# Relation-Aware Spreadsheets for Multimodal Volume Segmentation and Visualization

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**Abstract.** Multimodal volume data commonly found in medical imaging applications present both opportunities and challenges to segmentation and visualization tasks. This paper presents a user directed volume segmentation system. Through a spreadsheets interface, the user can interactively examine and refine segmentation results obtained from automatic clustering. In addition, the user can isolate or highlight a feature of interest in a volume based on different modalities, and see the corresponding segmented results. Our system is easy to use since the preliminary segmentation results are organized and presented to the user in a relation-aware fashion based on the spatial relations between the segmented regions. We demonstrate this system using two multimodal datasets.

**Keywords:** User Interface, Multimodal Volume Data, Segmentation, Visualization.

## 1 Introduction

Medical doctors routinely rely on multimodal volume data in their diagnosis and surgical planning tasks. Segmentation is a critical step in medical imaging where a particular material of interest is separated from the surrounding materials and background. Even though many segmentation techniques have been developed, segmenting multimodal volume data is still a challenging task because of the different natures and complexities of the data and the absence of an integrated tool for examining and refining the segmentation results. In general, user intervention is required for sophisticated volume segmentation tasks [8]. As such, the best results may be obtained by coupling expert user's knowledge with machine intelligence, which suggests the need of an intuitive interactive interface for the user to visually compare different segmentation results and make corrections until satisfactory results are obtained.

In our study, we put our emphasis on intelligent visualization and user interface design for multimodal volume segmentation. We have developed a spreadsheet-style visualization system to facilitate image segmentation and result refinement. In the case studies involving PET and CT volume data, as regions of interest are suggested by the PET data, we advocate an interactive PET-guided segmentation approach. The system initially generates a number of

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clusters from the multimodal data using k-means clustering and then presents them on the spreadsheets. A user can start from the PET data and select the cluster of interest. The clusters of CT or MRI data covered by the selected PET cluster will be highlighted in the spreadsheets. With an artificial intelligence technique called *region connection calculus* [1,3], the spatial relations of the clusters can be derived automatically. With the estimated relations, the system can generate a relation-aware layout for the spreadsheets to clearly reveal the spatial relations between the clusters. This enables users to efficiently and interactively refine the clustering results on the spreadsheets. Our contributions are as follows. First, we design a new spreadsheet-style user interface that allows for efficient segmentation and visualization of multimodal data. Second, we propose a PET-guided and relation-aware segmentation procedure based on region connection calculus. Our system is used primarily for segmentation refinement and is not limited to k-means clustering. It can also be adapted to other segmentation approaches based on different machine learning techniques.

## 2 Related Work

*Spatial Relation* Spatial relations between 3D objects have been widely studied in computer graphics [11] and artificial intelligence [3,9]. Cohn et al. [9] introduced a theory which uses the connectivity between regions to reason the spatial relations between objets. Based on the theory, region connection calculus (RCC) [3] has been developed to estimate the spatial relations. Chan et al. [1] employed RCC to define various relations in volume data which are then represented using relation graph for relation-aware volume exploration. Other relation estimation and representation methods such as contour tree [12] and local histograms [7] have also been used in visualization. As opposed to RCC, these approaches cannot fully address the general spatial relations such as separate, enclose, and overlap relations in a volume. Our system adopts the approach in [1] for spatial relation reasoning for volume data because of its simplicity and robustness.

*Segmentation and User Interface.* Segmentation of three-dimensional medical volume data is a well-established problem in medical imaging. Fully automatic methods is extremely difficult because of restrictions imposed by image acquisition, pathology, and biological variation [8]. A great number of interactive approaches have been proposed in literature. They can be roughly classified into three groups: user-steered methods, user-intervened techniques, and segmentation refinement tools [4]. Our method can be treated as a segmentation refinement tool. Tzeng and Ma [13] proposed a volume visualization system that allows users to work on the cluster space and refine the clustering results interactively. Compared with other methods, our method works in cluster space and is relation-aware. It allows users to intuitively select and manipulate the clusters, whose spatial relations are clearly shown, for improving the results.

