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Interactive Diffusion Tensor Imaging Fiber Data Visualization via Leap Motion

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ABSTRACT Diffusion Tensor Imaging (DTI) reveals subtle abnormalities associated with stroke, multiple sclerosis, schizophrenia and dyslexia, which has a broad application prospect in the medical field. The densely sampled 3-D DTI fiber tracts in biological specimens have high geometric, spatial and anatomical complexity. To provide users with more immersive and convenient interactions in exploring DTI fibers, we design specific interactions based on the APIs of Leap Motion. Leap Motion is a somatosensory interaction device focusing on hand tracking. We design four different interaction modes for users to analyze the data in different interaction stages and scenarios, in order to better explore the DTI fibers which users are interested in by Leap Motion gestures. They are *Normal Mode*, *Box Basic Interaction Mode*, *Box Logic Operation Mode*, and *Cluster Exploration Mode*. Users can conduct tradition manipulations over the whole DTI fiber data in *Normal Mode*. Boxes are employed to filter out uninteresting tracts in *Box Basic Interaction Mode*, and expression-based queries are further designed to get logic set operations based on multiple boxes in *Box Logic Operation Mode*, e.g., the intersection, union and complement of boxes. Complex logic combination queries are allowed to perform to reduce visual clutter and help users explore DTI fibers more precisely. In *Cluster Exploration Mode*, DTI fibers can be classified by clustering them into spatially and anatomically related tracts and then different clusters can be explored individually by designed gestures. Compared with the explorations through traditional input devices, the evaluation tests show that the proposed approach is more intuitive and efficient in 3-D explorations and provides an immersive experience for users to explore the DTI fiber data.

INDEX TERMS Data visualization, data analysis, graphical user interfaces, human computer interaction.

I. INTRODUCTION

Diffusion Tensor Imaging (DTI), a method of describing the structure of human organs, e.g., the brain and the heart, is a special form of magnetic resonance imaging (MRI). If MRI tracts hydrogen atoms in water molecules, DTI fibers map the moving directions and trajectories of water molecules. They reveal subtle abnormalities associated with stroke, multiple sclerosis, schizophrenia and dyslexia, which have a broad application prospect in the medical field. The densely sampled 3-D DTI fiber data in biological specimens have high geometric, spatial and anatomical complexity. It is difficult for users to analyze the whole DTI fiber data without any auxiliary tools.

Traditional hardware interaction devices for DTI fiber explorations include mouses, keyboards, touch screens, etc. However, there are some limitations of these traditional input devices. Due to the limitations of the traditional devices, the mouse and multi-touch devices (iPad and other touch screen devices) show poor performance in terms of depth-direction moving and hybrid interactions. In addition, users cannot get an immersive experience when they use multi-touch devices. Multi-touch devices are often too expensive. Besides, the operating space of multi-touch devices is limited in the 2-D space of the screen.

Except for the traditional 2-D interaction devices, there are some 3-D somatosensory interaction devices such as XTion,[1] Kinect and Leap Motion which provide types of interactions with the help of built-in cameras. Compared with other devices such as XTion and Kinect, Leap Motion has some superiorities . First, it is about 200 times greater than Kinect in the accuracy about hand-gesture recognition. It can

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[1]XTion: http://www.xtion.com.cn/

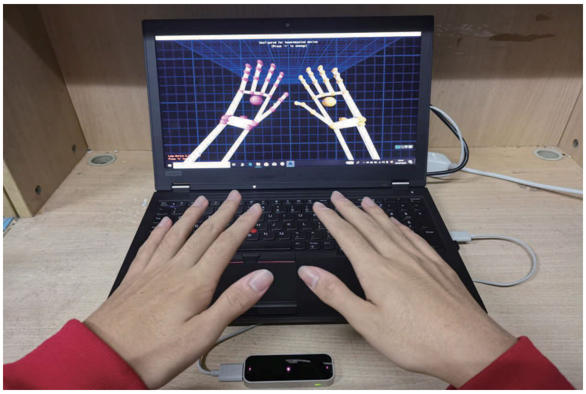

FIGURE 1. The black and silver cube at the bottom is the Leap Motion. It sets up a 3-D coordinate system. The device has two built-in cameras that capture images from different angles to create a 3-D state of hands. Users can manipulate the target object directly by different gestures.

capture and recognize fine-grained gestures [1], e.g., finger-level gesture, even finger bone-level gesture, which is quite useful in DTI fiber data exploration. It requires considerable well-designed interactions in DTI fiber visualization system. This feature allows users to map types of interactions onto different gestures. Second, Leap Motion is much cheaper than the other commonly-used 3-D somatosensory devices.

A novel DTI fiber exploration scheme [2] was successfully builded for DTI data analysis and exploration. In this method, box is considered as a tool which the DTI fiber tracts passing through can be highlighted and chosen as a new bundle. Users can perform basic interactions on the box through controls. As shown in Figure 2, two boxes of different colors are added to filter out DTI fibers. From Figure 2(a) to Figure 2(b), the green box is moved to the lower right and the blue box is zoomed in. Besides, an anatomical visualization technique [3] was presented to abstractively represent and explore in hierarchically clustered DTI fiber tracts. However, there are some limitations of traditional input devices which show poor performance in terms of depth-direction moving, hybrid interactions and the view of clustered DTI fiber tracts. Besides, the fiber bundle select selected by multiple boxes is limited.

In this paper, we use Leap Motion replacing traditional devices to explore DTI fiber data based on four modes. It provides users with intuitive and immersive experiences. The main contributions include:

- Four interaction modes is designed for different stages of DTI fiber data analysis.
- Users can successfully use gestures via Leap Motion by replacing traditional devices availably to explore DTI data.
- Complex logic combination queries based on multiple boxes are designed to perform to reduce visual clutter and help users explore DTI fibers more precisely.
- The feasibility and effectiveness are demonstrated by evaluation test tasks including depth-direction moving task and hybrid interaction task.

The rest of this paper is organized as follows. Section II provides a brief summary of related work; Section III describe the details of our method; Section IV demonstrates the efficiency of our method and a user evaluation about two tasks;Section V state some limitations about our method; and Section VI presents our conclusions.

II. RELATED WORK

We divide the related works into two categories, such as interactive scientific visualization by multiple devices and DTI fiber visualization. The work on interactive scientific visualization by multiple devices can be further categorized into two types: gesture interactions and common interactions in scientific visualization.

A. INTERACTIVE SCIENTIFIC VISUALIZATION BY MULTIPLE DEVICES

We categorize this sub-section into gesture interactions and common interactions in scientific visualization.

1) GESTURE INTERACTIONS

In recent years, the novel acquisition devices, such as Leap Motion and Kinect, have been used for accurate gesture recognition.

