: **a**. the original MRI image; **b**. before the merging process; **c**. after the first step in the merging process; **d**. after the second step; **e**. after the third step; **f**. after the fourth step

ing ROIs in medical images. In this paper, we propose a recursive merging method of in which smaller segments are gradually merged into larger segments based on both the local and the global information in the image. The most similar segments can be merged with the aid of local information. In additional, during each merging step, the global information on the average segment size in pixels can be utilized to determine where merging is necessary. Figure 3 demonstrates this step conducted with an MRI medical image. In practice, additional stop criteria for the merging process can be introduced in accordance with the preferences of radiologists.

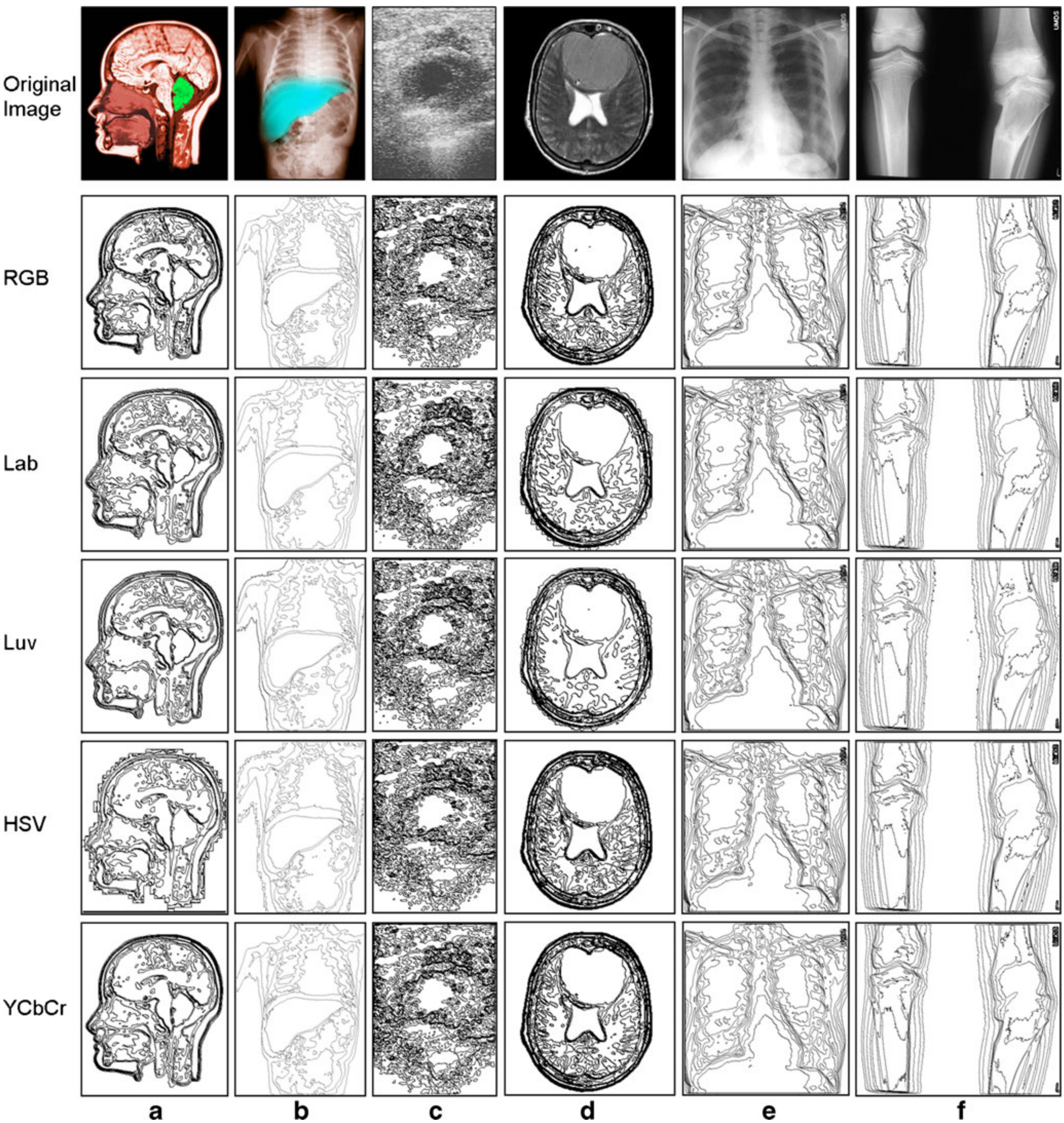

Fig. 4 Testing medical images and corresponding segmentation results using different color models: **a**. a brain MRI image with color enhancement; **b**. a body X-ray image with color enhancement; **c**. a breast ultrasound image with a cyst; **d**. a brain MRI image with abnormal meninges; **e**. a breast X-ray image; **f**. a leg X-ray image with an abnormal tribal bone

