Visualization of multidimensional and multimodal tomographic medical imaging data, a case study

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Multidimensional tomographic datasets contain physical properties defined over four-dimensional (e.g. spatial–temporal, spatial–spectral), five-dimensional (e.g. spatial–temporal–spectral) or even higher-dimensional domains. Multimodal tomographic datasets contain physical properties obtained with different imaging modalities. In medicine, four-dimensional data are widely used, five-dimensional data are emerging, and multimodal data are being used more often every day.Visualization is vital for medical diagnosis and surgical planning to interpret the information included in imaging data. Visualization of multidimensional and multimodal tomographic imaging data is still a challenging task. As a case study, our work focuses on the visualization of five-dimensional (spatial–temporal–spectral) brain electrical impedance tomography (EIT) data. In this paper, a task-based subset definition scheme is proposed: a task model named Cubic Task Explorer (CTE) is derived to support the visualization task exploration for medical imaging data, and a structured method for visualization system development called Task-based Multi-Dimensional Visualization (TMDV) is proposed. A prototype system named EIT5DVis is developed using the CTE model and TMDV method to visualize five-dimensional brain EIT data.

Keywords: visualization; multidimensional image; multimodal image; task-based visualization; Cubic Task Explorer; electrical impedance tomography

1. Introduction

Electrical impedance tomography (EIT) is a relatively new imaging method that has evolved over the past 20 years (Bayford 2006). The physiological basis of EIT is that different tissues have different impedances. The human body can be considered as a composite volume conductor comprising a number of spatially distributed tissues with differing electrical properties. EIT is sensitive to changes in electrical conductivity and produces images of the distribution of impedance within the tissues. Unlike metallic conductors, electrical conduction within...
biological tissues is due to the movement of ionic rather than electronic charge carriers. During EIT imaging, impedance signals are generated and collected using a set of electrodes placed on the imaged object or a part of the body. A current source is applied between either an adjacent or an opposite (across the object) pair of electrodes, and voltage signals are measured on all other electrode pairs in turn. Sequential pairs are then used for current injection until all possible combinations have been used. With the injected current and the measured voltages on the boundary, the impedance or its reciprocal, the conductivity, inside the object is estimated by reconstruction.

The EIT systems used in medical research can be classified into three sorts: absolute, dynamic and spectroscopic. Absolute EIT imaging is an attempt to quantify the conductivity of an object in an absolute way. A dynamic EIT imaging system conducts measurements during a time interval, and a four-dimensional spatial–temporal EIT dataset results. Spectroscopic (or multiple-frequency) EIT imaging systems allow images of frequency-dependent impedance changes; therefore, a four-dimensional spatial–spectral EIT dataset is achieved. Medical image modalities usually create three- or four-dimensional data. For example, anatomical medical imaging methods, such as computed tomography (CT) and magnetic resonance imaging (MRI), depict the three-dimensional morphology of subjects, and functional medical imaging methods, such as positron emission tomography (PET), functional MRI (fMRI) and magnetoencephalography (MEG), represent four-dimensional information on the metabolism of the underlying anatomy. However, EIT imaging is able to collect five-dimensional (spatial–temporal–spectral) impedance variation data by using a spectroscopic EIT system over a time interval.

In the medical imaging domain, one imaging modality usually collects one type of physical property associated with biological structures or functions. Different medical imaging modalities are based on separate physical interactions of energy with biological tissues and thus provide measurements of different physical properties. Different imaging approaches have different advantages and disadvantages, and so have particular application areas in medicine. It is possible that two (or more) tissues similar in one physical property may well differ widely in another. Consequently, it is quite reasonable to combine features from different imaging modalities, and the fused dataset is multimodal. Multimodal medical data are being used more often every day.

As the complexity of image information increases, the analysis and diagnosis of disease condition rely on the successful interpolation of these images. Visualization is a vital tool for medical diagnosis and surgical planning to interpret information included in imaging data. Various approaches have been developed for the visualization of tomographic medical imaging data. However, many methods can process only three-dimensional datasets obtained from a single modality. Visualization of multidimensional and multimodal tomographic imaging data is still a challenging task.

In this paper, we take five-dimensional brain EIT data as a case study for the visualization of multidimensional and multimodal tomographic imaging data. Our visualization approach is subset based. A task-based subset definition scheme is proposed in this work; a task model named Cubic Task Explorer (CTE) is derived to support the visualization task exploration for medical imaging data, and a structured method for visualization system development...
called Task-based Multi-Dimensional Visualization (TMDV) is proposed. A prototype system named EIT5DVis is developed using the CTE model and TMDV method to visualize five-dimensional EIT data.

The rest of this paper is structured as follows. We discuss related work in §2, and in §3 our approach is explained in detail. Section 4 describes implementation of the proposed approach to the visualization of five-dimensional brain EIT data. We present discussion and conclusions in §5.

2. Related work

(a) Visualization of EIT data

The most common approach for the visualization of an EIT dataset is to display it as a series of two-dimensional slices (Soni et al. 2004; Hahn et al. 2006; Isaacson et al. 2006), which is the traditional visualization method for tomographic medical images. The two-dimensional slice display approach is relatively simple and able to illustrate some important information in EIT datasets. Radiologists usually have some experience of understanding this form of presentation and are able to mentally construct the corresponding three-dimensional situation in the patient’s body. This construction largely depends on personal experience; it would be helpful to use some advanced visualization approach to perform this kind of task automatically. Furthermore, when the dimension of an EIT dataset is more than three, this kind of display will result in a large number of two-dimensional pictures, and the difficulty for radiologists to understand the information involved in the dataset will be greatly increased.

Besides the two-dimensional slice display, other methods have also been employed for the visualization of EIT datasets. For instance, Briggs et al. (2000) presented a volumetric visualization for a subset of data corresponding to a sample time point in a spatial–temporal (four-dimensional) EIT dataset. EIT and diffuse optical tomography reconstruction software provides volumetric visualization, arbitrary two-dimensional slices and an interface to the general visualization software, MayaVi (Ramachandran 2003), for the visualization of three- or four-dimensional EIT data (Adler & Lionheart 2006). EITviewer was developed to be a clinical visualization tool for thoracic EIT and included a region-of-interest analysis function (van Genderingen & Verbunt 2005). The NIM image display software developed by the UCL EIT research group is able to display three orthogonal planes in one view. However, to date, no publication on the visualization of five-dimensional spatial–temporal–spectral datasets has been found in a literature review.

