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An active contour model for medical image segmentation using a quaternion framework

V. Voronin[a], M. Zhdanova[a,b], E. Semenishchev[a], A. Zelensky[a], S. Agaian[c]; [a]Moscow State University of Technology "STANKIN", Moscow, Russian Federation; [b]Don State Technical University, Lab. «Mathematical methods of image processing and computer vision Intelligent Systems», Gagarina 1, Rostov on Don, Russian Federation; [c]CUNY/The College of Staten Island, Dept. of Computer Science, New York, United States

Abstract

This paper presents a new method for segmenting medical images is based on Hamiltonian quaternions and the associative algebra, method of the active contour model and LPA-ICI (local polynomial approximation - the intersection of confidence intervals) anisotropic gradient. Since for segmentation tasks, the image is usually converted to grayscale, this leads to the loss of important information about color, saturation, and other important information associated color. To solve this problem, we use the quaternion framework to represent a color image to consider all three channels simultaneously when segmenting the RGB image. As a method of noise reduction, adaptive filtering based on local polynomial estimates using the ICI rule is used. The presented new approach allows obtaining clearer and more detailed boundaries of objects of interest. The experiments performed on real medical images (Z-line detection) show that our segmentation method of more efficient compared with the current state-of-art methods.

Introduction

Image segmentation is one of the main tasks of image processing and analysis, the purpose of which is to separate objects in an image with similar properties, such as color, texture, brightness, contrast, etc. The segmentation of medical images (such as X-ray, CT, and MRI) is challenging because medical images are complex in nature and rarely have any simple linear properties. The segmentation process quality gets affected by the partial volume effect, the low signal-to-noise ratio in some scanning technics (MRI, ultrasound, endoscopy), the structure heterogeneity, small size and complex structure of objects of interest (blood vessels, bones and other soft and bone tissues of human organs)the presence of artifacts, the proximity of the gray level of different soft tissues [1].

In medical imaging, the quality of segmentation largely determines the success of early diagnosis and detection of the disease, treatment planning, detection of disease progression. Based on this the segmentation of medical images requires high accuracy [2].

This paper presents a color image segmentation framework using Hamiltonian quaternions for the modified model of active contour based on the calculation of an anisotropic gradient. Since for segmentation tasks, the image is usually converted to grayscale, this leads to the loss of important information about color, saturation, and other important information associated color. To solve this problem, we use the quaternion framework to represent a color image to consider all three channels simultaneously when segmenting the RGB image. As a method of noise reduction, adaptive filtering based on local polynomial estimates using the ICI rule (LPA-ICI) is used.

Related Work

Currently, a wide selection of algorithms is available for segmentation medical images. They are: thresholding, edge detection, region growing, clustering, split and merge and active contour methods.

Thresholding is a simple but popular segmentation method that shares an image with one or more threshold values [3]. The threshold processing approach works well for high-contrast objects with clear boundaries, but efficiency decreases when there are a noise component and blurring of the boundaries. For the segmentation of simple small structures, the region growing [4,5,6] is usually used, which is a popular method of segmenting medical images. The main drawback of this method is that it requires a manual initial of the start point, thus it is necessary to initialize the start point for each region that needs to be extracted. Various approaches based on k-means [7, 8], wavelet transform [9], the section of the graph [10] and self-organizing maps [11] are used for image segmentation.

One of the widely used methods of segmentation in medicine are the methods of active contour [12]. The active contour or snake model is widely used in the case of complex object geometry or large shape changes. There are two main categories for the active contour model: edge based [13, 14] and area based [15].

The main drawbacks of the classical approach are:

- the active contour model is parametric, that is, the shape of the contour described by the model is completely dependent and extremely sensitive to a certain number of parameters;
- the accuracy of the result depends on the given position of the curve: a sufficiently small neighborhood to the boundary of the selected object is necessary;
- extraction errors in the analysis of concave boundaries;
- the curve has a leakage boundary through the edges with insufficiently sharp boundaries of the object and not determined by the gradient;
- there is a smoothing of the lost edges in the presence of noise.