They can both control computer by using a natural gesture that replaces the traditional mouse and keyboard controls [4]. Leap Motion is one of the most popular gesture recognition sensors nowadays, which have two built-in cameras. Improvements in shot detection [5] have also facilitated the development of these devices. Li *et al.* [6] proposed a dynamic gesture recognition method based on HMM and D-S evidence theory to improve the performance of the Kinect on the recognition of complex gesture movement. Leap Motion is about 200 times greater than Kinect in the accuracy [1]. The principle of Leap Motion is to capture a hand image through two cameras and analysis the change of gesture to establish a 3-D model [7]. We can conduct research and development in different fields based on Leap motion, including education, gaming, robots, medicine etc. The integration of gaming applications was explored into the medical field [8]. For example, Suryanarayan *et al.* [9] present a novel algorithm to recognize hand poses dynamically. An improved DTW method [10] is proposed to address the problem of continuous repetitive gesture recognition. Then a system was developed to evaluate an abnormal finger motion using Leap Motion that are used to calculate the finger's angle [11]. With the detecting and tracking hands, Leap Motion can used to American Sign Language recognition [12]. An interaction tools [13] was designed for exploring volume dataset by interaction gestures vis Leap Motion to perform some tasks. Furthermore, the integration of gaming applications was explored into the medical field [8] such as a game for hand rehabilitation [14]. An interactive gesture controlled application [15] was presented and evaluated, which show the effectiveness and high satisfaction of the participants. Besides, Li *et al.* has successfully developed a adaptive controller based on the

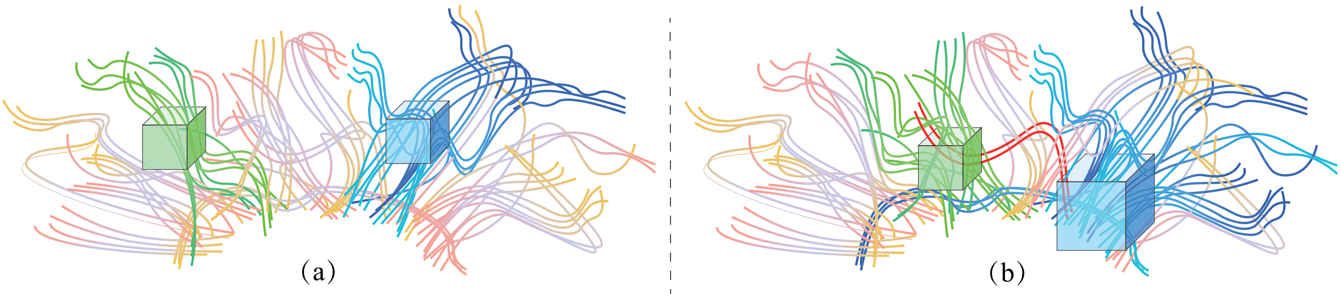

FIGURE 2. **Users add two boxes of different colors to filter out DTI fibers they are uninterested in. From (a) to (b), the green box is moved to the lower right and the blue box is zoomed in via Leap Motion device. The filtered DTI fiber tracts are highlighted in the same color of the corresponding box they pass through. The DTI fiber tracts highlighted in red in (b) are those go through the blue box and the green box simultaneously.**

neural network (NN), which can realize the teleomerization of a DLR-HIT II robot hand [16], [17].

2) COMMON INTERACTIONS IN SCIENTIFIC VISUALIZATION

Interactive visualization is the foundation of this work implementation. Traditional interaction designs can effectively interact between users and data, such as using the mouse and keyboard to explore data. For example, traditional devices are employed by the oil/gas exploration experts to interactively illustrate the seismic data [18], [19]. Liu *et al.* [20] proposed an interactive stratigraphic data slice interpretation system to interpret and visualize the 2-D seismic slice. In order to better help experts solve interaction issues on efficiency or effectiveness, some new methods were proposed such as interactive transfer function design [21] in seismic data visualization, interactive progressive seed point tracing [22], interactive user-defined feature exploration [23] and LCSS-based approach [24] to visualize ensemble field lines. The field lines in vector fields are similar to DTI fibers in visualization space. Compared with interactive approaches explored by traditional devices, the proposed approach can generate more expressive and meaningful approach because it well matches to the domain knowledge. Besides, interactive visualization has a wide range of applications in medical data.

B. DTI FIBER VISUALIZATION

The studies of DTI are increasingly popular among researchers and clinicians. DTI is to use the present MRI technology and is an advanced variant of MRI, which can track the trajectories and the moving patterns of the water molecules in the white matter tissue of the brain [25]. Tensor field has been used in many applications [26], such as medical imaging. In a tensor field, DTI fibers usually integrate along the longest eigenvector. They can be expressed as streamlines, flow tubes and flow surfaces [27], [28]. The geometry of a set of fibers can be further reduced to more abstract visual forms, such as winding streamlines [29] or topological simplification [30] or the use of hierarchical master curves [3]. In order to visually distinguish paths, several different pattern styles were used to encode different local information of the fiber, resulting in an online navigation tool for fiber connection [31]. The differences between a group of fibers can be represented in cross section with the appropriate staining scheme, so that a cluster can be easily identified through color. Other features from the fibers can also be identified and visualized, such as noise and uncertainty caused by partial volume effects. Most of these schemes focus on representing DTI fibers in 3-D space, limiting the amount of information that can be displayed and explored before excessive visual clutter [2]. DTI has been shown to be capable of building 3-D fibrous structures, such as nerve fibers in muscles and in brain [32]. In order to present these structural data more intuitively, we adopted Leap Motion to realize the interaction between data and doctors, so that doctors could visually see these fibrous structures from any angle. The work shows that the potential of this technique in a clinical setting is clear, because many diseases of the brain affect the white matter [33].

III. OUR METHOD

DTI is a technique that measures the speed and direction of water diffusion in biological tissues and is widely used for visual analysis of DTI datasets. The 3-D DTI fibers sampled in the biological specimen have a high degree of geometric and spatial complexity. The use of box and clustering techniques can filter out specific fiber tracts. This fiber tract reduces the visual complexity of the DTI fiber data, which facilitates the exploration for users. Chen *et al.* [2] have developed a system to implement these functions. However, we find that traditional interactive devices used in this system have some limitations in the interaction process. The introduction of Leap Motion can availably break these limitations. We implement all the basic interactions via Leap Motion based on the open source code provided by Chen *et al.* [2]. More importantly, the expression-based queries are implemented to perform complex logic set operations on multiple boxes. Besides, DTI fibers can be grouped by fiber clustering into spatially and anatomically related tracts and then different related tracts can be explored individually by designed gestures. In our system, users can explore the DTI