(b) Visualization of multimodal data

A multimodal tomographic medical imaging dataset can be visualized in two ways: treating information obtained from each modality separately and visualizing the multimodal dataset as \( m \) unimodal datasets, where \( m \) is the number of modalities involved in the multimodal dataset; or visualizing information from different modalities together in one view. With the first way, all approaches suitable for visualization of unimodal datasets can be applied to multimodal datasets. It is feasible to visualize information corresponding to...
different physiological properties in different displays simultaneously, while the individual presentation weakens the correspondence established by fusing. For the second way, 

\textit{glyphs} (Ward 2002) represent a powerful and widely used method. Kniss \textit{et al.} (2004) presented a visualization approach in an immersive environment, where multimodal data can be viewed by assigning each modality to a colour channel. Blaas \textit{et al.} (2007) developed a coordinated view-based visualization approach for dealing with multimodal medical data.

\begin{itemize}
\item \textit{(c) Visualization of multidimensional data}
\end{itemize}

The dimension of a medical imaging dataset is defined as the number of independent variables included in the dataset. Methods for the visualization of multidimensional datasets can be grouped into three main types. Some methods attempt to show all the dimensions visually as one display, some try to reduce the dimensionality of a dataset before visualization, whereas others allow the user to select subsets for display. Different features are contained in the data from different research fields, and different criteria exist for the selection of appropriate visualization approaches for specific data. For multidimensional tomographic medical imaging data, two typical features must be considered in the visualization: first, spatial or anatomical information is vital for medical implementations; and second, it is critical to keep all useful information collected by medical imaging, although sometimes it is not significant and is difficult to identify from noise.

With methods to show all dimensions of a multidimensional dataset as one display, the dimensions are expressed on a two-dimensional interface, usually with little consideration of its internal structure. Take an fMRI dataset, which includes four independent variables (three dimensions for space and one for time) and so is four-dimensional, as an example; it is viable to display it using \textit{parallel coordinates} (Inselberg & Dimsdale 1987), where the axes of a multidimensional space are defined as parallel vertical lines separated by a distance \(d\), and a point in Cartesian coordinates corresponds to a polyline in parallel coordinates. It is very difficult for a clinician to connect those polylines with actual spatial or anatomical information about subjects. Generally speaking, if a method cannot represent spatial or anatomical information intuitively and meaningfully, it is not suitable for visualizing medical imaging data. Unfortunately, it is a common limitation for visualization methods to show all dimensions of a multidimensional dataset as one display.

Dimension reduction is very attractive for the processing of multidimensional datasets. However, it is not always possible to reduce the dimensions of a tomographic medical imaging dataset. Take the famous dimension reduction approach, \textit{principal component analysis} (PCA; Anderson 1984), as an example. If the original coordinates are orthogonal to/independent of each other, PCA cannot create a new coordinate with fewer dimensions. For instance, it is impossible to express the spatial Cartesian coordinates, which are composed of three axes, with a two-dimensional coordinate without significant loss of information. In medical imaging data, dimensions are independent variables that are orthogonal to each other. This fact limits the feasibility of using methods based on dimension reduction to visualize medical imaging datasets. Furthermore, it would be difficult to preserve the spatial or anatomical structure in a medical imaging dataset by visualizing it with approaches based on dimension reduction.
Subset-based approaches for the visualization of multidimensional datasets are usually achieved either by using multiple views of the data, each communicating a subset of the dimensions, e.g. *HyperSlice* (van Wijk & Liere 1993), or by embedding/combining data dimensions to form composite spatial dimensions, e.g. *dimension stacking* (LeBlanc et al. 1990) and *worlds within worlds* (Feiner & Beshers 1990). Unlike the methods above, subset-based multidimensional visualization approaches use the original dimensions of datasets and are able to maintain spatial or anatomical structure and present it in a way similar to the Cartesian system. The difficulty in subset-based visualization is how to define a subset in each display.

Considering its special features, a subset-based method may be the most suitable method for the visualization of multidimensional medical imaging data among the three kinds of generally used visualization approaches. This paper proposes a novel task-based subset definition scheme.

### 3. Methods

(a) **Task-based subset definition**

As a lead-in, let us analyse a visualization task for a five-dimensional EIT imaging dataset.

**Question 1:** ‘At a given point position, say \((x_1, y_1, z_1)\), how did the impedance change under different frequencies along the time course?’

To address this question, it is sensible to focus on a two-dimensional (time and frequency) subset corresponding to the given position, and present the spatial context of the given point in another display. In other words, to accomplish this visualization task, a subset with fewer dimensions, compared with the whole dataset, is logically defined. In fact, it is not unusual for a visualization task to correlate with a subset. This phenomenon motivated the authors to propose a task-based subset definition scheme.

As pointed out by Arnheim (1997), ‘The mind is always steered by purpose’. A visualizer looks not only at data but also for something ‘interesting’. The ‘interestingness’ can be understood as relevance to the major research question that the visualizer puts to himself/herself, or, in other words, the primary task of data visualization, the motive for doing the visualization. Respecting the fact that tasks always exist, explicitly or implicitly, and it is possible to reduce the visualization complexity of multidimensional datasets according to the users’ requirements, the authors consider that it is useful to explicitly analyse potential tasks at an initial stage for multidimensional medical imaging data visualization.

(b) **The CTE model**

Commonly, there are two kinds of approaches to reveal potential visualization tasks related to a dataset: one is practical investigation with cooperation from people such as domain experts; and the other is theoretical generation according to a task model. The advantages of practical investigation include that the obtained tasks are usually concrete, understandable and it is relatively easy to discover the most interesting tasks for the analyser/visualizer. However, it is not
trivial to ensure the completeness of the revealed tasks with this approach. Particularly, in some cases, there is neither abundant experience nor domain expertise available. By contrast, the completeness of tasks generated theoretically according to a model depends on the integrity of the adopted model. Another advantage of theoretical generation approaches is that some important but not very obvious tasks, which may be ignored in practical investigations, can be identified through theoretical deduction. Theoretically generated tasks are logically meaningful but may be relatively abstract and not easy to understand. In this section, a model named CTE is proposed as a novel approach to theoretically generate potential visualization tasks for a multidimensional dataset.

(i) Relevant research on theoretically generated tasks

Using different task taxonomies, diverse approaches are available to explore possible tasks in data analysis and visualization. As a pioneer, Bertin (1983) proposed a typology about possible analysis tasks based on ‘question types’ and ‘reading levels’. Since then, several improvements to Bertin’s typology model have been made, which include Koussoulakou & Kraak (1992), Peuquet (1994) and Blok (2000). Besides Bertin’s work and those improvements, Shneiderman (1996) proposed a task by data type taxonomy (TTT) for dynamic display; Qian et al. (1997) described a taxonomy of operations using a set-based information model that is application and data model independent; and Zhou & Feiner (1998) introduced a visual task taxonomy that interfaces high-level presentation intents with low-level visual techniques. Among the different approaches, one particular model that attracted the authors was developed by Andrienko and his colleagues in Sankt-Augustin, Germany. The CTE model is based on Andrienko’s model.