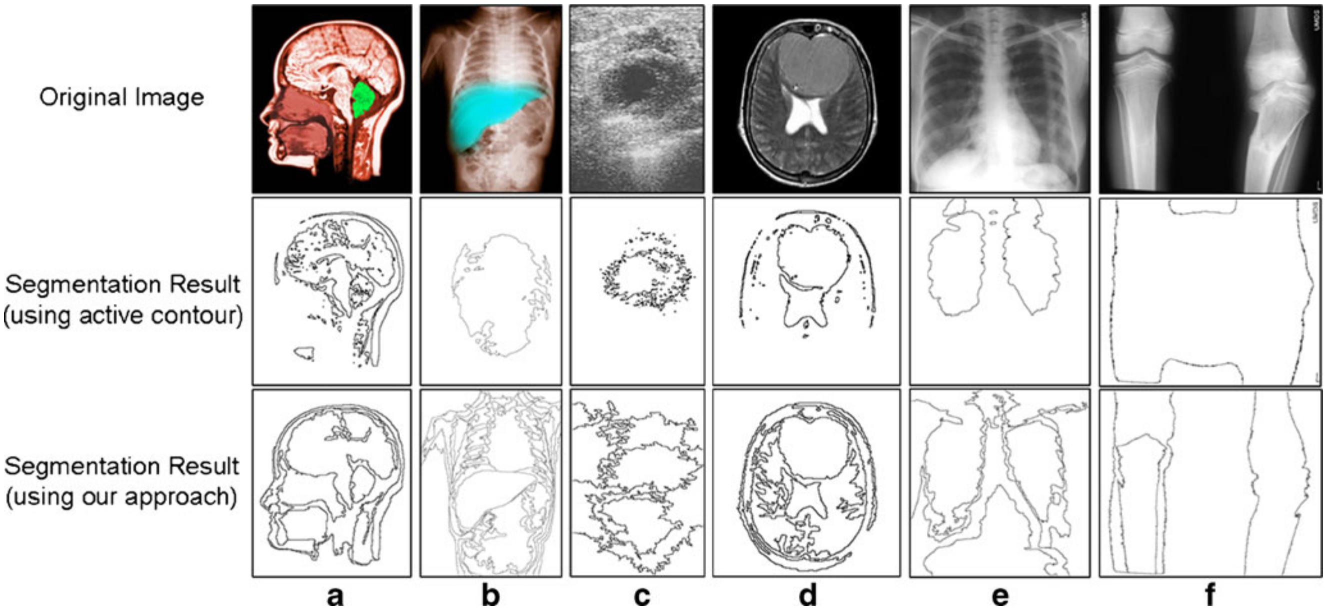

Fig. 5 Testing medical images and corresponding segmentation results using two different techniques: **a**. a brain MRI image with color enhancement; **b**. a body X-ray image with color enhancement; **c**. a breast ultrasound image with a cyst; **d**. a brain MRI image with abnormal meninges; **e**. a breast X-ray image; **f**. a leg X-ray image with an abnormal tribal bone

Empirical studies

To evaluate the performance of our approach to image segmentation, we have conducted several experiments. Details of the experimental environment are introduced in "Experimental environment". The experimental results used to verify the qualitative advantages of our technique are presented in "Feasibility of our approach". In "Objective measurements of our approach", the revised two-stage SOM procedure is evaluated by using a quantitative metric to determine how it improves the results of image segmentation.

Experimental environment

Our testing platform is a desktop PC with an Intel Xeon 3.0 GHz CPU and 1 GB main memory. For comparison purposes, we also employ a widely used *active contour* [15, 16] approach to object segmentation. The basic aim of an active contour model [15] is to evolve a curve based on the constraints of a given image to detect objects in that image. During the iterative process, the curve should evolve until its boundary segments the object of interest. However, this model has two main drawbacks. First, initial seeds for the evolution must be placed close to the object boundary. Second, it is difficult to move a contour into cavities due to the existence of internal energy which tends to smooth the shape of the contour.

A number of testing images have been collected here with the permission of online image archives [17–19]; the images are presented in Fig. 4. To indicate the feasibility of our approach in practical applications, we have included several common types of medical images in our analysis, including MRI, X-ray, and ultrasound images. Furthermore, preliminary segmentation results are also presented in Fig. 4 to show the impact of using different color models, i.e., RGB, Lab, Luv, HSV and YCbCr. Specifically, these preliminary results are all obtained by using our two-stage SOM approach but without the last merging steps. Surprisingly, only subtle distinctions can be found among the results of using different color spaces. Without loss of generality, the RGB color model is used in subsequent experiments.