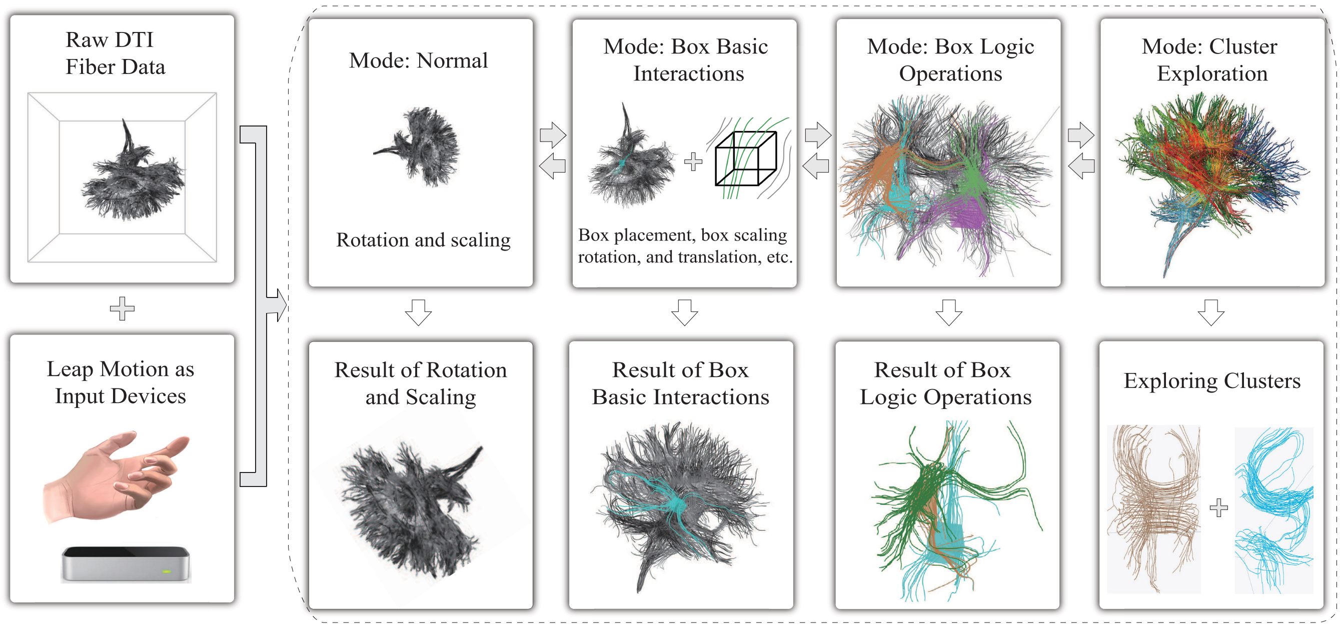

FIGURE 3. The pipeline of the proposed approach. The system is divided into four modes, and users can use a series of operations to control the DTI fibers through the gestures which are mainly captured and detected via Leap Motion. Each mode will get a corresponding result.

fibers in four different modes. The four modes are listed as follows:

Normal Mode: Users can manipulate the whole DTI fibers with gestures. They can rotate, scale, and rotate the whole DTI fibers in this mode. Besides, they can also place boxes to filter and highlight the fiber tracts they are interested in.

Box Basic Interaction Mode: Operations carried out on the box are considered as in *Box Basic Interaction Mode*. As shown in Figure 2, users can change the size and the position of the box by scaling and translating the box with gestures. In fact, users can put as many boxes as they want. If there are three boxes in the DTI fiber, users can select the box to be modified by *Circle Gesture* (refer to the appendix).

Box Logic Operation Mode: In this mode, we provide expression-based logic queries. Users usually only need to select one or several of the placed boxes to perform the *intersection*, *union* and *complement* operation. Our work supports entering multiple expressions and the choice of their results. This query is similar to domain-specific language (DSL) which can help domain experts submit complex queries.

Cluster Exploration Mode: The existing DTI data visualization methods [2], [34], [35] have developed some clustering methods to support traditional mouse exploration. We extend the clustering methods to support interactive exploration through Leap Motion.In this mode, users can select each classified fiber by gesture to view.

Figure 3 shows the pipeline of the proposed approach. The exploration of DTI fiber data is conducted in four modes. The switching between each mode depends on the *Mode-Change Gesture* (refer to section Appendix). For example, users execute each mode in order. First, DTI fiber data is operated in the *Normal Mode*. The whole DTI fibers can be adjusted to an appropriate size and angle by gestures. Second, users can enter the *Box Basic Interaction Mode*. In this mode users are allowed to place multiple boxes and adjust them to the appropriate size and position. Third, the *Box Logic Operation Mode* can be entered from the *Box Basic Interaction Mode*. Users can input a logic expression to query. The resulting image can also be scaled and rotated to a appropriate size and angle. Fourth, the classified fibers can be produced and further explored in the *Cluster Exploration Mode*.

A. BASIC INTERACTIONS BY LEAP MOTION

The *Normal Mode* is designed to conduct overall operations on DTI fiber data. The traditional method uses the mouse to operate the DTI fiber data. In previous method, users use the mouse scroll wheel to scale. When it scrolls up or scrolls down, the DTI fiber data accordingly zoom in or out. The DTI fiber data is rotated with the method of dragging the mouse. With the proposed approach, users can use gestures to replace mouse availably and achieve the same interactions, including the rotation, translation and scaling operations in the whole 3-D space. Using Leap Motion can not only achieve the same result, but also shows better effect in some terms such as depth-direction moving and hybrid interactions.

Leap Motion can capture and recognize the gestures, and it can get the distance of two hands, fingers or even finger bones. When the distance between two hands becomes bigger or smaller, it means to zoom in or zoom out the DTI fiber. When users want to perform rotation, they can make a *Scaling Gesture* (refer to section Appendix) and rotate the hand. When Leap Motion detects a gesture, it will provide a corresponding finger curvature value. When it classified the

TABLE 1. The three basic logic combinations of multiple box queries. The commonly-used arithmetic expression is exploited to specify the logic combinations. They include *intersection*, *union*, *complement* and their arbitrary logic combinations.

Operation	Expression	Representation
Intersection	$1*2$	The DTI fiber tracts passing through Box #01 and Box #02 simultaneously
Union	$1+3$	The DTI fiber tracts passing through either Box #01 or Box #03
Complement	$/1$	The DTI fiber tracts without passing through Box #01

current gesture as *Scaling Gesture*, we use two thresholds to filter the finger curvature values from noise gesture inputs, they are *THRESHOLD_MIN_CURVATURE_SCALING* and *THRESHOLD_MAX_CURVATURE_SCALING*. Then, we can get the normal vector of the hand. As the normal vector of the hand changes, a rotation angle can be calculated between the starting vector and the ending vector.

B. EXPRESSION-BASED BOX QUERIES TO FILTER DTI FIBERS

The basic box operations include box placement, selection, scaling and translation in the *Box Basic Interaction Mode*. Besides, we also design an expression-based complex box queries. Specifically, we use easy-to-understand arithmetic expressions to do the box queries in *Box Logic Operation Mode*.