The research group led by Andrienko have concentrated their work mainly on spatial–temporal geographical data. Their first model for the classification of analytical tasks was published in Andrienko et al. (2000). Later, they combined their research results with Bertin’s theory (and its developments) and proposed an exploratory task typology for spatial–temporal data (Andrienko et al. 2003). Recently, the task model has been refined further and presented in a book (Andrienko & Andrienko 2006). Andrienko’s task typology model synthesized other pioneers’ achievements and is the latest model for task typology.

The original purpose for Andrienko et al. (2000) to investigate task typology was to understand what essential criteria are used or should be used in choosing or designing tools for exploratory data analysis. In the study presented in this paper, Andrienko’s model is adopted as a basis to develop a new model to reveal potential visualization tasks and further define subsets to be displayed corresponding to those tasks. Andrienko et al. claimed that their model can be applied to general datasets. However, the authors noted that Andrienko’s research work, including the work of some other pioneers in this area, such as Bertin, mainly concentrated on geographical data. No application of this sort of task typology to the medical field has been found through a literature review so far.

(ii) Definition of the CTE model

The CTE model comprises three task dimensions, which are called searching level dimension, searching mode dimension and searching direction dimension. Before the description of the three dimensions, the presentation of the task
(or question) used in the CTE model should be introduced. A task can be split into two parts: a target, which defines what information needs to be obtained; and the constraints, which describe what condition the information related to the target needs to fulfil. So a formula expression of a task can be

\[ ?(target) : (constraints), \]  

where ‘?’ is employed to label the task target and ‘:’ is applied to separate the target part and the constraint part. The goal of a task is to find the initially unknown information corresponding to the specified information. Both the target and the constraints can be defined with independent variables, dependent variables or combinations of them, or with relationships between independent/dependent variables. This formula expression of the task is inherited from Andrienko’s model.

**Searching level dimension**

Searching level dimension is used to classify tasks according to the level of data analysis. The idea of searching level was originally proposed by Bertin (1983). Andrienko refined the concept and defined two kinds of searching level: elementary level tasks refer to individual elements of independent variable sets; and synoptic level tasks deal with an independent variable set or its subsets as wholes rather than addressing their elements. The CTE model adopts Andrienko’s definition for searching level. Each independent variable in a dataset can be considered at different searching levels independently. However, the searching level of dependent variables relies on the searching level of independent variables. So, for an N-dimensional dataset, there are \( 2^N \) possible combinations of searching levels.

**Searching mode dimension**

Searching mode dimension is introduced to describe the role that relationship played in a task. Tasks always concern some kind of relationship between variables. When a dataset is expressed by a functional formula, the function represents relationships between dependent and independent variables. Besides the relationships represented by the function, which will be called \( R_1 \) below, relationships also exist between independent variables or between dependent variables, which will be mentioned as \( R_2 \) and \( R_3 \) separately later.

For a dataset, two basic questions are expected.

**Q1:** Given two (or more) variables, identify what relationship exists between them.

**Q2:** Given one (or some) variable(s), and a relationship, find other variables, related in the specific way to the given variable(s).

Variables in these two basic questions can be at elementary or synoptic searching levels. Combining the relationships and basic questions, six types of tasks can be identified: \( R_1\-Q_1, R_1\-Q_2, R_2\-Q_1, R_2\-Q_2, R_3\-Q_1 \) and \( R_3\-Q_2 \). For a given dataset, it is assumed that all the relationships between independent and dependent variables, or, at least, all such relationships that are of interest to a data analyst, are defined by the data function. Hence, basic question Q1 does not come up when the focus is put on relationships between independent and
dependent variables (relationship $R_1$): there is no sense in asking what kind of relationship exists between a given independent and dependent variables. So for relationship $R_1$, only question $Q_2$ is reasonable, and the task type $R_1$-$Q_2$ is named a lookup task. For relationships $R_2$ and $R_3$, both questions $Q_1$ and $Q_2$ make sense. In these cases, question $Q_1$ is called a comparison task, and question $Q_2$ is a relationship-seeking task. Comparison tasks aim to determine what relationships exist between two (or more) independent/dependent variables. In a relationship-seeking task, a certain relationship is specified, and items that are related in the specified way need to be detected.

The classification of searching mode into lookup, comparison and relationship seeking was included in Andrienko’s model. Searching mode can be applied to different searching levels. By separating similarity/difference relationships from other possible relationships, Andrienko divided synoptic tasks into ‘descriptive synoptic’ tasks and ‘connectional synoptic’ tasks. This division may be acceptable, ‘because cognitive operations and efforts involved in these two sorts of tasks are different’ (Andrienko & Andrienko 2006). In the research conducted by the authors, a task typology is used to assist the definition of subsets for the visualization. It focuses on dimensions of subsets corresponding to different types of tasks instead of cognitive operations and efforts involved in a relationship discovery or description. To make the task model more convenient to apply, this research prefers to treat all potential relationships between independent and/or dependent variables equally and not to divide synoptic tasks further. However, for lookup tasks at synoptic level, the involved relationships are between independent and dependent variables. In medical imaging, those relationships are between physical properties associated with biological structures or functions and the imaging context, such as biological position, sample time points, etc. It is awkward to classify these relationships into relationships such as similarity, difference or correlation. Consequently, it seems unreasonable to classify synoptic lookup tasks into descriptive synoptic tasks or connectional synoptic tasks. This difficulty further strengthens the decision to treat synoptic tasks as a basic element on the searching level dimension.

A relationship may be the target of a task or be specified as a task constraint. The list of potential relationships among variables of a dataset is numerous. This research focuses on binary relationships: relationships involving two items. In fact, relationships in which more than two items participate can be represented by collections of binary relationships. Comparison tasks aim to determine what relationships exist between variables. However, not all combinations of independent or dependent variables are meaningful: the components involved must be comparable, which generally requires the components to have coincident or at least overlapping value domains. In this research, besides relationships defined by the data function, only relationships between two values (or two value sets) of a variable are considered.

Searching direction dimension

The third dimension in the CTE model is searching direction. With this dimension, tasks can be grouped into direct tasks and inverse tasks. Goals for direct tasks are dependent variables or relationships between dependent variables, while inverse tasks aim to identify independent variables or relationships between independent variables.

