Information-Guided Transfer Functions and Selective Enhancements for Volume Visualization

Publication No. ____________________

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Volume data is widely used in scientific and medical research, and volume visualization has been proven to be an effective and flexible method for visualizing complex structures. This thesis examines the methods for exploring of volume data by optimization of visualization parameters and through the use of focus and context visualization techniques by selectively enhancing important parts of the data sets.

Volume visualization is a powerful technique for depicting layered structures in 3D volume data sets. However, it is a major challenge to obtain clear visualizations of a volume with layers clearly revealed. In particular, the specification of the transfer function is frequently a time-consuming and unintuitive task in volume rendering. We describe a global optimization and two user-driven refinement methods for modulating transfer functions in order to assist the exploration of volume data. This optimization is dependent on the distribution of scalar values of the volume data set and is designed to reduce general occlusion and improve the clarity of layers of structures in the resulting images. The user can explore a volume by interactively specifying different priority intensity ranges and observe which layers of structures are revealed. In addition we show how the technique can be applied for time-varying volume data sets by adaptively refining the transfer function based on the histogram of each time-step. Experimental results on various data sets are presented to demonstrate the effectiveness of our method.

Time-varying volume data is used in many areas of science and engineering. However visualizations of such data are not easy for users to visually process due to the amount of information that can be presented simultaneously. We propose a novel visualization approach which modulates focus, emphasizing important information, by adjusting saturation and brightness of voxels based on an importance measure derived from temporal and multivariate information. By conducting a voxel-wise analysis of a number of consecutive frames, we acquire a volatility measure of each voxel. We then use intensity, volatility and additional multivariate information to determine opacity, saturation and brightness of the voxels. The method was tested in visualizing a multivariate hurricane data set. The results suggest that our approach can give the user a deeper understanding of the data by presenting multivariate information variables in one self-contained visualization.

Contents

Chapter 1

Introduction

Volume visualization is an active branch of scientific visualization. It is a method of extracting meaningful information from volumetric data (3D discretely sampled data sets) using interactive graphics and imaging (see Section 2.1). The study of volume visualization involves volume data representation, modelling, manipulation and rendering [1]. First introduced by Levoy [2] for visualization of volume data, volume visualization has been widely used in various sciences to create insightful visualizations from both simulated and measured data. Volume visualization is a powerful technique which aims to visualize the 3D structures in volume data sets and thus facilitates the user's exploration into the data. It has become an important technique for various applications such as medical imaging and scientific visualization and is especially useful in diagnostics for physicians in medicine. With the advance of various data acquisition hardware, time-varying volumetric datasets are increasing dramatically both in size and complexity. However, the visualization of time-varying volume data remains a challenging problem due to the large size and the dynamic nature of the underlying information. Previously established techniques, such as in flow visualization, struggle to deal with the increasing complexity of the most recent datasets.

The rendering of volume data requires every sample value (also called voxel, which is a volume element (or volumetric pixel)) to be mapped to visual properties (e.g. opacity and colour). This mapping is done with a transfer function, which can be a simple ramp, a piecewise linear function or an arbitrary table. The design of an effective transfer function (see Section 2.2 for details) is essential for visualizing volume data. A wealth of techniques have been developed for transfer function design for static volume data [3] [4] [5] [6] [7]. However, transfer function design for time-varying volume data has not been studied thoroughly. A fundamental challenge in the analysis and classification of time-varying volume data is the lack of capability to track data change or evolution over time [8].

Much of the work in the field of volume visualization has been focused on the synthesis of photorealistic images to assist in the visualization of structures contained in volume data sets. However, traditional depictions of the same types of data, such as those found in medical textbooks, deliberately use non-realistic techniques to draw the viewer's attention to important aspects [9]. Using abstraction, visual overload is prevented and thus result in a more effective visualization.