The aim of our work is to develop a new method for segmenting medical images is based on Hamiltonian quaternions and the associative algebra, method of the active contour model and LPA-ICI (local polynomial approximation - the intersection of confidence intervals) anisotropic gradient.

Proposed method

The main steps of the segmentation algorithm are shown in figure 1. There are two basic steps: anisotropic gradient calculation, and image segmentation [16].

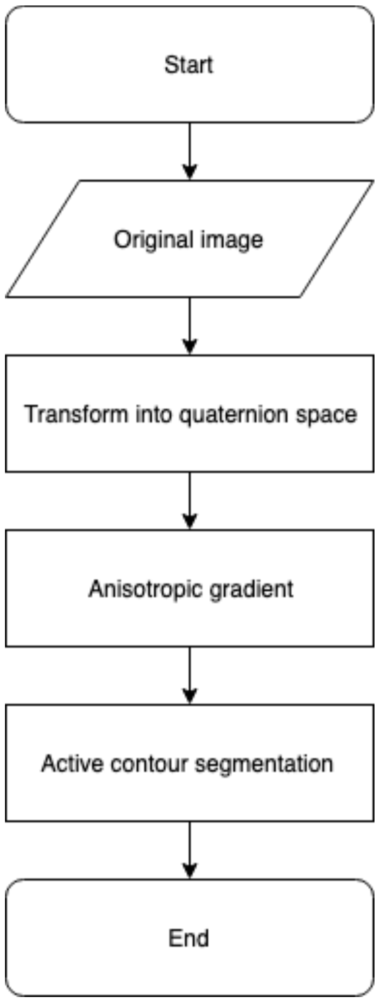


Figure 1. The general flowchart of the proposed segmentation method

On the segmentation step, a modified active contour method is applied. We use standard active contour definition of Energy Function what is defined as the sum of the three energy terms [17]:

$$E_{snake} = \int_0^1 E_{snake}(v(s))ds = \int_0^1 (E_{internal}(v(s)) + E_{image}(v(s)) + E_{con}(v(s)))ds$$

.

The image energy is derived from the image data as follow:

$$E_{image} = \omega_{line} E_{line} + \omega_{edge} E_{edge} + \omega_{term} E_{term},$$

where ω is an appropriate weighting function.

The edge functional in this equation is defined by proposed anisotropic gradient. The concept of the anisotropic gradient proposed in [18]. It combines two technique – the local polynomial approximation (LPA) and the intersection of confidence interval rule (ICI). This approach constructs an adaptive neighborhood for each point in the image domain for the anisotropic gradient estimation.

The proposed gradient calculation algorithm is shown in figure 2.

Algorithm Gradient calculation

Input: Original image $I_{i,j}$

for all pixels
  calculation $Q = q_0 + q_1 i + q_2 j + q_3 k$
    for every direction from i =1 to 8 **step** 1
      building the neighborhood ω
      design a bank of linear filters of various bandwidth
      convolution with different derivative kernels
      construct 'ideal' neighborhoods ω in the discrete image domain using LPA filters
      estimate the anisotropic gradient in the neighborhoods ∇I
    end
end
gradient fusion

Output: Gradient image $\tilde{I}(i,j)$

Figure 2. The general flowchart of the proposed gradient calculation algorithm

The color images of the *RGB* type store three colors in each pixel (red, green and blue). For segmentation tasks, the image is usually converted to grayscale, thereby losing important information about color, saturation, and other important information associated color. Components of a color image can be represented as a quaternion Q. It is usually described using the form, where the basic algebraic form for a quaternion $q \in \mathbb{H}$ is [19]:

$$Q = q_0 + q_1 i + q_2 j + q_3 k,$$

where $q_0, q_1, q_2, q_3 \in \mathbb{R}$, the field of real numbers, and i, j, k are three imaginary numbers. $\mathbb{H}$ can be regarded as a 4-dimensional vector space over $\mathbb{R}$ with the natural definition of addition and scalar multiplication. Each pixel for the color image can be regarded as a pure quaternion with zero real part [19].