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A similar definition is used in Andrienko’s model, but Andrienko’s searching direction is used to classify just lookup and comparison tasks, not relationship-seeking tasks. Andrienko et al. described the fundamental idea of a relationship-seeking task as finding independent variables such that the corresponding dependent variables are related in a specific way, which is a kind of inverse task according to our definition. However, relationship-seeking tasks can also target dependent variables with corresponding independent variables related in a specified way, and such relationship-seeking tasks can be classified as direct tasks. In this research, the fundamental idea of a relationship-seeking task proposed by Andrienko et al. will not be adopted. Instead, a relationship-seeking task will be defined as: finding independent or dependent variables such that the corresponding dependent or independent variables are related in a specific way. Under this definition, searching direction can be adopted as a subcategory criterion for relationship-seeking tasks.

With the CTE model, task typology for a dataset can be illustrated as a cubic grid (figure 1); each voxel in this grid presents a type of task.

Considering relationships included in tasks on different searching modes: lookup tasks include one relationship, the data function; comparison and relationship-seeking tasks contain at least two relationships, one being the data function and the other being relationships between values (or value sets) of a variable. By treating lookup tasks as atomic tasks, comparison and relationship-seeking tasks can be considered as compound tasks. A compound task is built up from smaller operations, or subtasks. Usually, four kinds of subtasks can be identified for compound tasks such as comparison and relationship-seeking tasks:

1. direct lookup tasks,
2. inverse lookup tasks,
3. identify relationships existing between two values (or two value sets) of a
variable, and
4. for a variable, find a value (or value set) related to a given value (or value set)
with a specified relationship.

In general, direct comparison tasks can be compounded with subtasks 1 and 3,
inverse comparison tasks are formed with subtasks 2 and 3, and direct and
inverse relationship-seeking tasks are constituted with subtasks 1, 2 and 4.

(c) The TMDV method

Using the CTE model, potential visualization tasks for multidimensional
medical data can be deduced. To develop a visualization system based on the
deduced tasks, the TMDV method is proposed. The TMDV method contains
three main steps: first, specifying a visualization task/question; second, sorting
out the target of the visualization task; and finally, visualizing the task.

(i) Task specification

The specification of a task is carried out in two steps: defining the task type;
and then setting individual features for that task. Making use of the CTE
model, the type of a task is defined by values corresponding to the three task
dimensions. A concrete task comprises targets and constraints. With the
selection of searching direction, targets are specified to be dependent variables
(or relationships between dependent variables) for direct tasks, and independent
variables (or relationships between independent variables) for inverse tasks.
Task constraints can be defined with independent variables, dependent variables
or relationships between variables. Among the three task dimensions, searching
level significantly affects the setting of constraints. Generally, it is easier to set a
constraint with elementary variables than with synoptic variables.

(ii) Identify the target of the visualization task

Knowing questions (or type of questions), one may look at familiar techniques
from the perspective of whether they could help one to find answers to those
questions. In some cases, there may be a subset of existing tools that cover all
potential question types. It may also happen that for some tasks there are no
appropriate tools. In the latter case, the nature of the tasks gives a clue as to
what kind of tool would be helpful. This is an important initial step in designing a
new tool. Ideally, a visualization system must contain a set of tools that could
answer any possible visualization question. This ideal will, probably, never be
achieved, but a designer conceiving a system or toolkit for visualization needs to
anticipate the potential questions and at least make a rational choice concerning
which of them to support.

As mentioned at the end of §3b(ii), four basic subtasks 1–4 are included in tasks
revealed by the CTE model. The first two subtasks, direct lookup and inverse lookup,
are the main factors determining the choice of processing methods. For a direct
lookup task, it is relatively easy to obtain the target according to the given
independent variables, considering that medical datasets are generally indexed along
independent components when they were stored. Inverse lookup tasks are usually
more difficult to process. Many image processing technologies can be considered as efforts to solve certain kinds of inverse tasks. For example, thresholding can be described as an inverse task such as this: within a given image, find out pixels with grey value greater than a given value. Similarly, edge detection can be described as: in an image, find the pixels whose grey values satisfy a specific local neighbourhood relationship. Although a large number of image processing methods are available nowadays, some inverse tasks still cannot be addressed intuitively with existing tools.

Similar to its great influence on the setting of dependent variables as a constraint, searching level affects the selection of analysis method for inverse tasks a lot, because it determines the dimension of data involved in the process directly. An elementary variable is zero-dimensional, and each synoptic variable has at least one dimension. Commonly, the complexity to resolve an inverse task grows with the increase in the dimension of data involved in the process. For a potential visualization task, dimensions of data involved in the process can range from zero to the dimension of the dataset. Most image analysis approaches are performed using data with fewer than four dimensions. With the increasing complexity of medical imaging methods, more and more analyses have to be conducted with multidimensional data.

(iii) Subset-based visualization

The first two steps in the TMDV method define and locate the subsets for a visualization task, and the third step aims to support the multidimensional and multimodal tomographic medical data visualization with subset-based approaches.

For a specified task, two kinds of subsets can be defined for visualization: one includes data corresponding to the target for a task, which is named target subset; and the other contains data corresponding to the target and its constraints context defined in the task, which is referred to as target–constraint subset. The dimension of a target–constraint subset is equal to the dimension of the data involved in the process to answer the question, and is normally bigger than the dimension of the corresponding target subset. For example, in a five-dimensional EIT imaging dataset, the following question can be asked.

Question 2: ‘With a specified frequency, during a time interval, for a given impedance change pattern, find out the location where impedance change is similar to the given pattern’.

The target subset defined by this question is a three-dimensional brain region. The target–constraint subset related to this question is a four-dimensional dataset including the identified brain region, the time interval and impedance information corresponding to this region during the time interval at the given frequency.

Various algorithms are available for the visualization of data with three or fewer dimensions, and animation is a powerful approach to provide information on an extra dimension. It is acceptable to display a four-dimensional medical dataset in one view. Therefore, a principle for subset selection can be proposed as follows.

For the target subset and target–constraint subset corresponding to a task, if the dimensionality of the target–constraint subset is not more than four, then the target–constraint subset should be used preferentially in the subset-based visualization; otherwise, the target subset is adopted if its dimension is less than the dimension of the target–constraint subset.
Besides the presentation of the selected subset, other information in the dataset is important for further understanding of a task. So navigation is an essential feature for a subset-based visualization system. Considering the visualization task in question 2, it is desirable to display the target–constraint subset in one view, while the other information in the dataset can be inspected through navigation.