NPR techniques are effective forms of abstraction. They are commonly inspired by artistic styles and techniques that do not focus on a realistic depiction of scenes and objects, therefore, they can express features that cannot be shown using physically correct light transport. Non-photorealistic images are used in preference to photorealistic images in specific circumstances. For instance, an empirical study [10] reported that, when asked to compare a computer-produced sketch against a photorealistically rendered CAD image, architects showed a great preference for the sketch. NPR models were adopted in visualization and hence formed the field of illustrative visualization. Although illustrative visualization is a relatively novel category of visualization approaches, it has been successfully employed in medical and other visualization sub-fields [11] [12]. Illustrative visualization has proven its usefulness in revealing 3D structures due to its ability to hide less relevant details while emphasizing important details. The goal of illustrative visualization is to gain clarity compared to photo-realistic rendering by emphasizing important features and improving data exploration. In order to obtain more comprehensive images, it is necessary to highlight important aspects and omit less relevant details.

1.1 Motivation

Understanding and analysing complex volumetrically varying data is a challenging problem. Many visualization techniques have had only limited success in succinctly portraying the structure of 3D time-varying volume data. The main goal of our research is to investigate the optimization of visualization parameters (in particular transfer functions) and the use of NPR techniques, and develop a methodology which incorporates these two types of techniques to facilitate the user's exploration of the data sets. NPR techniques are effective forms of abstraction and they have proven their usefulness in expressing features that cannot be shown using realistic depiction of scenes and objects. The combination of standard volume visualization and NPR techniques will bring the opportunity to provide expressive visualization and assist the user in accomplishing his/her task efficiently.

We hypothesise that the importance of voxels (sample values in volume data) are associated with their information content. Therefore, the transfer functions of volume visualization can be optimized based on the information within the data sets and user input which indicates the user's interest. In addition, we investigate the feasibility of propagating the optimization approach from static volume data to time-varying data.

1.2 Scope

This thesis focuses on methods for enhancing user understanding of volume data by optimizing visualization parameters and incorporating NPR techniques. We investigate the optimization of transfer functions by exploiting the information inherent within the volume data and input from user interaction. In addition, we investigate NPR techniques which we believe are well suited for highlighting important details as well as simplifying less important details. Hence we combine the optimization of visualization parameters and NPR techniques in order to provide meaningful exploration of complex data.

In this research, we focus on the visualization of both static and time-varying volume data, particularly those scalar data acquired from CT, MRI and 4D MRI. Flow data which are often in the form of vector fields are not under the focus of our research. Furthermore, we investigate techniques which are applicable to consumer level devices rather than expensive dedicated visualization hardware. As such, this constrains the amount of memory and processing power available, and therefore fast techniques with low memory requirement are necessary.

1.3 Contributions

1.4 Summary of Chapters

Chapter 2

Related Work

In this chapter, we present a brief review of the literature related to the concepts that we discuss in this thesis.

2.1 Volume Rendering

Volume rendering is used to display a 2D image of a three-dimensional (3D) dataset. It can be seen as a projection of a 3D volumetric dataset into a two-dimensional (2D) image [13]. The majority of datasets are discretely sampled along a three dimensional grid and contain scalar values usually acquired from medical imaging devices such as CT or MRI machines. The data then takes the form a 3D array of voxels (a three dimensional extension of pixels). In flow visualization, the datasets are often generated from simulations.

Volume rendering can be performed using two main techniques, either by extracting a number of surfaces from the data and rendering these surfaces to the screen, called isosurface rendering or by rendering the volume itself as a complete block of data with no intermediary structures, usually called direct volume rendering (DVR).

An example of volume rendering is provided in Figure 2.3, which shows a sliced image and a volume rendered image of a head data set.