1) SINGLE BOX QUERY BY LEAP MOTION

Boxes can be used to filter DTI fibers, each group of filtered fibers named a tract [2], [32]. In DTI data exploration, a box is usually placed to the position of a tissue or an organ to view the tracts passing them.

When the Leap Motion detects the *Mode-Changing Gesture* successfully, the exploration will enter the *Box Basic Interaction Mode* from the *Normal Mode*. In this mode, an individual box is selected as the focused object. Boxes can be added, removed, scaled, translated and highlighted.

The gesture of the scaling operation is the same as the *Scaling Gesture* in the *Normal Mode*. In this mode, *Scaling Gesture* is employed in box scaling in *Box Basic Interaction Mode*. In order to achieve the desired query results, users need to move the box by translation operations.

Users can use *Translation Gesture* to move either the whole DTI fiber or an individual box. When Leap Motion detects a gesture, it will provide a corresponding finger curvature value (the normal vector of the hand). We use a threshold to filter the finger curvature values from noise gesture inputs, i.e., *THRESHOLD_MIN_CURVATURE_TRANSLATION*. Then Leap Motion gets the coordinates of the center point of the hands, and we use it as the criterion. We calculate the distance between two consecutive hand position values captured by Leap Motion. If the distance is larger than *THRESHOLD_MIN_CURVATURE_TRANSLATION*, the translation operation will be applied to the box.

When the DTI fiber data is rotated, the image coordinates will be also rotated, which results in inconsistences between the image coordinates of visualization space and world coordinates of Leap Motion interaction space. For example, when a box is translated after rotating the DTI fiber data, the moving direction of the hand and the visualized box are often opposite. We use a transformation matrix to record the interaction process and make the two coordinates unified. We use an additional transformation matrix to record the current status of image coordinates. The transformation matrix can be written as follows,

$$\begin{pmatrix} x_j \\ y_j \\ z_j \end{pmatrix} = \begin{pmatrix} X_x & X_y & X_z \\ Y_x & Y_y & Y_z \\ Z_x & Z_y & Z_z \end{pmatrix} \begin{pmatrix} x_i \\ y_i \\ z_i \end{pmatrix} \tag{1}$$

The unit vectors of the X-axis, Y-axis, and Z-axis in the image coordinate system can be calculated in the world coordinate system, and we use (X_x, X_y, X_z), (Y_x, Y_y, Y_z), (Z_x, Z_y, Z_z) to represent the unit vectors of each coordinate after rotation. The original moving vector $(x_i, y_i, z_i)^T$ can be transformed into the new moving vector $(x_j, y_j, z_j)^T$. After the transformation, the moving direction in world coordinates can be visually consistent with the that in image coordinates.

2) EXPRESSION-BASED BOX QUERIES BY LEAP MOTION AND KEYBOARD

The *Box Logic Operation Mode* is based on the *Box Basic Interaction Mode*. In this mode, we use Leap Motion and keyboard to achieve some logic combinations of basic box queries. We design expression-based box queries which support selecting multiple boxes to conduct complex logic combinations of queries. They are *intersection*, *union* and *complement* on multiple boxes. We employ commonly-used symbols, i.e., arithmetic expressions, to represent these operations. We use the symbol '+', '*', '/' represent *intersection*, *union* and *complement* operation, respectively. The boxes are represented by Arabic numerals according to the placement order of them. For example, '1' represent Box #01, '2' represent Box #02, etc.

Table 1 shows the three basic logic combinations on multiple box operations. A box is usually placed to cover a tissue or a a part of a tissue. For example, when users experiment on heart data, they can place Box# 01 and Box #02 to the positions of the left atrium and right ventricle, respectively. The expression "`1*2`" represents the queried DTI tracts passing through the left atrium and the right ventricle simultaneously. Then the expression "`1+2`" represents the queried DTI tracts passing through either the left atrium or the right ventricle simultaneously.

More importantly, users can design more complex logic combinations of box queries based on these three basic expressions, for example, the expressions like "`1*2*3`" and "`(1*2)+(3*4)`", etc. The parentheses here mean the operation priority similar to the arithmetic expression.

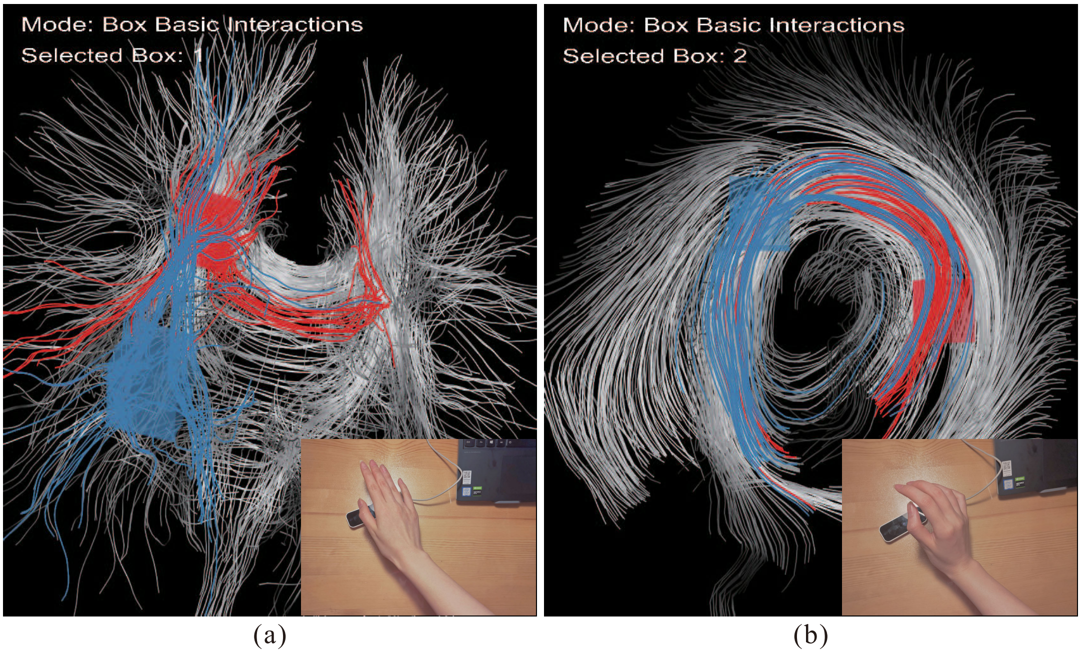

FIGURE 4. The result of placing two boxes through Leap Motion. Box #01 is red and Box #02 is blue. The fiber tracts selected by boxes are marked by corresponding colors predefined in the framework. The whole fibers can be rotated, scaled, translated by different gestures detected by leap motion.