\(d\) Statistical parametric mapping for EIT data

As for other areas of image processing, it is important to define and visualize regions of interest (ROIs) in an EIT dataset. To date, there are only limited data available on the approaches to ROI definition in EIT images, which can be classified into two main types. The first type is based on the calculation of the pixel values (Smallwood et al. 1999; Frerichs et al. 2001, 2005). The selection of a proper edge criterion value is the key issue for this kind of method: too low values of the edge criterion would make the selected ROIs too large, and vice versa. The second kind of method defines ROI as a simple geometrical object (Victorino et al. 2004; Odenstedt et al. 2005). Pulletz et al. (2006) demonstrated that, for ROI definition in lung functional EIT images, the first kind of approach is more convenient than the latter one. Nevertheless, defining the ROI suitably is still a challenge for EIT researchers. However, ROI locations for other types of neuroimages have been widely researched for many years. Statistically based algorithms have significant advantages in the processing of brain medical images. Several statistical packages have been developed for the analysis of neuroimages. Each package contains many useful features; but they are neither comprehensive nor interchangeable. One of the most widely used packages is statistical parametric mapping (SPM), which has been applied worldwide and is a standard for the processing of fMRI data.

SPM refers to the construction of spatially extended statistical processes to test hypotheses about regionally specific effects (Friston et al. 1991). SPM is generally used to identify functionally specialized brain regions and is the most prevalent approach to characterizing functional anatomy and disease-related changes. Brain EIT imaging can also create neuroimages; it seems plausible to apply SPM to identifying ROI in brain EIT images. The current SPM method and software are designed for PET, single photon emission computed tomography, fMRI, electroencephalography (EEG) and MEG neuroimages; there has been very little research effort to combine the SPM method with brain EIT image analysis. In our earlier work, a novel scheme (figure 2) for the processing of brain EIT data with SPM to detect ROIs was proposed based on a theoretical analysis, and the experimental results demonstrate that SPM is able to localize the expected ROI in EIT data correctly (Zhang et al. 2005; Yerworth et al. 2007).

\(e\) Registration of brain EIT data with anatomical brain data

EIT imaging has high temporal resolution and poor spatial resolution. Little anatomical information is included in EIT imaging datasets. However, clinicians usually have abundant knowledge about human morphology; the understanding of EIT images could be enhanced by visualizing EIT imaging data in an anatomical context.
Both CT and MRI can provide good structure information of the human body with millimetre resolution. Images obtained from CT scans include high-quality information about bones, but are not suitable for tissue visualization. Although MRI images are less sensitive to changes inside bones, different tissues can be identified more clearly in MRI images than in CT images. The human brain is composed within the skull of different tissues, such as grey matter, white matter and cerebrospinal fluid. Functional activities revealed by brain EIT imaging generally appear in these tissues. It is thus suitable to choose MRI images as an anatomical context in the visualization of brain EIT images.

Voxel intensities in an EIT image represent the impedance change or absolute impedance value with poor spatial resolution. It is very difficult to use those intensities as registration features directly. Moreover, it is hard to select any geometrically meaningful features inside the brain in an EIT image and find out their correspondence to an MRI image. However, there is some geometric information that can be traced on the brain surface in EIT images.

EIT imaging of the human brain is conducted with electrodes attached to the scalp. Currently, 31 electrodes are used in brain EIT imaging. Twenty-seven of the 31 electrodes, which will be called the 27 system electrodes later, are located according to the international 10–20 system for EEG electrode placement (Binnie et al. 1982). The fundamental of the 10–20 system are the positions of the four basic fiducial points: nasion; inion; left preaurical point; and right preaurical point. The other four of the 31 electrodes, which will be called the four additional

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electrodes, are added to optimize current distribution in the brain: two of them are placed on the mastoid bones behind each ear, and the other two are placed over the base of the occiput. The positions of those 31 electrodes and the four basic fiducial points are projected on the surface of the head mesh used in the reconstruction algorithm. EIT reconstruction produces volumetric impedance data wrapped by the head mesh. The impedance value at each voxel in an EIT image dataset is obtained by rasterizing the corresponding volumetric impedance data. There is a direct mapping between the coordinates used in the head mesh and the reconstructed image dataset: the axes in the two coordinate systems have the same directions but use different units. So, with the positions of the 35 landmarks on the head mesh, it is relatively easy to identify the position of those landmarks in EIT images. In the following, these 35 landmarks are marked as $P_{\text{EIT}}$; the *four basic fiducial points* and the *four additional electrodes* are represented as $P_{\text{EIT, A}}$; and the other 27 landmarks are described as $P_{\text{EIT, B}}$.

Among the 35 point features, points in $P_{\text{EIT, A}}$ have clearly defined anatomical locations. Considering the rich anatomical information included in MRI images, it is possible to identify these eight features in MRI images, which will be named $P_{\text{MRI, A}}$ below. After the recognition of the four basic fiducial points, the corresponding positions for the 27 system electrodes can be located in MRI images consequently according to the rules of the 10–20 system, which will be presented as $P_{\text{MRI, B}}$ below. A two-level landmark-based registration scheme is proposed and illustrated in figure 3.

The main processes in this scheme are *initial registration* and *refined registration*. As a preparation, the positions of the 35 landmarks $P_{\text{EIT}} = \{P_{\text{EIT, A}}, P_{\text{EIT, B}}\}$ in the EIT image are located by mapping their corresponding positions in the head mesh used for reconstruction to the volumetric image space, and the positions of the eight landmarks in subset $P_{\text{MRI, A}}$ are manually segmented in the MRI image. The initial registration is based on the eight pairs of landmarks in $P_{\text{EIT, A}}$ and $P_{\text{MRI, A}}$. An affine transformation $T_1$ is determined by the least-squares method in this registration. With the transformation $T_1$, the MRI image $I_{\text{MRI}}$ and the landmark subset $P_{\text{MRI, A}}$ are transformed and resampled to align with the EIT image

$$\begin{align*}
\left\{ P'_{\text{MRI, A}} = T_1(P_{\text{MRI, A}}) \right. \\
I'_{\text{MRI}} = T_1(I_{\text{MRI}})
\end{align*}$$

(3.2)

Based on the resampled MRI image $I'_{\text{MRI}}$ and the landmark subset $P'_{\text{MRI, A}}$, the other landmark subset $P'_{\text{MRI, B}}$ in the MRI image is calculated according to the rules in the international 10–20 system. Up to this point, 35 landmarks have been identified in both EIT and MRI images. Therefore, the refined registration is carried out with the 35 pairs of landmarks in $P_{\text{EIT}}$ and $P'_{\text{MRI}} = \{P'_{\text{MRI, A}}, P'_{\text{MRI, B}}\}$, and affine transformation $T_2$ is calculated by the least-squares method.