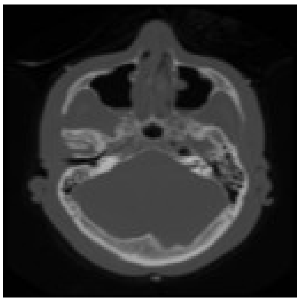

Figure 2.1: A sliced image of the data set

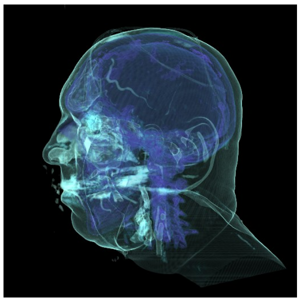

Figure 2.2: Volume rendering of the data set

Figure 2.3: The VisMale data set [14]

2.2 Transfer Functions

Volume data are 3D entities with information inside them, but the data might not consist of surfaces and edges. Because of the lack of explicit geometric information, it is a major challenge to provide clear visualizations of the structures contained in a volume dataset. Volume data may be rendered directly by mapping scalar values to visual properties (e.g. opacity and colour), or an intermediate geometric representation may be extracted using techniques like Marching Cubes [15] and then rendered as geometric surfaces. The mapping, which assigns visual properties to volume data, is called a transfer function.

Transfer function specification is an essential part in volume visualization. A simple one-dimensional transfer function is a mapping from scalar values to RGB and alpha values. The resulting visualization largely depends on how well the transfer function captures features of interest [5]. However, it is non-trivial to obtain an effective transfer function. The specification is often a trial-and-error process, which involves a significant amount of tweaking of colour and opacity. Figure 2.7 shows how slight changes in the transfer function lead to significant changes in the resulting images. The adjustment of transfer functions is unintuitive and often difficult.

In practice, major factors that have a great influence on transfer function setting are: partial volume effect [1], non-uniform distribution of materials and noise [18].

[1]During the acquisition of data, the finite resolution causes contributions of different materials combined into the value of a single voxel. This is generally referred to as the partial volume effect,

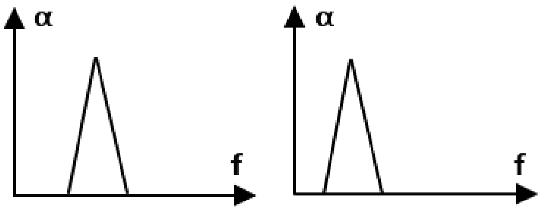

Figure 2.4: Two transfer functions (TF)

Figure 2.5: The result from the TF on the left in 2.4

Figure 2.6: The result from the TF on the right in 2.4

Figure 2.7: Slight changes in the transfer function causes significant difference in the resulting images [16]

Among these, two challenging problems that need to be tackled could be elaborated as follows: firstly, for volume datasets, e.g. those obtained by MRI and CT, different tissues are represented in similar or even overlapping ranges of scalar values; secondly, interesting interior structures are often partly or completely occluded by surrounding tissue. Consequently, feature detection and understanding volume data become a big challenge.

In volume rendering, these problems are handled by transfer function specification. Good transfer functions reveal important structures in the data without obscuring them with less important regions. Various strategies have been proposed to simplify transfer function specification [4]. Data-centric strategies examine the properties of volume data sets. Overlapping intensity intervals corresponding to different materials make boundary detection difficult. Classical approaches try to detect boundary information between tissues by introducing derived attributes such as first and second-order derivatives to isolate materials [3] [5]. In this case, the transfer functions are extended to multidimensional feature spaces. As a result, the interaction of transfer functions becomes more complex and unintuitive. There are other multi-dimensional transfer functions approaches, such as spatialized gradient-based transfer functions [19], distance-based transfer functions [20], size-based transfer function [21], texture-based transfer functions [22] and curvature based transfer functions [23]. Another strategy

which results in blurred boundaries and hampers the detection of small or thin structures. [17]

is based on the selection of rendered images. This strategy lets the user select one or more favourite images to guide the further search of transfer functions [24] [25]. More recent approaches introduced visibility [26] or measures derived from information theory [27] [28] [29] [30]. Despite the advances of these methods, transfer function design for volume rendering is still an open research problem.

However, certain features of interest in volume data are difficult to extract and visualize with 1D transfer functions. For instance, many medical data sets created from CT or MRI scans contain a complex combination of boundaries between multiple materials. This situation is problematic for 1D transfer functions because of the potential for overlap between the data value intervals spanned by the different boundaries. When one data value or data range is associated with multiple boundaries, a 1D transfer function is unable to render them in isolation [5].