C. EXPLORING CLASSIFIED FIBERS BY LEAP MOTION

Diffusion tensor imaging has been confirmed to reconstruct fibrous structures [36]. Domain experts often require to explore the DTI fibers which follow similar shapes or patterns. Some clustering and classification techniques have been developed to solve this issue. The proposed method classify DTI fibers into fiber clusters in the white matter region [37], [38]. Another visualization technique was presented to reduce the geometric complexity of the fiber models [3]. It uses meanshift algorithm to automatically generate cluster tracts. However, the rendering of the cluster tracts will still be affected by occlusion (i.e, one cluster obscuring another). It impedes further selection and analysis of specific fibers [39]. Our method enable users to explore each classified fiber tract in *Cluster Exploration Mode*. Each classified fiber tract can be displayed separately, which can avoid one cluster obscuring another. Users can switch the different clusters by using a simple Leap Motion gesture.

IV. RESULT AND EVALUATION

This section shows the results and the evaluation about the proposed approach. The data is provided by the work Chen *et al.* [2]. The experiment codes of the paper are developed based on the open source codes provided by Chen *et al.* [34], [35]. We test our method on medical data include dataset BRAIN and dataset HEART.

In our experiments, we assign *THRESHOLD_MIN_CURVATURE_SCALING* as 0.2, *THRESHOLD_MAX_CURVATURE_SCALING* as 0.8 and *THRESHOLD_MIN_CURVATURE_TRANSLATION* as 0.9 as mentioned in Section III. The experiments are conducted on a workstation. The workstation is with the configuration of Intel Core i7-6700 CPUs operating at 2.70 GHz and 16 GB RAM.

A. RESULTS OF BOX PLACEMENTS AND BASIC OPERATIONS

Pat Gesture and *Circle Gesture* (refer to section Appendix) are designed to place a new box and select a box, respectively. However, there are some limitations of the gesture detection of *Pat Gesture*. The original *Pat Gesture* is too sensitive. To solve this problem, we set a minimum time interval of each creation of box. That means one *Pat Gesture* of users can only creates one box at a time. When a box is selected, it can be removed, translated, scaled, and even rotated.

In our experiment, two boxes have been added to a given position to filter the fibers passing through them, as shown in Figure 4. The fiber tracts are marked in red which pass through Box #01 and marked in blue for Box #02.

B. RESULTS OF EXPRESSION-BASED BOX QUERIES

Users can explore the results queried by multiple boxes through arbitrary logic combinations. We use arithmetic expression to achieve logic combinations of multiple box queries. The combination operations include *intersection* (*), *union* (+), and *complement* (/) as shown in Section III.

Figure 5 shows the results queried by simple expression-based logic combination (at most two boxes) for dataset BRAIN (the top row) and dataset HEART (the bottom row), respectively. The queried results are highlighted in yellow.

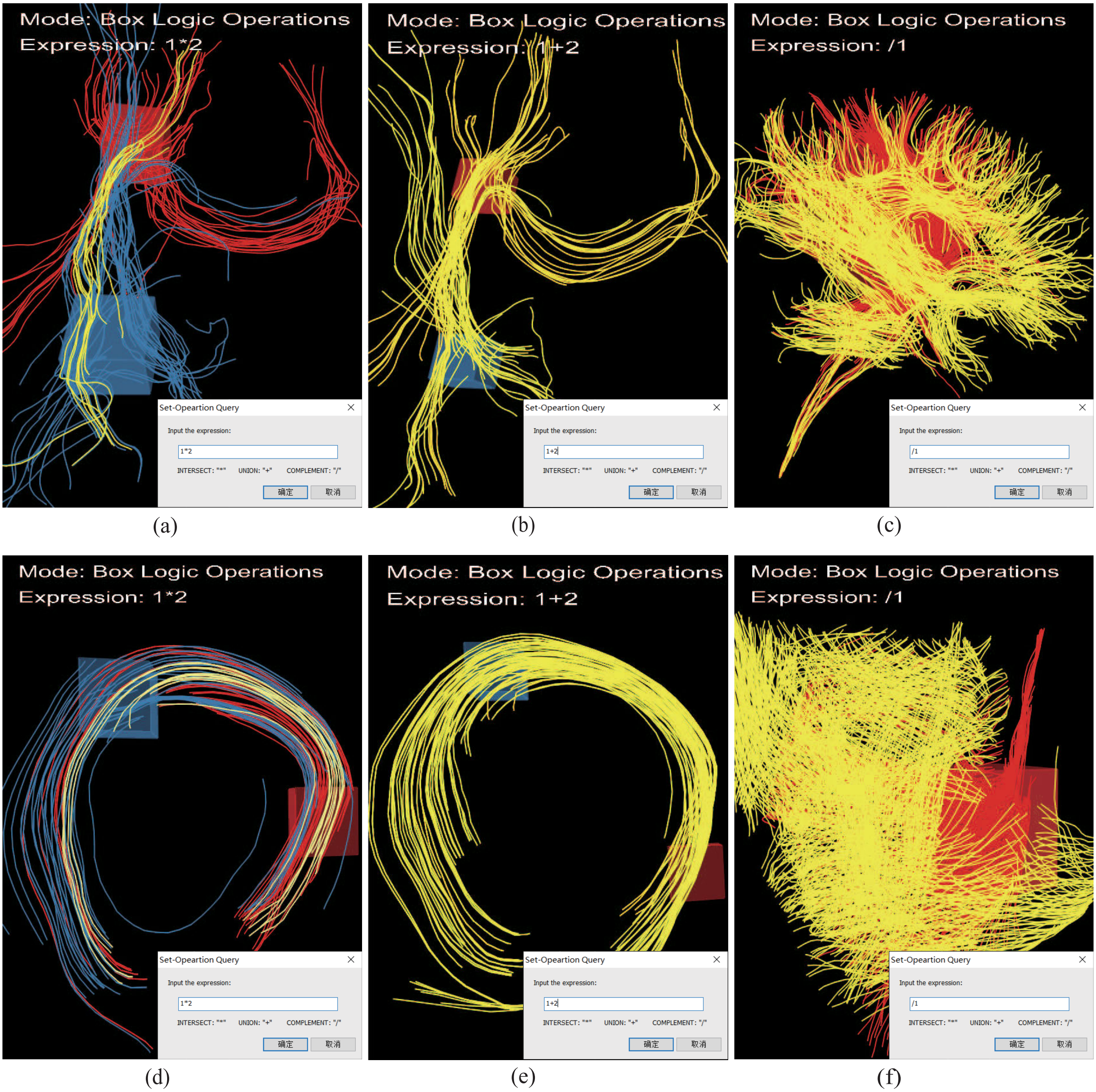

FIGURE 5. The results of a simple (at most two boxes) expression-based query for dataset BRAIN (the top row) and dataset HEART (the bottom row), respectively. The fibers in yellow are the final queried results for all the individual expressions. (a) The results queried by logic *intersection* (1*2) in dataset BRAIN. (b) The results queried by logic *union* (1+2) in dataset BRAIN. (c) The results queried by logic *complement* (/1) in dataset BRAIN. (d) The results queried by logic *intersection* (1*2) in dataset HEART. (e) The results queried by logic *union* (1+2) in dataset HEART. (f) The results queried by logic *complement* (/1) in dataset HEART.

