Interactive curved planar reformation based on snake model

Xinrong Lv*, Xinbo Gao, Hua Zou

Video/Image Processing System Laboratory, School of Electronic Engineering, Xidian University, Xi’an 710071, China

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Abstract

Visualization of tortuous tissues such as tracheas plays a very important role in medical image processing. Displaying them in a curved plane for diagnosis is a better function which is called curved planar reformation (CPR). In this manuscript, we use snake model to generate contours of tubular structures in all slices selected by users of medical volume data sets. Then, centerline of these structures can be obtained. CPR of these structures segmented by snake model is realized based on the obtained contours and centerlines. We use B-spline to generate a contour along tubular structures through points determined by mouse in three view planes. An improved method is used to initialize a snake contours before using gradient vector flow (GVF) snake model generating the final contour. A head aneurysm data set scanned with computed tomography (CT) is used to illustrate the performance of our CPR method. Furthermore some enhancements are introduced to our method: adjustment of window width and window level, rotating CPR.

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1. Introduction

In medical image processing, explicit display of tortuous structures (i.e., blood vessels, colon, trachea) is a topic of high interest. The latest technology, such as computed tomography (CT) and magnetic resonance imaging (MRI) provide three-dimensional volume data of the human body, which contain these objects of interest. The data sets obtained from CT and MRI, contain most parts of interest and a few parts of little or no interest. This makes the several popular rendering technologies (i.e., maximum intensity projection (MIP), shaded surface display (SSD), volume rendering (VR) [1–3]) without preprocessing often impossible or inaccurate. Furthermore the objects of interest always cannot be shown entirely in a single plane. How to better display these tissues has been a problem and some solutions have been proposed with different properties concerning reliability, speed and accuracy [4].

Another way to visualize these tortuous structures in a single image according to their properties such as shapes is called curved planar reformation (CPR). A certain tortuous structure of interest will be displayed along a curved plane passing the centerline in a single image. Vascular abnormalities (i.e., stenoses, occlusions, aneurysms and vessel wall calcifications) can be investigated by physicians. This process is sometimes referred to as multi planar reformation (MPR). However the term MPR is not precise enough, as what this term uses is a plane. Most tissues cannot be displayed entirely in a plane because the tortuous structures rarely lie within one cut plane (hence the requirement for curved reformation). The operator must draw a curve to cut along the course of a vessel in curved reformation. The curved cutting plane is then spread and displayed. X-ray attenuation is preserved on curved reformation images. It has been reported that reformation is very accurate in visualizing stenoses of renal arteries and coronary arteries. Reformation is also reported to be useful for displaying the extent of pulmonary embolism and determining the extent of the intimal flap of an aortic dissection.

Even though CPR is an established technique in the medical community, the visual properties, the advantages and the problems of different types of CPRs have not been specifically addressed in the literature. Understanding such a problem is essential for accurate interpolation of the resulting images. Typically medical workstations contain some types of CPR, however important properties like volume of tubular structures and position of minimum diameter are often not known to users. When drawing curves, it is difficult to accurately draw the curve along the axis of the vessel and it is difficult to illustrate the minimum diameter. This paper thus focuses on the generation, properties,
and enhancements of CPR without concentrating on illustrating all the structures with branches.

The rest of this paper is organized as follows. Section 2 describes the related works in this area. In Section 3, the traditional snake model and gradient vector flow (GVF) snake model which is one of improved snake models are introduced, and a new method to initialize snake contours is also present. Short evaluations of the proposed method on a head aneurysm data set and some enhancements for our method are present in Section 4. Section 5 gives some conclusions and possible improvements.

2. Related works

The development of multiple detector-array CT provides high resolution and large size volumetric data sets. Investigating the original images slice by slice for physicians is not an effective way. Therefore volume visualization and data reformation play an important role in medical imaging. CPR is a very useful tool for physicians from a medical point of view. There is little literature available on the technical aspects and on issues relevant for implementation of CPR.

The tubular structures of interest must be segmented from other organs before carrying out CPR method to them. This is necessary for avoiding being impacted by others in observation. Some different algorithms of centerline extraction are proposed to track the tubular structures. And the structures will be rendered using some different methods such as CPR, surface rendering, VR, MIP and so on.

Avants and Williams [5] presented a vessel tracking method consisting of two parts. From user defined seed points a surface expansion was computed based on the eikonal partial differential equation. A minimal cost path was calculated from these regions. From this path a cross-sectional area/radius profile was generated.