The introduction of multidimensional transfer functions alleviates this problem. Instead of classifying a sample based on a single scalar value, multi-dimensional transfer functions allow a sample to be classified based on a combination of values. Multidimensional transfer functions are very effective means to extract materials and their boundaries for both scalar and multivariate data. However, the parameter spaces of multidimensional transfer functions are more complex (compared to 1D transfer functions) and thus introduce problems such as requirement for large amount of user interaction, missing precision or the means of handling it being unintuitive [7].

Moreover, transfer function specification in general is an unintuitive or even monotonous task for average users, because it is usually an iterative process of trial and error. For instance, there are skin and fat tissues around the brain, and their intensities lie in the same range as the brain. If we want to visualize the brain by setting the scalar value range of the brain to opaque, the surrounding skin and fat tissue will also become opaque. Then the brain will be occluded by the surrounding soft tissues which make it difficult to explore the brain structure. Common approaches to this problem are to introduce explicit segmentation of structures of interest before the volume rendering process [31]. In fact, the process of applying the transfer function could be interpreted as a segmentation problem.

2.2.1 Multidimensional Transfer Functions

Multidimensional transfer functions [3] [32] [5], which are mappings from intensity and other variables, such as first and second derivatives to colour and opacity, have demonstrated their effectiveness in distinguishing boundaries between materials in volume data. For higher-dimensional transfer functions, the generation of transfer functions could be memory intensive and costly to compute, and exploration of the transfer function domain might not be intuitive. Therefore, two-dimensional (2D) histograms are often used in multidimensional transfer functions [33]. An example is a 2D histogram with axes representing a subset of the feature space (e.g. scalar value vs gradient magnitude), with each entry in the 2D histogram being the number of voxels for a given feature space pair.

As one of the most common representations of voxel distributions, histograms are used in transfer function design to assign visual properties to voxels [4]. Bajaj et al. [34] introduced the contour spectrum to determine voxels corresponding to important isosurfaces in the volume. To overcome the difficulty of using one-dimensional transfer functions (solely based on scalar values stored in the voxels) to extract inner structures of interest from the volume data, Levoy proposed the use of gradient magnitude to emphasize strong boundaries between different tissues [2].

The introduction of gradient magnitude as a data metric aims to detect voxels that are of large deviation compared with other voxels by approximating gradient magnitude at each sample point in the volume, because the exact distribution of data is unknown due to information lost in the discrete sampling process.

Kindlmann and Durkin extended Levoy's work by introducing a higher dimensional transfer function domain based on gradient magnitudes and second derivatives [3]. To emphasize different structures, Kniss et al. [32] presented a technique for interactively manipulating 2D histograms of gradient magnitudes and data values. In their work, material boundaries appear as arcs in the 2D histogram and can be selected with interactive widgets [5]. Kindlmann et al. [23] proposed curvature-based transfer function to enhance the expressive and informative power of volume rendering. In their approach, volume data is rendered with contours to exhibit constant thickness in image space. Maciejewski et al. proposed a non-parametric method to generate transfer function [33]. Wang et al. introduced clustering of 2D density plots in their automating transfer function [35].

2.2.2 Transfer Functions for Time-Varying Volume Visualization

Although researchers have developed a great number of visualization techniques for time-invariant volume data, how to effectively explore and understand time-varying volume data remains a challenging problem. Finding good transfer functions for time-invariant volume data itself has proven difficult [4]. Finding good transfer functions for time-varying volume data is even more difficult, as data value ranges and distributions change over time.

Coherence is an important issue of transfer function design for time-varying volume data. Ideally, a single transfer function should be used for the whole time-varying data set in order to obtain coherent visualization. More than one colour or opacity map can be misleading or physically meaningless, because the transition from one transfer function to another may cause sudden changes in the resulting images. However, this practice is not always applicable to general time-varying data sets.