Users can input a logic *intersection* expression based on two boxes to query the fibers passing through Box #01 and Box #02 simultaneously, as shown in the yellow tracts in Figure 5 (a) and Figure 5 (d). Users can also input a logic *union* expression to query the fibers (in yellow) as shown in Figure 5 (b) and Figure 5 (e). Besides, they can input a logic *complement* expression to query the fibers (in yellow) as shown in Figure 5 (c) and Figure 5 (f).

The proposed approach also provides some complex logic combinations based on an arbitrary number of box queries. For example, users can query the DTI fibers passing through both Box #01 and Box #02, together with the DTI fibers passing through both Box #03 and Box #04. The individually queried fibers are marked in red, blue, green and purple for Box #01, Box #02, Box #03 and Box #04, respectively. The corresponding expression is "`(1*2)+(3*4)`".

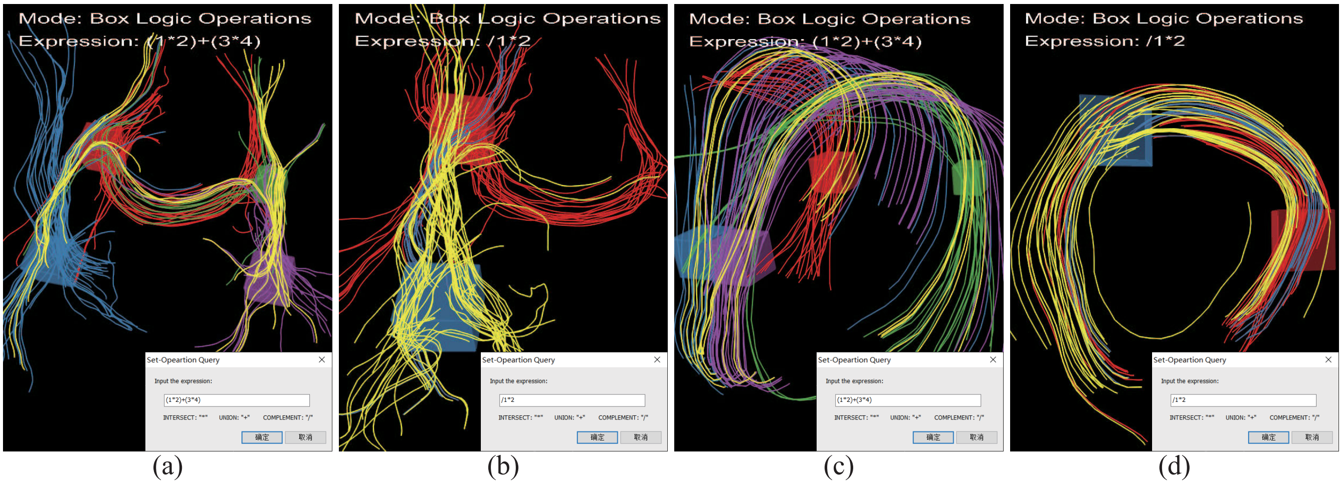

FIGURE 6. More complex logic combinations based on an arbitrary number of box queries. The queried results are in yellow. (a) The queried result by the expression "`(1*2)+(3*4)`" in dataset BRAIN. (b) The queried result by the expression "`/1*2`" in dataset BRAIN. (a) The queried result by the expression "`(1*2)+(3*4)`" in dataset HEART. (b) The queried result by the expression "`/1*2`" in dataset HEART.

The fibers in yellow are the queried results from dataset BRAIN, as shown in Figure 6 (a). Similarly, the results queried by the same expression from dataset HEART are shown in Figure 6 (c).

Besides, we use another expression "`/1*2`" to show the queried fibers passing through Box #02 without passing through Box #01 for dataset BRAIN and dataset HEART, respectively. The queried results are in yellow as shown in Figure 6 (b) and Figure 6 (d). Finally, users can still scale and translate each box by Leap Motion to specify its new boundaries.

C. EXPLORATION RESULTS OF CLASSIFIED FIBERS

Users are also allowed to perform different classification methods to group DTI fibers and explore the individual clusters. When users enter the *Cluster Exploration Mode*, the DTI fiber data automatically generate cluster tracts by pre-defined parameters. We use mean-shift clustering algorithm in our approach. The generated cluster tracts are named classified fibers. Each classified fiber shows in different colors. Users can use the gesture captured by Leap Motion to select which cluster to view. We select the seven clusters from the total 32 clusters for the dataset BRAIN as shown in Figure 7. Figure 7 (a) shows the whole clusters.

Similarly, we select the seven clusters from the total 26 clusters for the dataset HEART, as shown in Figure 8, while Figure 8 (a) shows the whole clusters.

D. EVALUATIONS

We conduct a user study to evaluate the interactive visualization performed by Leap Motion compared with the traditional input devices. User study was designed to prove that Leap Motion can replace the traditional input devices to achieve the same results availably and shows better effect in some terms. We conduct two evaluation tasks including the depth-direction moving and hybrid interactions. In the depth-direction moving task, participants are required to move a 3-D box into the screen along the view direction through the two input devices. In the hybrid interaction task, users are required to scale, translate a box simultaneously, or scale, translate and rotate a box simultaneously by the two input devices.

In our study, we measured and recorded the time of each experiment. Every experiment are tested by three times, and we calculated the average timing results for two tasks with two input devices. We recruited three participants, all participants are without prior knowledge about the data and data analytics. Two of the participants are majored in biology or medicine. All of them have no experience about the usage of Leap Motion and Kinect.

1) TASK I: EVALUATION OF DEPTH-DIRECTION MOVING

In the experiment of depth-direction moving (Task I), users are required to move a box along the depth-direction of the screen. If they use mouse, they need to rotate the DTI fibers with an appropriate angle (90-degree) in order to reduce errors, it is quite hard for users to determine when to stop to get an approximate 90-degree angle. In the meantime, they need to click the center of the box by mouse, and move the mouse pointer just along the axis without a big bias. Then they can translate the box along the axis to accomplish the depth-direction moving task. This method is obviously more complex and time consuming. Users need to constantly adjust the angle of the DTI fibers using controls to achieve desired results. However, in our method, users can achieve the task just by a simple gesture of moving inward. The error of the operation is often not too high.