Spreadsheets have been widely used in computer graphics and visualization because of their expressiveness and scalability [6]. With spreadsheets, users can

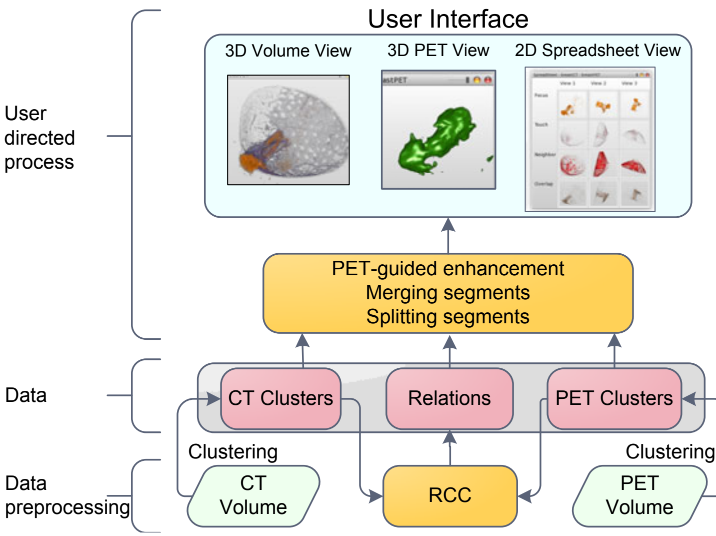



**Fig. 1.** Our segmentation refinement pipeline

create multiple visualizations of several data sets simultaneously, manipulate these visualizations together or separately, and compare and contrast them visually [2]. Jankun-Kelly and Ma [5] proposed a spreadsheet-like interface for visualization exploration and encapsulation. Our system also employs the spreadsheets paradigm, to facilitate segmentation refinement, which has not been studied before.

## 3 System Overview

Figure 1 shows our segmentation refinement process including a data preprocessing stage and a user directed stage. In the data preprocessing stage, our system creates an initial set of clusters from the input multimodal volume data, and evaluates the spatial relations between each pair of clusters using RCC. In a subsequent user-directed process, the system provides an intuitive user interface with a 3D volume view, a 3D PET view, and a spreadsheets view to help users interactively refine the clusters. The spreadsheets organize the preliminary clusters and presents them to the users in a relation-aware manner based on the estimated spatial relations between the clusters. Users can merge or split the clusters in the spreadsheets to refine the segmentation results. The system updates the spatial relations between the newly refined clusters and other clusters, and adjusts the spreadsheets layout to reflect the changes. The spreadsheets also enables PET-guided enhancement, in which users can isolate or highlight a feature of interest in a volume from CT or MRI using the data from the PET for further refinement.

## 4 Spatial Relation

Spatial relations between structures, such as the spatial composition of the structures and their spatial locations and relative positions in a volume, have significant impacts on medical image segmentation refinement. After an initial automatic clustering process, our system generates a set of clusters (or structures) from the volume data, which users can refine and improve. However, users may feel difficult to recognize the clusters if we present the clusters to them without proper visual cues. In the system, we try to address this issue by providing users with the visual cues of the spatial relations of the clusters in a volume for segmentation refinement. The previous work on spatial reasoning for volume data using *Region Connection Calculus* (RCC) [1] provides a means for an abstract and qualitative description of spatial relations between volume structures. In this section, we briefly introduce this approach, which we employ to determine the spatial relations of volume structures.

RCC is a widely used region-based approach in spatial reasoning. It can derive the spatial relations based on the connectivity $C$ between regions $S$ through a set of algebraic relations. Interested readers can refer to [3] for more details about RCC. Given a set of clusters of a volume $S = \{s_i | i = 1 \cdots n\}$, we adopt the approach proposed by Chan et al. [1] to quantitatively measure the relations of the clusters, such that the relations can be expressed by RCC in a numeric and precise manner. Their approach can identify four typical relations in the volume, i.e., separate, touch, part-of, and partially overlap. In addition, they also incorporate fuzzy logic [10] into RCC for estimating fuzzy relations between regions, as precise structure boundaries may be difficult to define. Thus, the relations are defined as:

$$R = \{((s_i, s_j), r_{con}(s_i, s_j)) | (s_i, s_j) \in S \times S\} \tag{1}$$

where $(s_i, s_j)$ is a pair of regions in $S$ and $r_{con}$ is a membership function. The portion of the regions being connected with other regions indicates the degree of connectivity. Thus, the membership function $r_{con}$ for connectivity can be defined as