Jankun-Kelly and Ma [36] examined how to combine transfer functions for different time-steps to generate a coherent transfer function. Woodring et al. [37] considered time-varying volume data as four-dimensional data field and provided a user interface to specify hyperplanes in 4D. Woodring and Shen [38] introduced an alternative approach to render multiply time-steps in a sequence with different colours into a single image. This approach provides the context of surrounding time steps but coherence of colour among time-steps is hard to maintain.

Tikhonova et al. [39] presented an explorative approach based on a compact representation of each time step of the dataset in the form of ray attenuation functions. Ray attenuation functions are subsequently used for transfer function generation.

2.3 Non-Photorealistic Rendering (NPR)

In contrast to traditional computer graphics, which has focused largely on creating photorealistic images of synthetic objects, non-photorealistic rendering (NPR) is an area of computer graphics that focuses on creating abstract images with a wide variety of expressive styles [40]. NPR has been an active research area for a long time. A number of approaches have been proposed to produce convincing artistic styles for both off-line and on-line rendering. For example, there are various types of commonly used styles including painterly rendering, edge stylisation, sketch-shading, cel-shading, hatching. In certain situations, non-photorealistic renderings are considered more effective and expressive than an equivalent photograph [41].

2.3.1 Illustrative Visualization

NPR models were adopted in visualization and hence formed the field illustrative visualization. Illustrative visualization, as a novel category of visualization, aims at visualizing data in a clear and understandable way using techniques from traditional hand-crafted illustrations. Illustrative visualization has been successful employed in medical visualization [11] [42]. Illustration-based styles are believed to be effective in conveying information. Researchers in the field of computer graphics and visualization have applied illustration-based styles in order to produce effective and expressive visualization. Stompel et al. [43] introduced feature enhancement techniques, such as strokes based, temporal domain enhancement, to enhance time-varying data obtained from the field of computational fluid dynamics (CFD).

2.3.2 Visualising Time-Varying Volume Data with NPR

An essential problem in time-varying volume visualization is to visualize temporal variation and analysis of features. Traditionally, time-varying data has been visualized as snapshots of individual time steps or animation of snapshots of a sequence of time steps. These techniques are effective in making time-varying data understandable. However, they struggle when the complexity of datasets increased dramatically in recent years [44].

Compared to flow visualization, which is a well established branch of scientific visualization [44], general time-varying volume visualization is still a relative young field. Illustrations for time-varying rendering could be divided into two categories, one is to enhance time-invariant features and the other is to enhance temporal features of time-varying volume data. The techniques in the first category focus on enhancing structural perception of volume models through the amplification of features and the addition of illumination effects [45] [46]. Examples of these techniques include boundary enhancement, oriented feature enhancement (silhouettes, fading, and sketch lines). The techniques in the second category focus on illustrating dynamic aspects such as movement of features. A few kinds of techniques have been proposed for this purpose. For example, there are speadlines, flow ribbons and strobe silhouettes, which are inspired by traditional animation [46] [47] [48]; and there are extended silhouette and boundary enhancement domains, which are inspired by the techniques used by illustrators and other artists [11]. Nevertheless, illustrations of temporal features of time-varying data requires more attention from researchers in the visualization community. The usefulness of illustrative approaches in time-varying volume visualization has not been studied as thoroughly as in other areas.

2.3.3 Painterly Stylization and Texture-Based Techniques

Streamlines and textures are often used to represent flow directions [49]. Interrante and Grosch [50] introduced volume LIC (Line Integral Convolution) to visualize 3D flow via volume textures. Figure 2.8 shows a volume texture generated with LIC. In this figure, vorticity magnitude is mapped to streamline colour and the striations along the axial direction reveal the presence of periodic waves propagated down the jet axis. Since volume LIC is limited to steady flows, Liu and Moorhead [51] introduced a accelerated unsteady flow LIC algorithm to generate volume flow textures (Figure 2.9). In their approach, magnitude-based transfer functions and cutting planes in volume rendering are employed to show the flow structure and the flow evolution.