Figure 3 shows the color map of the RGB colors into the quaternion [19, 20].

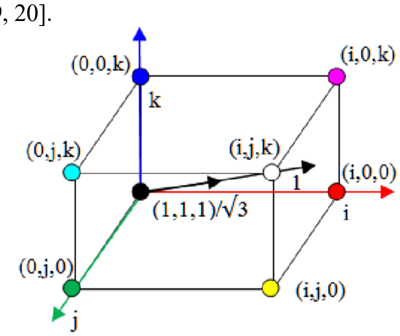


Figure 3. RBG color cube in the quaternion space

We use the LPA-ICI method to build the 'ideal' neighborhood ω in the discrete image domain using LPA filters having directional supports for the image $f(x, y)$ (Fig. 4).

The anisotropic gradient concept allows the existence of a few neighborhoods V_l at the pixel p with the corresponding a few possible different vectors $(\nabla f(p))_l$ such that

$$f(p+v)-f(p)-v^T(\nabla f(p))_l = o(|v|), v \in V_l.$$

The ICI adaptive anisotropic differentiation is aimed at estimating simultaneously both the gradients $(\nabla f(p))_l$ and the neighborhoods V_l . We propose to use the convolution quaternion metrology, which described in [21] for calculation convolution with different derivative kernels.

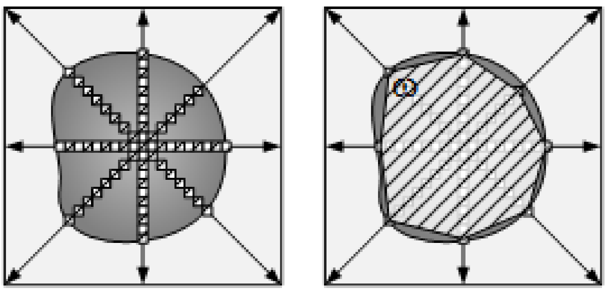


Figure 4. Building neighborhoods using LPA-ICI method

Figure 5 demonstrates the image gradient calculation results obtained by the proposed and the derivative-based algorithm respectively.

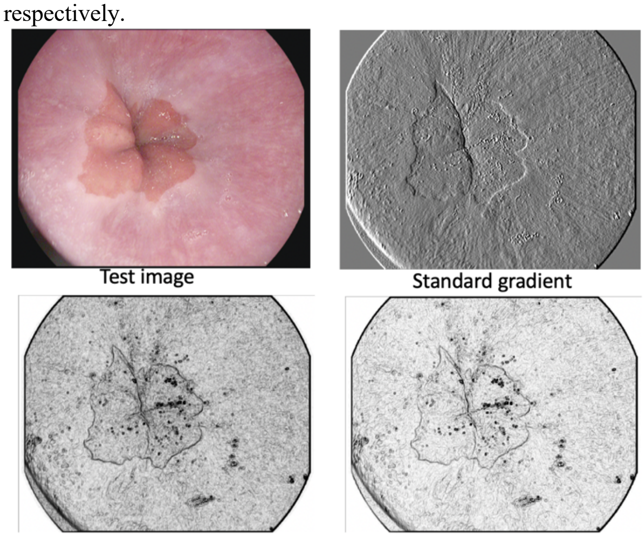


Figure 5. Gradient image

Experiments

For experiments we used the Kvasir dataset [22]. The Kvasir dataset consists of images, annotated and verified by medical doctors (experienced endoscopists), including several classes showing anatomical landmarks, phatological findings or endoscopic procedures in the GI tract, i.e., hundreds of images for each class.