He et al. [6] proposed a path extraction method based on a two-dimensional region-growing algorithm with a subsequent shortest path algorithm. The resulting path was refined using the multi-scale medial response. The vascular tree was flattened in a semiautomatic method called medial axis reform.

Kanitsar et al. [7] dealt with tubular structures such as blood vessels on assumption that they had been segmented and whose central-axis had been extracted. Three different algorithms of centerline extraction were proposed which were projected CPR, stretched CPR and straightened CPR. A short evaluation was given by a phantom in three aspects which are spatial perception, isometry and occlusion. Analysis showed that straightened CPR was the best one. And some enhancements were added to the rest two CPR methods. Furthermore an advanced CPR of whole vascular structures was proposed by Kanitsar et al. [8].

Some researchers proposed to take the central-axis as an input for the generation of an abstract vessel model. Abstract vessel models allowed fast rendering, as polygonal meshes of low complexity were generated [9]. Furthermore non photorealistic rendering provided the possibility to emphasize global properties of the vascular tree [10].

Cai [11] introduced a three-dimensional (3D) curved MPR method, VCAS planar reformation (VPR) by a convex hull, called a biconvex slab. The entire vessel was enclosed within a biconvex slab and rendered in one image by VR, such as MIP or X-ray. The method was applied to computed tomography angiography (CTA) data sets.

Another segmentation method named active contours which is also called snake model is widely used in medical image processing. In each slice of medical imaging volume dataset, snake model [12] is used to segment some regions of interest. Similarly, voxels which belong to the same kind of tissues will be separated.

Anthony Yezzi et al. [13] proposed a geometric snake model for segmentation of medical imaging including MRI, CT and ultrasound medical imaging. Their method was based on defining feature based metrics on a given image which in turn led to a novel snake paradigm in which the feature of interest might be considered to lie at the bottom of a potential well. Thus, the snake was attracted very quickly and efficiently to the desired feature.

Huang et al. [14] used GVF snake to segment liver from CT images. Avoiding blurring the liver boundary generating the edge map with Gassian function, a Canny edge detector was used. When an initialization encountered deep concavities, GVF snake often did not work well. An algorithm to generate the initial contour which crossed the “bottleneck” of the deep concave was realized to make GVF snake easily reach the boundary of liver. A new “maximum force angle map” used to evaluate the direction variability of the GVF forces was introduced. With it, they initialized a trace whose contour was suitable for using as initial contour for GVF snake. By this means the liver was segmented slice by slice correctly.

Liu et al. [15] also used GVF snake to segment liver from CT images. They developed a method for semiautomatic delineation of the liver contours on contrast-enhanced CT images. To improve the performance of the GVF snake in the segmentation of the liver contour, an edge map was obtained with a Canny edge detector, followed by modifications using a liver template and a concavity removal algorithm. With the modified edge map, for which unwanted edges inside the liver were eliminated, the GVF field was computed and an initial liver contour was formed. The snake algorithm was then applied to obtain the actual liver contour. This algorithm was extended to segment the liver volume in a slice by slice fashion, where the result of the preceding slice constrained the segmentation of the adjacent slice.

3. Theory (snake model)

In 1987, it was suggested by Kass that it should be possible to follow edges in images by suggesting a curve (e.g., the circumference of an object) in an image, and then letting the curve itself move to a suitable shape and position. This curve should have physical properties like elasticity and rigidity, and also be attracted by edges in the image. Such curves are called active contours or snakes and have become popular especially in medical image analysis.
Unfortunately, there are two key difficulties with active contour algorithms. First, the initial contour must, in general, be close to the true boundary or else it will likely converge to the wrong result; the second problem is that active contours have difficulties progressing into boundary concavities. Although several methods, such as multi-resolution methods, pressure forces, control points, and directional attractions have been proposed, most of the methods proposed to address these problems solve only one problem while creating new difficulties. A new class of external forces for active contour models which addresses both problems listed above was presented by Xu and Prince [16]. He used GVF fields as the snake’s external force. The fields are dense vector fields derived from images.

Often the CT images are corrupted by noise and sampling artifacts, it is hard to partition tubular structures using common methods. To segment them from the CT images, GVF snake was then chosen to fulfill the task.