Artists recognize patterns and flows in a target scene and express them through brush strokes. They use stroke orientation corresponding to the actual movement [52]. This type of techniques from master painting and human perception are used to visualize multidimensional data sets [41]. Tateosian et al. [53] use the colour, orientation and size of strokes to represent the magnitude, flow orientation and pressure of a 2D slice of a simulated supernova collapse (Figure 2.10). Lee et at. [52] presented a painterly rendering technique based on the motion information (magnitude, direction, standard deviation) extracted from a image sequences of the same view.

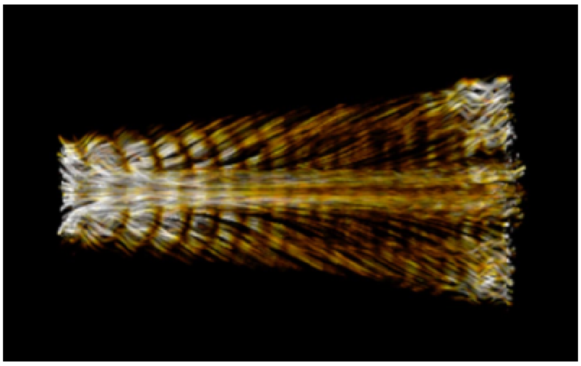

Figure 2.8: Streamlines are represented as a volume texture, which provides an intuitive impression of the 3D flow. [50]

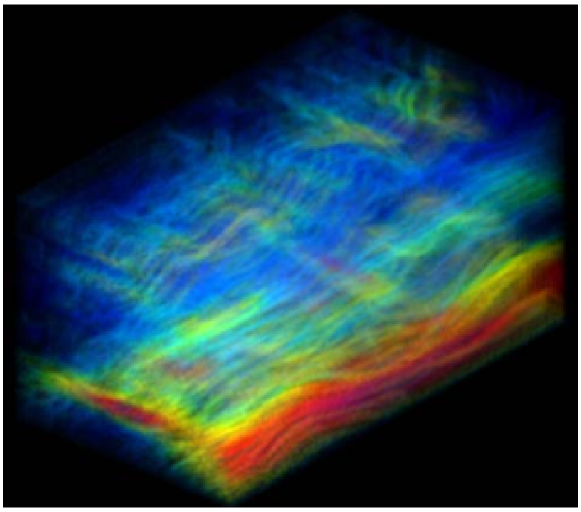

Figure 2.9: Streamlines are represented as a volume texture, which provides an intuitive impression of the 3D flow. [51]

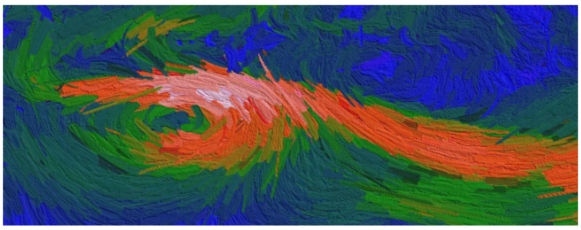

Figure 2.10: A visual complexity style visualization of flow patterns in a 2D slice though a simulated supernova collapse, using the mappings: flow orientation $\rightarrow$ stroke orientation, magnitude $\rightarrow$ order and pressure $\rightarrow$ stroke size [53].

Figure 2.11: The motion directions determine stroke orientations in the regions with significant motions, and image gradients determine stroke orientations where little motion is observed [52].

2.4 Feature Tracking

Feature extraction and tracking is an established technique for the analysis of time-varying data in various research fields, such as video analysis, computer vision and flow visualization [54]. In time-varying data, features are objects that evolve over time. Feature tracking aims to determine the correspondence between features in successive time steps and describe the evolution of features through time [55].

In practice feature extraction and tracking are often employed in the exploration and analysis of time-varying volume visualization in order to better understand the dynamic nature of the underlying phenomena [56] [57] [58] [8]. Feature extraction methods are often based on an analytical description of the feature of interest. Consequently, feature extraction and tracking could become a manual-driven and trial-and-error process in the case that the properties cannot be easily defined and are sometimes unknown [59].