The anatomical landmarks include Z-line, pylorus, cecum, etc., while the pathological finding includes esophagitis, polyps, ulcerative colitis, etc. The Z-line marks the transition site between the esophagus and the stomach. Endoscopically, it is visible as a clear border where the white mucosa in the esophagus meets the red gastric mucosa.

Recognition and assessment of the Z-line is important in order to determine whether disease is present or not. For example, this is the area where signs of gastro-esophageal reflux may appear. The Z-line is also useful as a reference point when describing pathology in the esophagus [22].

We compare the classic active contour method and proposed. Figures 6-9 demonstrate the image segmentation results obtained by its algorithms respectively (a – original image; b - the image segmentation by the active contour method; c - the image segmentation by the proposed method).

The images processed by the proposed method have clearly the boundaries of the segmented area. The artifacts are nullified and small objects are segmented in more detail.

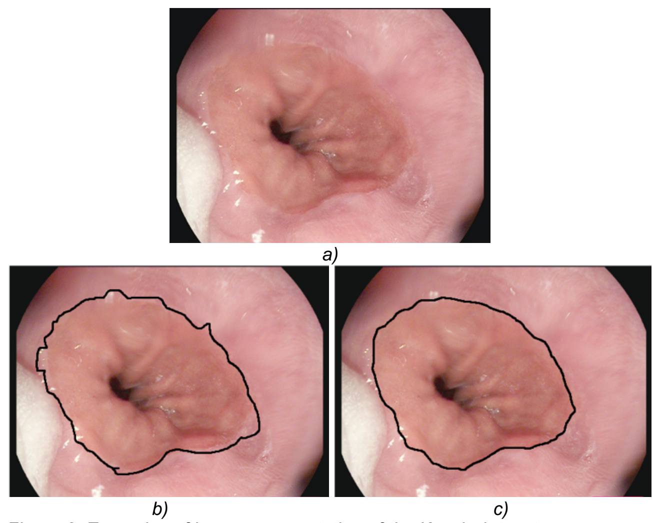


Figure 6. Examples of image segmentation of the Kvasir dataset

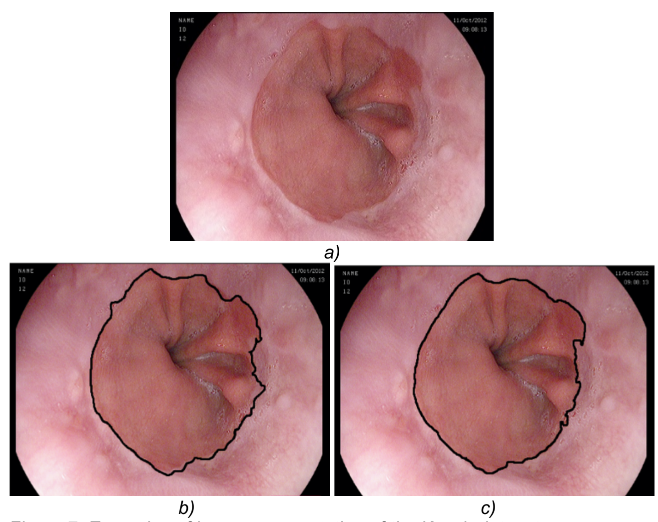
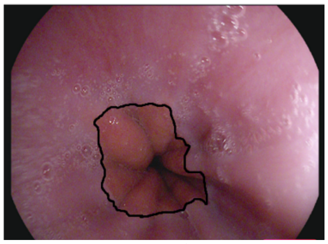
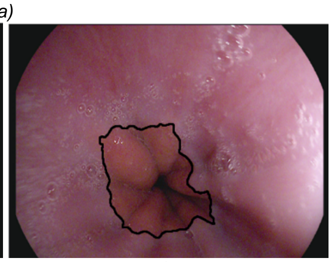