GVF snake has larger capture range than traditional snake. Also it can push an active contour into boundary concavities. Unfortunately, the shape of some tubular structures is so complex that there are very deep concavities in some CT image. GVF snake cannot converge correctly in these images if the shape of initial contour is not approximate to the real shape. To solve this problem, we introduce a new method named easily initializing contour which can easily get a better contour approximating the cavity. For the reasons listed above, we turn to GVF snake to segment CT images.

3.1. Traditional active contour (snake)

A traditional snake is a curve, \( X(s) = [x(s), y(s)], s \in [0,1] \), that moves through the spatial domain of an image to minimize the energy function:

\[
E = \int_0^1 \left[ \frac{1}{2} |X'(s)|^2 + \beta |X''(s)|^2 \right] + E_{ext}(X(s)) \, ds
\]

(1)

where \( \alpha \) and \( \beta \) are weighting parameters that control the snake’s tension and rigidity, and \( s \) is a position variable. Respectively, \( X'(s) \) and \( X''(s) \) denote the first and second derivatives of \( X(s) \) with respect to \( s \). The external energy function \( E_{ext} \) is derived from the image so that it takes on its smaller values at the features of interest, such as boundaries. Given a gray level image \( I(x,y) \), viewed as a function of position variables \( (x,y) \), typical external energies designed to lead an active contour toward step edges are

\[
E_{ext}(x,y) = -|\nabla I(x,y)|^2
\]

(2)

\[
E_{ext}(x,y) = -|\nabla[G_\sigma(x,y)I(x,y)]|^2
\]

(3)

where \( \nabla[G_\sigma(x,y)] \) is a two-dimensional Gaussian function with standard deviation \( \sigma \) and \( \nabla \) is the gradient operator. If the image is a line drawing (black or white), then appropriate external energies include:

\[
E_{ext}(x,y) = I(x,y)
\]

(4)

\[
E_{ext}(x,y) = \nabla[G_\sigma(x,y)I(x,y)]
\]

(5)

It is easy to see from these definitions that larger \( \sigma \) will cause the boundaries to become blurry. Such large \( \sigma \) are often necessary, however, in order to increase the capture range of the active contour.

A snake that minimizes \( E \) must satisfy the Euler equation

\[
\alpha X''(s) - \beta X''''(s) - \nabla E_{ext} = 0
\]

(6)

where \( X''(s) \) and \( X''''(s) \) denote the second and fourth derivatives with respect \( s \). To find a solution to (6), the snake is made dynamic by treating \( X \) as function of time \( t \) as well as \( s \), i.e., \( X(s,t) \). Then, the partial derivative of \( X \) with respect to \( t \) is then set equal to the left-hand side of (6) as follows:

\[
X_t(s,t) = \alpha X''(s,t) - \beta X''''(s,t) - \nabla E_{ext}
\]

(7)

When the solution \( X(s,t) \) stabilizes, the term \( X_t(s,t) \) vanishes and we achieve a solution of (6).

The weakness of the traditional snake runs as follows: First, it is extremely sensitive to parameters and has small capture range; secondly, there is no external force acting on points which are far away from the boundary thus convergence is dependent on initial position. This makes it fail to detect concave boundaries. External force cannot pull control points into boundary concavity. For the reasons listed above, we turn to GVF snake to segment CT images.

3.2. GVF snake

The GVF field is defined to be a vector field \( V(x,y) = (u(x,y), v(x,y)) \), which comes from the force balance condition (6) by replacing the potential force \( -\nabla E_{ext} \) with \( V(x,y) \), where \( (x,y) \) is defined same as above. Then we rewrite (7) as

\[
X_t(s,t) = \alpha X''(s,t) - \beta X''''(s,t) + V
\]

(8)

where \( s \) can be replaced by \( (x,y) \), and \( V(x,y) \) is defined such that it minimizes the energy function

\[
E = \int \int \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2 |V - \nabla f|^2 \, dx \, dy
\]

(9)

where \( f(x,y) \) is the edge map of the image, \( u_x, u_y, v_x, v_y \) are first partial derivatives of \( u \) and \( v \) to \( x \) and \( y \), respectively. The parameter \( \mu \) is a regularization parameter governing the tradeoff between the first term and the second term in the integral. This parameter should be set according to the amount of noise present in the image (more noise, increase \( \mu \)). GVF field can be obtained by solving following Euler equations

\[
\mu \nabla^2 u - (u - f_x)(f_x^2 + f_y^2) = 0
\]