After the initial registration and refined registration, the brain EIT image $I'_{\text{EIT}}$ is transformed with $T_1$ and $T_2$ and resampled to align with the reference MRI image in the final step of this scheme

$$I'_{\text{EIT}} = T_1^{-1}T_2(I_{\text{EIT}}).$$

(3.3)
Making use of the TMDV method, a prototype system named EIT5DVis is developed for the visualization of five-dimensional EIT data. The TMDV method uses the CTE model to explore potential visualization tasks for a medical imaging dataset. Ideally, a visualization system should be able to fulfill any possible visualization tasks. However, this idea may never be achieved. On the one hand, for some tasks, no existing tool is available to sort out the target of the task. For example, in the development of the EIT5DVis system, new approaches for ROI identification and registration of EIT data are needed to support corresponding visualization tasks. On the other hand, not all the tasks have the same importance for medical research and clinical application; it largely depends on the practical requirements to decide which tasks are to be supported in a

Figure 3. The landmark-based registration scheme.

4. Implementation
Visualization system. In this section, the implementation of the CTE model to reveal potential visualization tasks for five-dimensional EIT brain data is described first; then an overview of the EIT5DVis system is presented; finally, some visualization examples are given to illustrate how EIT5DVis works.

(a) Task exploration for five-dimensional brain EIT data visualization

(i) Functional representation of five-dimensional brain EIT imaging data

A five-dimensional brain EIT dataset is obtained by using a spectroscopic EIT imaging system to examine impedance variation during a time interval. There are five independent variables and one dependent variable in the dataset. The functional representation of the five-dimensional brain EIT dataset is

\[ p = g(x, y, z, t, f). \] (4.1)

where \( x, y, z \) represent three spatial coordinates; \( t \) stands for the time; \( f \) for the frequency; and \( p \) describes the impedance values inside the brain.

(ii) Customize task dimensions for the EIT data

The CTE model is based on three task dimensions. Values of searching mode dimension and searching direction dimension are fixed, and values of searching level dimension depend on the number of references in a dataset. For the five independent variables, it is reasonable to treat the three spatial coordinates as a whole, because they specify positions in Cartesian space together. Therefore, if \( l \) symbolizes the location defined by \((x, y, z)\), formula (4.1) can be rewritten as

\[ p = g(l, t, f). \] (4.2)

With this representation, three independent variables and one dependent variable are included in a five-dimensional EIT dataset. It should be emphasized that this is just a simplification for task exploration and not a dimension reduction for visualization. When a five-dimensional EIT dataset is represented with formula (4.2), \( 2^3 \cdot 2^3 = 8 \) values exist on the searching level dimension for this dataset, as listed in Table 1. In this table, ‘1’ and ‘0’ denote that the corresponding reference is at elementary and synoptic levels, respectively. Symbols A–H stand for eight combinations of the three references on different searching level. For example, symbol C, which corresponds to the combination ‘1 0 1’ in the table, means location is on elementary level, time is on synoptic level and frequency is on elementary level.

Table 1. Values of searching level dimension for five-dimensional brain EIT data.

<table>
<thead>
<tr>
<th>reference</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>location</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>time</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>frequency</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

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Deduce potential tasks with the CTE model

With the customization of task dimensions, it is now possible to use the CTE model to deduce the task typology and explore potential tasks for the visualization of five-dimensional EIT data. Figure 4 illustrates the task typology for a five-dimensional EIT dataset.

Table 2 lists the general task formulae for different task types.

<table>
<thead>
<tr>
<th>task type</th>
<th>general task formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>lookup</td>
<td>direct ( ?p : (l,t,f) )</td>
</tr>
<tr>
<td></td>
<td>inverse ( ?(l,t,f) : p )</td>
</tr>
<tr>
<td>comparison</td>
<td>direct ( ?p_1 : (l_1,t_1,f_1) )</td>
</tr>
<tr>
<td></td>
<td>( ?p_2 : (l_2,t_2,f_2) )</td>
</tr>
<tr>
<td></td>
<td>( ?R_P : (p_1,p_2) )</td>
</tr>
<tr>
<td></td>
<td>inverse ( ?(l_1,t_1,f_1) : p_1 )</td>
</tr>
<tr>
<td></td>
<td>( ?(l_2,t_2,f_2) : p_2 )</td>
</tr>
<tr>
<td></td>
<td>( ?R_L : (l_1,t_2) )</td>
</tr>
<tr>
<td></td>
<td>( ?R_T : (t_1,t_2) )</td>
</tr>
<tr>
<td></td>
<td>( ?R_F : (f_1,f_2) )</td>
</tr>
<tr>
<td>relationship-seeking</td>
<td>direct ( ?(l_1,t_1,f_1) : p_1 )</td>
</tr>
<tr>
<td></td>
<td>( ?l_2 : (R_L,l_1) )</td>
</tr>
<tr>
<td></td>
<td>( ?t_2 : (R_T,t_1) )</td>
</tr>
<tr>
<td></td>
<td>( ?f_2 : (R_F,f_1) )</td>
</tr>
<tr>
<td></td>
<td>( ?p_2 : (l_2,t_2,f_2) )</td>
</tr>
<tr>
<td></td>
<td>inverse ( ?p_1 : (l_1,t_1,f_1) )</td>
</tr>
<tr>
<td></td>
<td>( ?p_2 : (R_P,p_1) )</td>
</tr>
<tr>
<td></td>
<td>( ?(l_2,t_2,f_2) : p_2 )</td>
</tr>
</tbody>
</table>

(iii) *Deduce potential tasks with the CTE model*

With the customization of task dimensions, it is now possible to use the CTE model to deduce the task typology and explore potential tasks for the visualization of five-dimensional EIT data. Figure 4 illustrates the task typology for a five-dimensional EIT dataset.

Table 2 lists the general task formulae (represented with a series of subtasks for each task type) for tasks with different searching modes and different searching directions. The searching level dimension does not appear in the task type column of this table, because, for a specified searching mode and searching direction, the same formula presentation can be used for tasks at different searching levels.

*Phil. Trans. R. Soc. A* (2009)
Table 3. Visualization tasks for five-dimensional brain EIT data.