Table 2 (the left part) shows the time (in seconds) the participants spent in the Task I. We can find that it takes 2.6 times of the time in Task I through a mouse compared with Leap Motion. The average time tested by mouse is 14.1 seconds. However, the average time tested by Leap Motion is just

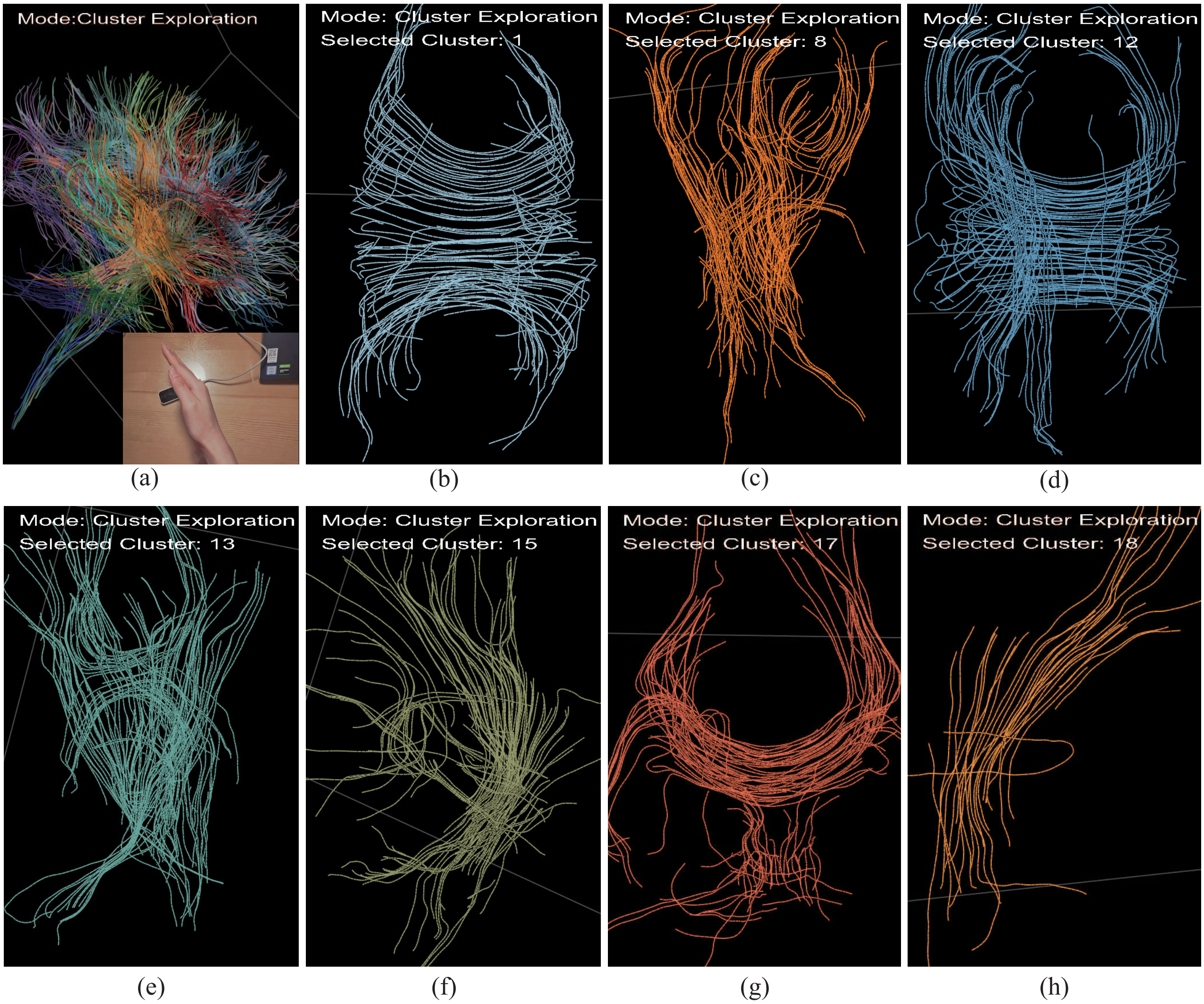

FIGURE 7. The results of classified DTI fibers of the dataset BRAIN with (a) the whole cluster fiber (b) the first cluster fiber (c) the eighth cluster fiber (d) the eleventh cluster fiber (e) the thirteenth cluster fiber (f) the fifteenth cluster fiber (g) the seventeenth cluster fiber (h) the eighteenth cluster fiber.

TABLE 2. The average timing results of the traditional method using mouse and the proposed approach (in seconds). "The Traditional" means the existing method using mouse as interaction input. "The proposed" means the proposed approach in this paper. Each user respectively did depth-direction moving and hybrid interactions three times. All the final results in the table are the averages of three times of tests.

Users	Task I: Depth-Direction Moving		Task II: Hybrid Interactions	
	The traditional mouse	The proposed approach	The traditional mouse	The proposed approach
User #01	11.18	5.19	36.76	21.77
User #02	15.25	5.85	29.93	14.86
User #03	15.99	5.43	26.96	14.39

5.5 seconds. The reason is that the users need to divide the task into two steps. More importantly, the rotation and translation should along the axis without a big bias. Otherwise, users need to rotate and translate the box in a time-consuming trial-and-error way to move it to the given position.

2) TASK II: EVALUATION OF HYBRID INTERACTIONS

The second task is called hybrid interactions (Task II). In this task, participants need to move the box and scale it at the same time. In traditional method (by mouse), users are required to perform it by at least two steps It is hard for users to click multiple buttons to finish this task. However, it is easy to finish it by Leap Motion, because it is easy for users to move their hands and scale the scope of the fingers. This gesture can significantly improve operational efficiency. Besides, it is also easy to design a hybrid gesture to scale, translate, and rotate a box, simultaneously.

Table 2 (the right part) shows the time (in seconds) the participants spent in the Task II. The average time of the three participants is 31.2 seconds through mouse, while the average time by Leap Motion is 17.0 seconds, which is 1.8 times of the efficiency compared with the traditional mouse.