$$r_{con}(s_i, s_j) = \frac{\sum_{x \in s_i \bigcup s_j} \mu_x \phi(x)}{\sum_{x \in s_i \bigcup s_j} \mu_x} \tag{2}$$

$$\mu_x = \max\{p_x(s_1), \cdots, p_x(s_n)\} \tag{3}$$

where $x$ denotes a voxel in the volume space, $\mu_x$ represents the maximum confidence at $x$, $\phi(x)$ returns 1 if it is connected to $s_i$ and $s_j$, or else 0, $p_x(s_i)$ represents the probability of $x$ that belongs to $s_i$, which can be modeled as

$$p_x(s_i) = \frac{p_x(s_i | I(x))}{\sum_{k=0}^{n} p_x(s_k | I(x))} \tag{4}$$

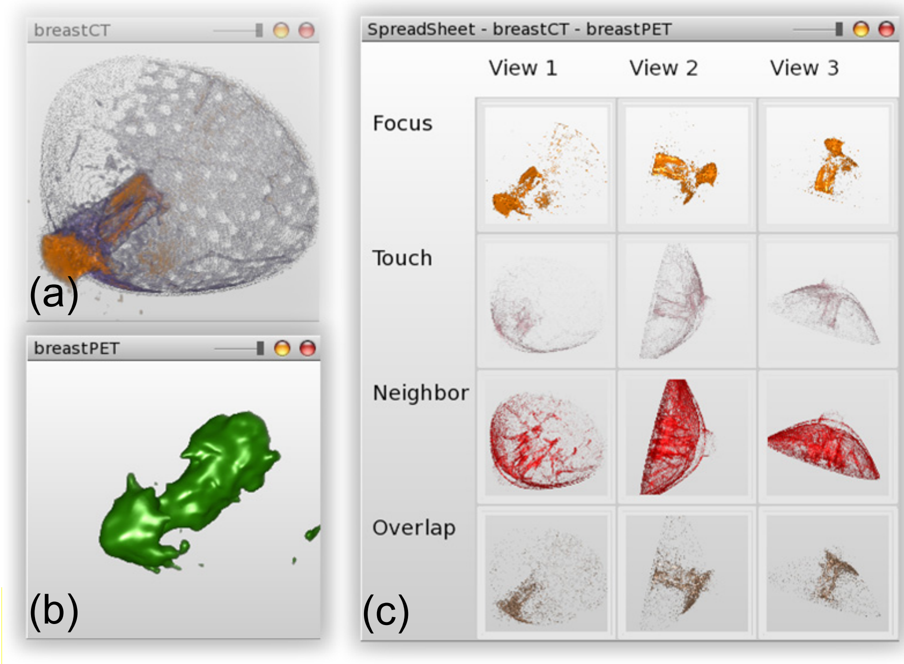



**Fig. 2.** Our user interface includes a 3D volume view (left) and a spreadsheet (right)

where $I(x)$ is the intensity at voxel $x$ and $n$ is the number of the clusters. The membership functions of other spatial relations can be derived from $r_{con}$ [3] as

$$\begin{cases} r_{dc}(s_i, s_j) = 1 - r_{con}(s_i, s_j) \\ r_p(s_i, s_j) = min_{s_k \in S}\{max\{1 - r_{con}(s_k, s_i), r_{con}(s_k, s_j)\}\} \\ r_o(s_i, s_j) = max_{s_k \in S}\{min\{r_p(s_k, s_i), r_p(s_k, s_j)\}\} \\ r_{po}(s_i, s_j) = min\{r_o(s_i, s_j), 1 - r_p(s_i, s_j), 1 - r_p(s_j, s_i)\} \\ r_{ec}(s_i, s_j) = min\{r_{con}(s_i, s_j), 1 - r_o(s_i, s_j)\} \end{cases} \quad (5)$$

where $r_{dc}, r_{ec}, r_p, r_{po}$ represent separate, touch, part-of, and partially overlap relations, respectively. With these rules and membership functions, our system can automatically determine the relations between the regions of a volume.