In addition to qualitative tests, a quantitative metric is used in our experiments to evaluate the image segmentation results. Specifically, the following evaluation function [20,

Table 1 Efficiency evaluation: active contour algorithm approach vs. our approach

Image ID	Image size (pixel × pixel)	Active contour	Our approach
		Execution time (sec.)	Execution time (sec.)
(a)	267×317	23.5	19.7
(b)	600×800	341.3	93.6
(c)	235×331	13.1	18.8
(d)	256×256	16.7	16.3
(e)	443×462	271	43.8
(f)	591×500	213.5	61.3

Table 2 Average Q values achieved when utilizing the one-stage and two-stage SOM techniques for image segmentation

Image ID	(a)	(b)	(c)	(d)	(e)	(f)
One-Stage SOM	50.71	2721.43	2562.36	156.50	33.56	326.60
Two-Stage SOM	26.60	1571.68	34.36	10.40	19.48	61.86

21] is utilized, which considers the number and the homogeneity of segments.

$$Q(I) = \frac{1}{10000(N \times M)}\sqrt{N_R} \times \sum_{i=1}^{R}\left[\frac{e_i^2}{1+\log A_i} + \left(\frac{N_R(A_i)}{A_i}\right)^2\right] \tag{3}$$

where I is the segmented image, $N{\times}M$ is the image size, N_R is the number of regions in the segmented image, A_i is the area of the i-th region, e_i^2 is the sum of the squared color error in the i-th region, and $N_R(A_i)$ represents the number of regions with an area equal to A_i. Note that the Q value increases with the color error value. Also, the Q value decreases based on $\frac{N_R(A_i)}{A_i}$ when the segmentation results contain too many regions (i.e., when over-segmentation occurs). Consequently, a better segmentation technique yields a smaller Q value when the same image is used. On the other hand, it is meaningless to compare the Q values with the segmentation results of different input images. Q can be used as an objective measurement to establish a benchmark for comparison purposes and either adjust the segmentation approach further or evaluate the quality of various approaches.

Feasibility of our approach

We utilize both the algorithm active contour and our approach to segment the six testing images. The corresponding results, which can be used to evaluate the effectiveness of both approaches, are shown in Fig. 5. It is clear that our approach yields better segmentation results. In general, the active contour algorithm does not work well with blurred regions and disjunctive objects (e.g., Fig. 5b and e). On the other hand, all results as shown in Fig. 5 indicate that our approach can be used to properly identify image segments. In addition, proper ROIs are identified by using our approach. Specifically, in Fig. 5(a) through (f), the ROIs of our testing images are the cerebrum and cerebellum, the liver, the cyst, the abnormal meninges, the lung lobes and the abnormal tribal bone, respectively. Note that the effectiveness of image segmentation plays a crucial role here; in our approach, each ROI is generated by merging the corresponding segments.

To further indicate the usefulness of our approach, we have tabulated the corresponding execution times, which are reported in Table 1. Note that our approach is more efficient than the competing approach in most cases. Consequently, we can conclude that our approach is both effective and efficient, helping us to process several types of medical images.

Table 3 Standard deviations of the Q values achieved by using the one-stage and two-stage SOM techniques for image segmentation

Image ID	(a)	(b)	(c)	(d)	(e)	(f)
One-Stage SOM	26.18	431.33	830.55	62.12	14.00	32.54
Two-Stage SOM	6.20	226.12	11.89	2.34	1.74	11.32

Objective measurement of our approach

Here, we present the advantages of utilizing the proposed two-stage SOM procedure according to quantitative studies. For this purpose, we can compare the image segmentation results achieved by utilizing the one-stage SOM [10, 22] and revised two-stage SOM procedures. Without loss of generality, the map size is 6×6 neurons for the one-stage SOM procedure and 3×3 neurons for the two-stage SOM procedure. All the images were tested five times; the corresponding statistics are listed in Tables 2 and 3. Obviously, the segmentation results achieved by using our revised two-stage SOM approach are superior in terms of quality and steadiness.

Last but not least, the usefulness of the proposed step of eliminating the isolated pixels is evaluated here. As previously mentioned, this step helps to improve segmentation quality by removing noise that may limit the use of local information in the second-stage SOM process. All of the images were tested five times. The average Q values of the test results with and without using this step are reported in Table 4. It is clear that eliminating isolated pixels creates better segmentation results.

Table 4 Average Q values achieved by using our approach with and without eliminating isolated pixels during the image segmentation process

Image ID	(a)	(b)	(c)	(d)	(e)	(f)
Without the Eliminating step	65.16	2814.84	2186.09	77.84	42.41	1413.24
With the Eliminating Step	26.60	1571.68	34.36	10.40	19.48	61.86

Conclusions

In this paper, we have presented an approach that extends the applications of the SOM technique in the context of medical image segmentation. We have used a two-stage SOM for color reduction and have eliminated isolated pixels (i.e., noise in medical images) intermediately. We have also merged smaller regions into appropriately sized regions. Our empirical results reveal that our approach is both effective and efficient in handling several types of medical images. Nevertheless, due to privacy concerns, the volume of images tested here was limited; it is logistically difficult to gather a large volume of medical images for testing. More extensive results based on large-scale experiments are expected to result from future studies.

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