<table>
<thead>
<tr>
<th>Searching Level</th>
<th>Searching Mode</th>
<th>Searching Direction</th>
<th>General Formulae</th>
<th>Concrete Questions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Level G:</strong></td>
<td>Synoptic Location, Synoptic Time, Elementary Frequency</td>
<td>Direct</td>
<td>( ?P: (L,T,f) )</td>
<td>In a given location area ( L ), during a given time interval ( T ) and under a given frequency ( f ), find out the corresponding impedance change pattern ( P )?</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( ?P: (L,T,f) : P )</td>
<td>Concrete questions:</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>((L,T,F) : P )</td>
<td>For a given impedance change pattern ( P ), during which time interval ( T ), under which frequency ( f ), and in which location area ( L ) was it attained?</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>((L,F) : P )</td>
<td>In a given location area ( L ), during a given time interval ( T ), under which frequency ( f ), and in which location area ( L ) was it attained?</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>((F,L,T) : P )</td>
<td>During a given time interval ( T ), in which location area ( L ) and under which frequency ( f ) was a given impedance change pattern ( P ) attained?</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>((L,F,T) : P )</td>
<td>Under a given frequency ( f ), in which location area ( L ) and during which time interval ( T ) was a given impedance change pattern ( P ) attained?</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>((F,L,T) : P )</td>
<td>In a given location area ( L ), during a given time interval ( T ), under which frequency ( f ) was a given impedance change pattern ( P ) attained?</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>((L,F,T) : P )</td>
<td>In a given location area ( L ) and under a given frequency ( f ), during which time interval ( T ) was a given impedance change pattern ( P ) attained?</td>
</tr>
<tr>
<td></td>
<td>Synoptic Location, Synoptic Time, Synoptic Frequency</td>
<td>Inverse</td>
<td>( ?(L_2,T_2,F_2) : P_2 )</td>
<td>Concrete questions:</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( P_2 : (R_P,P_1) )</td>
<td>For a given impedance change pattern ( P_2 ), during which time interval ( T ), under which frequency ( f ), and in which location area ( L ) was it attained?</td>
</tr>
<tr>
<td></td>
<td>Synoptic Location, Synoptic Time, Synoptic Frequency</td>
<td></td>
<td>( P_1 : (L_1,T_1,F_1) )</td>
<td>In a given location area ( L ) and during a given frequency range ( F ), find out a frequency range ( F_2 ) (with corresponding impedance change pattern ( P_2 )), such that a specified relationship exists between ( P_2 ) and ( P_1 ), which was obtained under a given frequency range ( F_1 ).</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( P_2 : (R_P,P_1) )</td>
<td>In a given location area ( L ) and during a given frequency range ( F ), find out a time interval ( T_2 ) (with corresponding impedance change pattern ( P_2 )), such that a specified relationship exists between ( P_2 ) and ( P_1 ), which was obtained during a given time interval ( T_1 ).</td>
</tr>
</tbody>
</table>

(Continued.)
Details of some of the deduced questions are presented in table 3. Owing to space constraints, only a part of the questions for searching levels G (synoptic location, synoptic time and elementary frequency) and H (synoptic location, synoptic time and synoptic frequency) are listed here. These two levels contain the most complex task types for a five-dimensional brain EIT dataset.

(b) Overview of the EIT5DVis prototype system

The EIT5DVis prototype system is developed in Matlab, with support from C++ and the Visualization ToolKit (VTK). EIT5DVis is composed of relatively independent modules, which include a data processing module,
a task formulation module, a method selection module, a visualization module, an animation and navigation module, and a registration module. Figure 5 illustrates the communications among the modules and the main functions contained in those modules.

The task formulation module provides a graphic user interface. Through these interfaces, users can specify task types by choosing values on the three task dimensions of the CTE model, and then define the constraints and targets part of tasks. After task specification, EIT5DVis calls the method selection module to pick a processing algorithm to handle the formulated question. Algorithms included in the method selection module are extensible. It is not difficult to combine new methods into this module, or to communicate with other image processing software through this module. The visualization module displays the target subset or target–constraint subset corresponding to the specified task with four main methods: two-dimensional orthogonal display; two-dimensional matrix display; three-dimensional isosurface display; and three-dimensional volume display. The animation and navigation module is provided to visualize subsets of more than three dimensions and to enable browsing of the whole dataset.

(c) Visualization examples using EIT5DVis

There are a range of tasks that can be addressed in EIT5DVis, whose complexity is roughly determined by where they are drawn from on the scale of searching level. In order to demonstrate the feasibility of the methodology and explain how EIT5DVis works, some concrete visualization tasks are used in this section.

For the visualization of a five-dimensional brain EIT dataset collected in visual stimulation experiments, one of the most interesting questions is the following.
Question 3: ‘Which part of the brain is activated under visual stimulation?’

The expected answer to this question is to display the activated regions. The first step to process this question in EIT5DVis is to formulate the question. The target of question 3 is location, which is an independent variable in this dataset. Thus question 3 is an inverse task. This task considers action inside the brain along the whole experiment time interval and the whole frequency range instead of at a certain time point or under a certain frequency, so the searching levels for time and frequency are synoptic. Also, the target locations for this task are three-dimensional regions rather than isolated spatial points, so the reference location is at the synoptic level as well. In summary, this task is on level H (refer to the definition in table 1): synoptic location, synoptic time and synoptic frequency. The relationships concerned in this question are between independent (location) and dependent (impedance) variables, which means that the searching mode of this task is lookup. Table 4 summarizes the task type of question 3.

The next step for task definition is to set the target and constraints. The target of question 3 is location, and three constraints are involved in this question. The first constraint sets the synoptic time as the whole experimental time interval. The second one restricts the synoptic frequency to the whole frequency range in the experiment. The third constraint limits the value of impedance. In the original question, the third constraint is just mentioned as ‘activated’, and no further information about activated is given. It is not possible to define the impedance change pattern in an activated region directly. However, those activations are caused by visual stimulations in the experiment and should statistically relate to the changes in stimulation. So the ‘on’ and ‘off’ patterns of visual stimulation in the experiment are used as a constraint for the impedance change pattern in this task. Specifically, matrix $P$ in the following formula (4.3) is used as the constraint for the impedance change pattern:

$$
P = \begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
$$

\[ (4.3) \]
In matrix $P$, ‘0’ denotes that no visual stimulation is presented; ‘1’ indicates that visual stimulation is presented. Each column of this matrix represents a sample time point, and each row corresponds to a different frequency. For a visual stimulation experiment lasting 6 min and 15 s with a scalp impedance dataset acquired every 25 s, the visual stimulus was presented after the sixth sample time point for 75 s (Tidswell et al. 2001). So the visual stimulus across the experiment time can be represented with six ‘0’s, followed by three ‘1’s and then six ‘0’s. Impedance values under different frequencies are measured simultaneously, which means that the visual stimulus is the same for each frequency. Therefore, the same values appear in each row of matrix $P$.