(10)

\[
\mu \nabla^2 v - (v - f_y)(f_x^2 + f_y^2) = 0
\]

(11)

Where \( \nabla^2 \) is the Laplacian operator, \( f_x \) and \( f_y \) are partial derivatives of \( f(x,y) \) to \( x \) and \( y \), respectively. Making both equations above discrete, we can get \( u(x,y) \) and \( v(x,y) \) as follows:

\[
u_{n+1} = \mu \nabla^2 u_n - (u_n - f_x)(f_x^2 + f_y^2)
\]

(12)
\[ v_{n+1} = \mu \nabla^2 v_n - (v_n - f) (f_x^2 + f_y^2) \]  
(13)

where \( n \) is the iterations, \( u \) and \( v \) will be obtained after some iterations.

Note that GVF snake is still very sensitive to parameters, though it has larger capture range than the traditional snake. Although the initial contour does not have much influence on the convergence of GVF snake, arbitrary initialization of contour will lead to a time consuming work for GVF snake. To speed up convergence, a simple method named \textit{easily initializing contour} which can get a contour near to real contour is followed below.

3.3. Easily initializing contour for GVF snake

Almost the real contour is the local maximum of gradient in the image. If we draw a contour to guarantee that the real contour is the local maximum of gradient in it, we will easily find an initial contour near to the real contour. The initial contour is composed of all points with a local maximum of gradient surrounded by the contour we drew. This is the principle of method named \textit{easily initializing contour}.

As we all know, drawing a contour must be completed by users. In general, it is accomplished by using mouse to draw a curve along the real contour. This method not only is a time consuming work but also may result in some points inside the real curve along the real contour. This method is used to make the curve pass every control point. Its shape can be modified by dragging control points. The first point as indicated by the arrow in Fig. 2.

B-spline curve came into being when Gordon, Forrest and Riesenfeld developed Bezier curve replacing Bernstein function with B-spline function in 1972. Supposed that \( P(t) \) is a position vector in a curve, B-spline curve along parameter \( t \) will be defined as follows:

\[
P(t) = \sum_{i=0}^{n} B_i N_{i,k}(t), \quad t_{\text{min}} \leq t < t_{\text{max}}, \quad 2 \leq k \leq (n+1)
\]
(14)

\( B_i \) is position vector of a control point, short for control point whose quantity is \( n+1 \). \( N_{i,k} \) is normalized B-spline basis function. When the order is \( k \) while the power is \( k-1 \), the \( i \)th basis function \( N_{i,k}(t) \) is harmonic function, also called basis function defined as follows:

\[
N_{i,1}(t) = \begin{cases} 1 & \text{if } x_i \leq t < x_{i+1} \\ 0 & \text{otherwise} \end{cases}
\]
(15)

and

\[
N_{i,k}(t) = \frac{(t-x_i)N_{i,k-1}(t)}{x_{i+k-1} - x_i} + \frac{(x_{i+k} - t)N_{i+1,k-1}(t)}{x_{i+k} - x_{i+1}}
\]
(16)

Parameter \( x_i \) is the \( i \)th element of node vectors and less than \( x_{i+1} \). The range of parameter \( t \) is \( t_{\text{min}} \) to \( t_{\text{max}} \). \( 0/0 = 0 \) is supposed in equation (16). Curve with order equal to \( k \) satisfying:

(1) \( P(t) \) is a polynomial with power equal to \( k-1 \) in any intervals of \( x_i \);
(2) \( P(t) \) has differential continuity of power from 1 to \( k-2 \);
(3) For the same \( k \),

\[
\sum_{i=1}^{n+1} N_{i,k}(t) = 1
\]
(17)

(4) Any \( N_{i,k} \) is not less than zero and has only one maximum in the validated interval of \( t \). \( N_{i,k} \) is a continuous and smooth curve except for \( k \) being 1 and 2.

For example, a two-power B-spline curve equation is as follows:

\[
P(t) = \sum_{k=0}^{2} N_{k,2}(t) M_k
\]
\[
= \begin{bmatrix} 1 & -2 & 1 \\ -2 & 2 & 0 \\ 1 & 1 & 0 \end{bmatrix}
\begin{bmatrix} M_0 \\ M_1 \\ M_2 \end{bmatrix}
\]
(18)

\( M_k \) is a vertex of characteristic polygons of sectional curve. For the \( i \)th section of the curve, \( P_i, P_{i+1} \) and \( P_{i+2} \) are three points adjacent (see Fig. 1).