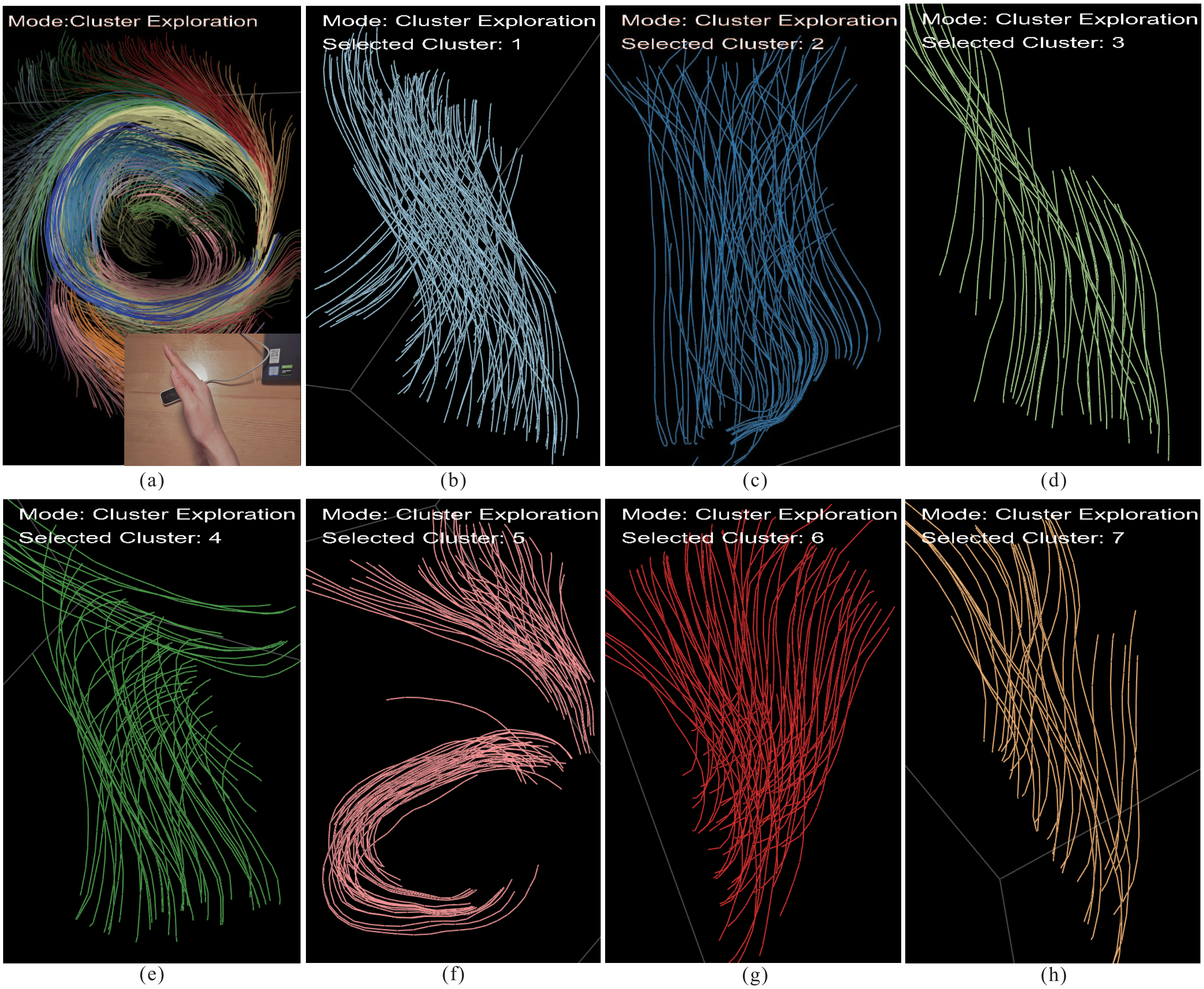

FIGURE 8. **The results of classified DTI fibers of the dataset HEART with (a) the whole cluster fiber (b) the first cluster fiber (c) the second cluster fiber (d) the third cluster fiber (e) the fourth cluster fiber (f) the fifth cluster fiber (g) the sixth cluster fiber (h) the seventh cluster fiber.**

V. DISCUSSION

The results and evaluations demonstrate that the Leap Motion is more efficient and effective than the mouse to explore DTI fiber data. Leap Motion can be used to achieve common interactions in an immersive way. Besides, it can be used to perform some complex tasks, for example, the depth-direction moving and the hybrid interactions. We also design expression-based box query to filter DTI fibers through an arbitrary logic combinations based on individual box queries. In addition, it allows users to use a gesture to explore each classified fiber tract. The interactions are real-time without obvious delay.

Nevertheless, there are some limitations on the accuracy due to the characteristics of the device. Leap Motion provides developers with some specific gestures such as circle selection, pat and swipe, etc. However, the original gesture APIs of Leap Motion just support five hand gestures and can not be modified, which limits the further development. Therefore, we make some customized gestures by specifying other parameter values. Furthermore, we need to solve another three issues due to the accuracy.

First, we are unable to fine tune the target objects. When users want to do some tiny adjustments on the boxes or the whole DTI fiber, their hands should move a short distance accordingly. However, Leap Motion cannot identify the tiny movement of hands because the calculated distances are often less than the pre-defined minimum sensitivity distance the device can detect.

Second, the gesture identification errors sometimes may occur during the interaction. Each gesture has its own minimum sensitivity value. It will be recognized as a gesture, as long as gestures satisfy the conditions. Therefore, there would be some mistakes when users make a similar gesture. /mmIn the actual operation, the frequency of gesture

TABLE 3. The explanation of all gestures used in this paper.

Name of Gestures	Explanation
Mode-Changing Gesture	One hand moves with turning the palm down. The users move to the left representing the previous mode, and to the right to represent the next mode.
Scaling Gesture	Both two hands are perpendicular to the ground. The distance between two palms show the scaling parameter. This gesture works on the whole DTI fiber data in Normal Mode and boxes in Box Basic Interactions Mode.
Rotation Gesture	Hold one hand in a semi-closed fist position and then rotate the palm with the angle you want to rotate it.
Translation Gesture	One fist moving horizontally. This gesture uses for moving boxes in Box Basic Interactions Mode.
Pat Gesture	One hand tap down. This gesture is provided by APIs of Leap Motion and uses for adding boxes.
Circle Gesture	The index finger to draw a circle parallel with Leap Motion. This gesture is provided by APIs of Leap Motion. Clockwise rotation means to select the next box while the counterclockwise means the previous box.

recognition errors is not high, and usually occurs in the stage when the user is not familiar with the gesture operation via Leap Motion. In addition, the error results due to gesture identification errors are very slight, so it usually doesn't interfere with users exploring the data. Third, the types of gestures would be still limited especially when there are a large number of different interactions should be designed in some scientific data visualization. In this paper, we design four interaction modes to enlarge the number of gestures, which solves the problem to some extent.

VI. CONCLUSION

In this paper, we design an interactive DTI fiber visualization framework based on a 3-D somatosensory device named Leap Motion. We design some gestures and interactions based on Leap Motion to achieve common interactions in an immersive way. For more complex tasks, for example, the depth-direction moving and the hybrid interactions. The interactions conducted through Leap Motion is also more efficient than that by the traditional input device, i.e., the mouse. In order to filter the DTI fiber tracts, we design expression-based box queries which allow users to query the fiber tracts through an arbitrary logic combination of basic box queries. Four different interaction modes are designed to support the gestures required by the extensive interactions in DTI fiber visualization. The evaluation tests show that the proposed approach is more intuitive and more efficient in 3-D space and provides an immersive experience for users to explore the DTI fiber data.

APPENDIX

Table 3 shows all the gestures defined in the paper.

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