After task formulation, EIT5DVis calls an appropriate algorithm included in the task analysis module to process the task. For question 3, SPM is called to address the target. The target subset of question 1 is three-dimensional, and the

Table 4. Task type of question 3.

<table>
<thead>
<tr>
<th>task dimension</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>searching level</td>
<td>synoptic location, synoptic time and synoptic frequency</td>
</tr>
<tr>
<td>searching mode</td>
<td>lookup</td>
</tr>
<tr>
<td>searching direction</td>
<td>inverse</td>
</tr>
</tbody>
</table>

Figure 6. Two-dimensional orthogonal display of the result for question 3 ($x$= left to right, $y$= back to front, $z$= down to up).
target–constraint subset is five-dimensional. According to the subset selection principle, the target subset is selected for the final visualization. Figure 6 shows a two-dimensional orthogonal display of the target subset, where locations activated under visual stimulation are presented with colour, and impedance in other parts of the brain is displayed in grey scale.

After the solution of question 3, another question may be presented subsequently.

Question 4: ‘Is the region of the brain activated under visual stimulation in the visual cortex?’

This is a comparison task. However, as we know, EIT imaging data contain little anatomical information. It is difficult to recognize the visual cortex within EIT data. Therefore, it is better to process question 4 in two steps instead of processing as a simple comparison task: first, question 3 is processed as a subtask for question 4, then the target subset and the EIT dataset for question 3 are registered to an MRI dataset with the scheme proposed in §3d, and the final visualization is multimodal, which combines the registered target subset, the registered EIT dataset and the MRI dataset. Figure 7 presents a two-dimensional orthogonal display of the target subset in the anatomical contours provided by the MRI dataset, where the locations activated under visual stimulation are presented with colour, and impedance in other parts of the brain is displayed in grey scale.

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Diverse relationships can potentially exist in tasks. Apart from the most common same/different relationship, Boolean spatial operators as used in constructive solid geometry (CSG), such as union, intersection and difference, commonly appear in tasks as well. Question 5 is a task involving a relationship in the form of a CSG operation.

Question 5: ‘For two specified frequencies, supposing $L_1$ and $L_2$ are the parts of the brain activated under visual stimulation under these two frequencies separately, then what are the union and intersection results of $L_1$ and $L_2$?”

Question 5 is an inverse comparison task. As mentioned in §3b(ii), inverse comparison tasks can be formed with ‘inverse lookup’ subtasks and subtasks to ‘identify relationships existing between two specified references’. Actually, the inverse lookup subtasks contained in this question are similar to question 3. So the same method can be adopted to deal with these inverse lookup subtasks for question 5. Figure 8 visualizes the result for those inverse lookup subtasks and question 5.

5. Discussion and conclusions

An informal interview on the usability of the TMDV method and the EIT5DVis system was conducted with a senior researcher in the EIT imaging area, three research associates from other medical imaging fields, one researcher in data mining and one from computer science. Because EIT has not been used routinely in clinical practice, no clinically competent reviewer is available at this moment. The main aspects examined in this interview included the completeness of the task model, the usefulness of the task definition interface and the general impression of the EIT5DVis system.

One aim of the EIT5DVis system is to describe questions that people may put forward and to address these questions properly. During the interview, an introduction to the CTE model is given. Question 6 was put to the respondents both before and after the introduction.

Question 6: ‘If you are visualizing a five-dimensional EIT dataset, what would be the question that most concerned you?’

It is interesting to note that, before the introduction, most respondents proposed questions belonging to direct lookup tasks; this also happened for the senior researcher in EIT. However, after the introduction, many respondents changed their responses by putting more inverse searching tasks and rating them of higher interest. This phenomenon suggested that, given the task model, some important while not intuitive tasks can be identified by the user. Concerning the general impression, most respondents concluded that the EIT5DVis system was able to address their question satisfactorily, and the task model is able to cover all the questions they can construct.

The task specifying interface of EIT5DVis was constructed according to the CTE model. It looked different from the interfaces used in common visualization systems. The usefulness of this task definition interface was another aspect to be examined through the investigation. As expected, when respondents tested the system without any instruction, they could formulate direct searching tasks and control the range of reference variables easily, but were rarely aware of the other features provided by the
After some introduction and demonstrations, respondents were able to define different types of tasks through the interface. On the whole, most respondents graded the task definition interface as user-friendly, although some of them thought that the approach for impedance feature setting was not in a satisfactory format. In other words, although the task specification interface in EIT5DVis is untypical of image processing systems, it was not difficult for users to learn how to master it, given reasonable help, information and examples.

On the question of the most useful feature provided by the EIT5DVis system, a variety of feedbacks were given by the respondents, partially because of their different research backgrounds. For example, some of them thought the multiple viewing formats and choice of animation dimension was quite attractive; some took the analysis function imported from SPM as his/her favourite feature; some preferred the anatomical information provided by the registered display; and others put the task-based subset selection to reduce the visualization complexity as the most favourite feature.

Figure 8. Three-dimensional volume display of the result for question 5. (a,b) Volume rendering of the activated regions detected under two specified frequencies. (c,d) The activated regions included in (a,b) simultaneously from different viewing positions. (e,f) The union and intersection of the activated regions detected under two specified frequencies.
Some useful suggestions on how to improve the EIT5DVis system were also obtained through the interview: for example, to include more examples in the system, provide help documentation, enhance the user interface, enable the simultaneous animation for both sets in a comparison window, etc.

The interview results demonstrate that, as a first trial to visualize five-dimensional medical imaging data, the prototype system, EIT5DVis, fulfils its main goal, although there are some features to be improved. The success of the prototype system demonstrates that the TMDV method, with CTE model as a core technique, is feasible for the visualization of multidimensional multimodal tomographic medical imaging data.

Owing to the specific features included in medical imaging data, showing subsets of a dataset seems to be the best way among general approaches to visualize multidimensional medical imaging data. The biggest challenge in subset-based visualization is to select subsets properly. In this paper, a task-based subset definition scheme has been proposed; the CTE model has been derived to support the task exploration for medical imaging data; the TMDV method has been proposed as a structured method for the development of a multidimensional and multimodal visualization system; and finally a prototype system named EIT5DVis has been developed using the TMDV method to visualize five-dimensional brain EIT imaging datasets.

This paper has used a five-dimensional brain EIT dataset as a case study for the visualization of multidimensional and multimodal tomographic medical imaging data. In fact, the CTE model can be employed to reveal visualization tasks for datasets with low dimensions as well as high dimensions. The TMDV method is proposed for general cases and can be applied to datasets collected with different modalities.

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Visualization of medical imaging data


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