B-spline is a flexible curve whose local shape is controlled by relevant vertexes. Vertex control method can make B-spline curve satisfy some special requests in several positions. For example,

(1) A line can be constructed in curve,
(2) Curve can be tangential to characteristic polygons,
(3) Curve can pass through some destined points.

B-spline curve in this paper is a two-power one. Vertex control method is used to make the curve pass every control point. Its shape can be modified by dragging control points. The first point and the last point appear in the same position which is the left point as indicated by the arrow in Fig. 2.

After generating a B-spline along and outside the real contour, we will get all the points in the curve and the center of the contour. Along the line from the center to every point in the curve, we can find a point with a maximum of gradient. This point will be stored as a point in the initial contour of GVF snake. Repeated points will appear because length of B-spline is larger than the initial contour. Traversing all the points in the initial contour, repeated points can determine a section of B-spline curve, such as \( (P_0, P_1 \) and \( P_2 \), \( P_1, P_2 \) and \( P_3 \)).
Fig. 2. A B-spline curve is modified by vertex control method so that it can pass each control point indicated by red cross, and the red cross the black arrow pointing at is the first point and the last point. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)

points must be eliminated. Points left will be the input contour of GVF snake. In Fig. 3, details which are zoomed can be found in upper right of each figure. The red curve is a B-spline curve we drew. The pink curve is the initial curve generated by our method. Although some points in the pink curve do not appear near the real contour, this has no major effect on the convergence of the algorithm of GVF. In each image, GVF converges quickly with the initial contour. The blue curve is the result of GVF snake after 50 iterations. Green point is the center of the final contour.

4. Results and discussion

To evaluate our CPR method, a head aneurysm data set was used, in which only contrasted blood vessels were visible. The data set was rotational angiography scanned at a resolution of $512 \times 512 \times 512$ voxels. The real world size of it was 100 mm both in transversal direction and in longitudinal direction and the spacing of it in three directions $(X, Y, Z)$ is equal to 0.1953. The default display window of CPR image was centered at 0 HU (Hounsfield Units) at a width of 255HU. Our platform for CPR experiments was a common PC with an operating system of Windows XP SP2, a CPU of Pentium 2.8 GHz, a memory of 1 GB and Visual C++ 2005 IDE (Integrated Development Environment). WinGDI was used to draw curves and BMP was used to display images.

For understanding the whole head aneurysm data set, 3D visualization of it in two directions with 3D texture VR [18] using post-classification [19] and phong illumination are shown in Fig. 4.

4.1. CPR without enhancement

Once GVF snake is done in all chosen slices, we will get a contour and a center point of the contour in each slice. Those center points will produce a centerline in the tubular structure we chose. With the centerline and all the contours, we will get the tubular structure segmented. Any direction of CPR along the centerline including direction of the maximum diameter can be easily done.

GVF snake can be performed in three views (traverse view, saggital view and coronal view). About 8.04 s were needed to process 100 slices. Fig. 5 illustrates two CPR results of GVF snake performing in two views including traverse view and coronal view. Fig. 5(a) is a CPR result of 100-slice data in traverse view and GVF snake is performed in traverse view, shown in Fig. 5(b). The volume of vessel in the 100-slice data is 531.32 mm$^3$ according to the spacing of the head aneurysm data set and voxel amounts included in the vessel. Fig. 5(c) is a CPR result of 50-slice data in coronal view, and GVF snake is performed in coronal view, shown in Fig. 5(d). The volume of vessel in the 50-slice data is 308.95 mm$^3$.

4.2. CPR with enhancement

The CPR method introduced has some limitations in common. First, all CPR images are displayed in default settings of the same window width and window level. The display resolution of different tissues is not similar. Second, only one direction cannot provide enough information of the tissue. In order to overcome these limitations of our CPR method, some enhancements are proposed in the following subsections.

Fig. 3. Two examples of initial contour with easily initializing contour method: the red curve is a B-spline curve we drew, the pink one is a curve generated by easily initializing contour method and it is used for the initial contour of GVF snake, the blue one is the final contour generated by GVF snake and the green point is the center point of the final contour. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)
Fig. 4. 3D visualization of the head aneurysm dataset in two directions with 3D Texture volume rendering using post-classification and phong illumination.