Figure 7. Examples of image segmentation of the Kvasir dataset

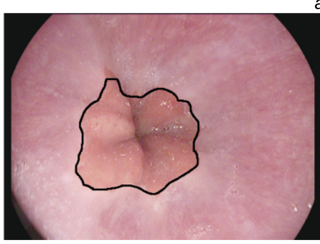
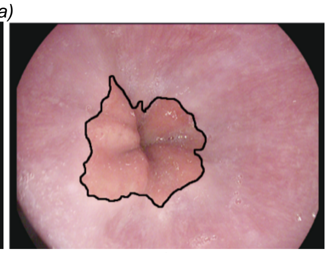
a)

b) c)

Figure 8. Examples of image segmentation of the Kvasir dataset

a)

b) c)

Figure 9. Examples of image segmentation of the Kvasir dataset

Conclusions

We proposed a color image segmentation framework using Hamiltonian quaternions for the modified model of active contour based on the calculation of an anisotropic gradient. The quaternion framework is used to represent a color image to take into account all three channels simultaneously when segmenting the RGB image. The anisotropic gradient calculation is based on local polynomial approximation – the intersection of confidence intervals. The proposed method used for Z-line contour detection for automated visual inspection in medical imaging. A series of experiments confirmed the high efficiency of the proposed segmentation method in comparison with traditional methods.

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Authors Biography

Viacheslav Voronin was born in Rostov (Russian Federation) in 1985. He received his BS in radio engineering from the South-Russian State University of Economics and Service (2006), his MS in radio engineering from the South-Russian State University of Economics and Service (2008) and his Ph.D. in technics from Southern Federal University (2009). Voronin V. is a member of Program Committee of conference SPIE. His research interests include image processing, inpainting, and computer vision.

Zhdanova Marina is Junior Researcher at Moscow State University of Technology "STANKIN". She received her BS in radio engineering from the South-Russian State University of Economics and Service (2012), her MS in radio engineering from the Don State Technical University (2014). Her research interests include image processing and collaborative robotics.

Evgenii Semenishchev was born in 1984. In 2007 he graduated Don State University of Service as radio engineer. He received his BS in radio engineering from the South-Russian State University of Economics and Service (2005), his MS in radio engineering from the South-Russian State University of Economics and Service (2007) and his Ph.D. in technics from Southern Federal University (2010). His research interests include image processing, medical imaging, and image stitching.

Alexander Zelensky is Vice Rector for Research and Scientific and Technical Policy at Moscow State University of Technology "STANKIN". He received his BS in radio engineering from the South-Russian State University of Economics and Service (2004), his MS in radio engineering from the South-Russian State University of Economics and Service (2006) and his Ph.D. in technics from Southern Federal University (2012). His research interests include image processing and collaborative robotics.

Sos Agaian (M'98–SM'00) is Distinguished Professor of Computer Sciences Department at CUNY Graduate Center, New York, USA. Dr. Agaian received the M.S. degree (summa cum laude) in mathematics and mechanics from Yerevan University, Armenia, the Ph.D. degree in math and physics from the Steklov Institute of Mathematics, Russian Academy of Sciences, and the Doctor of Engineering Sciences degree from the Institute of the Control System, Russian Academy of Sciences. He has authored more than 500 scientific papers, 7 books, and holds 14 patents. He is a Fellow of the International Society for Photo-Optical Instrumentations Engineers, a Fellow of the Society for Imaging Science and Technology(IS&T), and a Fellow of the Science Serving Society (AAAS). He also serves as a foreign member of the Armenian National Academy. He is the recipient of MAEStro Educator of the Year, sponsored by the Society of Mexican American Engineers and Scientists. The technologies he invented have been adopted across multiple disciplines, including the US government, and commercialized by industry. He is an Editorial Board Member of the Journal of Pattern Recognition and Image Analysis and an Associate Editor for several journals, including the Journal of Electronic Imaging (SPIE, IS&T) and the System Journal (IEEE). His research interests are Multimedia Processing, Imaging Systems, Information Security, Artificial Intelligent, Computer Vision, 3D Imaging Sensors, Signal and Information Processing in Finance and Economics, Biomedical and Health Informatics.