2.5 Vector Field Visualization

The visualization of vector fields plays a crucial role in visual interpretation and understand of the underlying flow features and patterns [60] [61]. Since flow patterns also exist in time-varying volume data, certain techniques for visualizing vector field could be incorporated into time-varying volume visualization, in order to depict the dynamic aspects of time-varying data.

Line drawings are effective ways to depict complex information with simple means [62]. Among vector field visualization techniques, streamline visualization is a simple but common way to convey the structure of 3D vector fields [63]. Streamlines have proven to give expressive visual representation if they are combined with appropriate seeding strategies [64]. Streamlines reveal flow patterns in an intuitive fashion by integrating the flow path.

2.6 Information Theory in Visualization

Information theory [65] was originally introduced to study the fundamental limit of reliable transmission of messages through a noisy communication channel. Traditional applications of information theory, such as data compression and data communication, focus on the efficient throughput of a communication channel, whilst visualization focuses on the effectiveness in aiding the perceptual and cognitive process for data understanding and knowledge discovery.

In recent years, there is an emerging direction towards using the principles of information theory to solve challenging problems in scientific visualization. [66]. Chen and Jï£ · enicke [67] presented an information-theoretic framework for visualization. They examined the theoretical aspect of information and its relation to data communication and interpret different stages of the visualization pipeline using the taxonomy of information.

Haidacher et at. [27] proposed an approach of transfer function specification for multi-modal data visualization. They considered the joint occurrence of multiple features from one or multiple variables so as to separate statistical features that only occur in a single variable from those that are present in both. Ruiz et al. [29] presented an approach to generate transfer functions from a target distribution provided by the user. Their approach is based on a communication channel between a set of viewpoints and a set of bins of a volume data set, and supports both 1D and 2D transfer functions including the gradient information. Bramon et al. [30] proposed an automatic method to visualize multi-modal data by combining several information-theoretic strategies to define colours and opacities of the multi-modal transfer function. They set an information channel between two registered input datasets to define the fused colour and minimize the informational divergence between the visibility distribution captured by a set of viewpoints and a target distribution proposed by the user to obtain the opacity.

2.7 Perceptual Evaluation

Due to the complex nature of the data being studied, simply displaying all available information does not adequately meet the demands of domain scientists [68]. User studies can be used to evaluate the strengths and weaknesses of visualization methods [69]. The evaluation of visualization methods that focus on human factors often employ user studies or expert evaluations to determine their effects on interpretation and usability.

There are a number of different evaluation strategies, such as measuring user performance, accuracy and experience [70]. Laidlaw et al. [71] compared six methods for visualising 2D vector fields and measured user performance on three flow-related tasks for each of the six methods. They used the evaluation results to identify what makes a 2D vector fields visualization effective. Joshi and Rheingans [47] evaluated the effective of their illustrative techniques by measuring user accuracy, time required to perform a task and user confidence.

2.8 Summary

We have presented a review of the literature in the field of volume visualization. The review suggests that it is feasible to optimise the parameters of volume visualization based on the information within the volume data. Existing research on multidimensional transfer functions, classification of volume data and information theory provides us the foundation to explore and understand how this optimisation may be achieved. In particular, the analysis and visualization of time-varying data is a compelling problem due to increasing availability of such data in recent years. Although some work has been published in this area it is clear that there is compelling work left to be done in optimising the rendering of such data sets. The use of NPR techniques can improve the expressiveness of the visualization and thus facilitate better user understanding of data. Further studies are required in order to better integrate NPR techniques into the visualization pipeline and enhance the expressiveness of the visualization by exploiting the information within the data sets.

Chapter 3

Transfer Function Refinement for Exploring Volume Data

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Chapter 4

Selective Saturation and Brightness for Visualizing Time-Varying Volume Data

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Chapter 5

Chapter 5

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Chapter 6

Conclusions and Future Work

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