Fig. 5. CPR result magnified of the head aneurysm data set while GVF snake is performed in different views: (a) CPR result of 100-slice data in traverse view, (b) traverse view of the head aneurysm data set, in which GVF snake is performed, (c) CPR result of 50-slice data in coronal view, (d) coronal view of the head aneurysm data set, in which GVF snake is performed.
Fig. 6. CPR result with different W/L: CPR result magnified of 100-slice head aneurysm data set in traverse view (left), GVF snake is performed in traverse view (right), while window level is −47 and window width is 166 in both figures.

Fig. 7. Rotating CPR results with the rotating angles being 0°, 30°, 60°, 90°, 120° and 150° from left to right, and GVF snake is performed in traverse view of the head aneurysm data set.

4.2.1. Window width and window level (W/L)

Window width is the range of gray scale in the image displayed and window level is the center gray level in the image displayed. To show different tissues, different window widths and window levels are needed. Adjustment of them can make different parts of the image displayed clear and obscure. It is similar to contrast enhancement. We can preset some W/L of some different tissues. We can also use mouse moving to get suitable window width and window level. Two methods are realized in this paper. A CPR result in different window width and window level of the head aneurysm data set is showed in Fig. 6.

4.2.2. Rotating CPR

Although direction of the maximum diameter is always displayed in clinics, rotating the longitudinal section around the centerline provides the possibility to inspect the entire vessel. This term is called rotating CPR. CPR of any direction has been realized in this paper. For example, 0° is a horizontal line which is from left to right while 180° is from right to left. 90° is a vertical line which is from top to bottom while 270° is from bottom to top. The rest may be deduced by analogy.

In Fig. 7, CPR results of the head aneurysm data set in different viewing directions are shown. The rotation axis is parallel to the z-axis and centered within the final contour. The rotation angles are given at 0°, 30°, 60°, 90°, 120° and 150° from left to right.

According to the spacing of the head aneurysm data set and voxel amounts included in the minimum diameters, the minimum diameters in the vessel from 0° to 150° can be computed as 1.953 mm, 1.7577 mm, 2.5389 mm, 2.1483 mm, 2.3436 mm, 1.7577 mm in 80th, 75th, 95th, 79th, 73th and 67th slice respectively (see the red arrows in Fig. 7). If there are occlusions in the vessel, they may exist near these slices in high probability.

5. Conclusions

In this paper, a CPR method is presented for tubular structures. It allows users to draw curves in three views to produce a contour which surrounds the tubular structure. An easily initializing contour method is used to generate an initial contour for GVF snake. The tubular structure of assigned length was segmented by GVF snake slice by slice. CPR images in any direction were generated which are aiming at visualizing the entire structures of tissues. CPR provides the possibility to visualize the interior of vascular structures. Targeting the drawbacks of our CPR method, two enhancements have been introduced. Adjustment of window width and window level can make the tissues seen clear, rotating CPR can make more information of tissues shown to us.

We present CPR for a single vessel. In future work, we plan to construct CPR for the entire vessel tree which has a lot of branches.
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References


Xinrong Lv was born in Shandong, China. He received the bachelor degree in electronic engineering from Xidian University, Xi’an, China, in 2000. He was recommended to study for the master degree and the PhD degree without examination in 2004 and in 2005, respectively. Now, he has been a PhD student in Xidian University. His research interests focus on scientific visualization and medical image processing.

Dr. Xinbo Gao was born in Shandong, China. He received the bachelor degree in electronic engineering from Xidian University, Xi’an, China, in 1994, the master degree in Signal and Information Processing from Xidian University, in 1997, and the PhD degree in Signal and Information Processing from Xidian University in 1999. From 1997 to 1998, he was a research assistant in the Department of Computer Science at Shizuoka University, Hamamatsu, Japan. From 2000 to 2001, he was a research associate in the Department of Information Engineering at the Chinese University of Hong Kong, Shatin, NT, Hong Kong SAR. Since 2003, Dr. Xinbo Gao has been a full Professor in the School of Electronic Engineering at Xidian University, Xi’an, China, and the Director of Video/Image Processing System Laboratory (VIPSL). His research interests include image/video processing and analysis, pattern recognition, machine learning and computational intelligence.

Hua Zou was born in Hubei, China. He received the bachelor degree from Xi’an University of Architecture and Technology, Xi’an, China, in 2001 and the master degree in the same university in 2004. Now, he has been a PhD student in Xidian University. His research interests focus on volume rendering and medical image processing.