## 5 User Interface

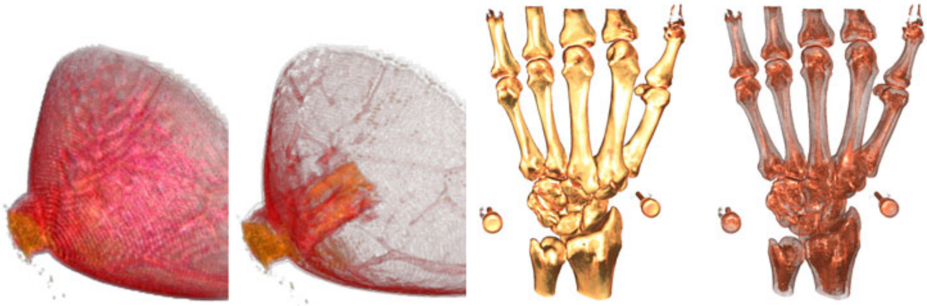
Our user interface includes a 3D fused view (Fig. 2-(a)), a 3D PET view (Fig. 2-(b)), and a spreadsheet-view (Fig. 2-(c)). The 3D fused view shows a comprehensive result by fusing the PET structure in Fig. 2-(b) and the structures selected from the spreadsheet in Fig. 2-(c). The spreadsheet can be divided into several parts, each of which shows the clustering results for one modality. Figure 2-(c) shows the spreadsheet for the CT data. The green PET structure in Figure 2-(b) is used to highlight or isolate a feature of interest in the CT data for result refinement. The first row of the spreadsheet contains a set of images for the isolated CT feature rendered using different transfer functions, lighting, or view parameters, so that users can visually compare the feature from different perspectives. The structures spatially related to the focus feature are presented in the following rows ("Touch", "Neighbor", and "Overlap") according to the estimated spatial relations with the focus feature. Thus, in the spreadsheet, each row presents a set of volume rendered images of a structure with a specific spatial relation to the focus feature but with different visual attributes. Each column, on the other hand, shows the volume rendered images of multiple features with the same visual attribute but with different spatial relations to the focus feature.

The spreadsheets allow users to interactively refine and visually compare the segmentation results. For example, given a PET volume and a CT volume, the system first creates an initial set of clusters of the data by k-means clustering. Users can identify the important regions from the initial set of PET clusters readily, which can then be used to isolate a feature of interest from the CT clusters. The spreadsheet shows the isolated CT feature in the "Focus" row. In addition, the spreadsheet also displays all other CT clusters with close spatial relations to the isolated feature at the same column as the isolated feature. Users can select multiple structures in the spreadsheet and merge them into one structure, or split one structure into multiple structures. After the merge or split operations, the affected structures are removed, and the newly created structures are inserted into the spreadsheet according to the spatial relations. This can greatly facilitate segmentation refinement. The spreadsheets are also capable of displaying all intermediate segmentation results side by side using different visual attributes, thus allowing users to visually compare the quality of each segmentation result from different perspectives. For instance, given a column of the spreadsheets, users can make several duplicate columns and apply different visual attributes to each column. Figure 2-(c) shows such an example where three columns of the segmentation results are visually compared from three different view angles.

## 6 Experimental Results

In this section, we demonstrate the effectiveness of our system using a breast cancer data set and a wrist data set.

*Breast Cancer.* The first data set used in this paper is a 150x150x70x32bits breast cancer volume. Radiologists usually need to see the tumor as well as its surrounding structures. However, without careful segmentation refinement, the spatial relations between the tumor and other structures such as ducts are often unclear in a traditional 3D volume rendered image (Fig. 3-(a)), because other irrelevant tissues such as subcutaneous fat, mammary hyperplasia and the lobules are also shown. With our system, the most relevant structures can be easily detected, compared, and refined in the spreadsheets. Fig. 3-(b) shows a volume rendered image of a refined result where the irrelevant structures that can be identified readily in the relation-aware spreadsheets are removed. In this case,



(a) (b) (c) (d)

**Fig. 3.** (a) volume rendered image of a breast cancer volume where spatial relations between the tumor and its neighboring tissues are difficult to identify; (b) image refined from (a) by the spreadsheets where the spatial relations are clearly shown; (c) image of a wrist volume where the inner bone layer is lost; (d) image refined from (c) where the missing inner bone layer is recovered and highlighted in red

the lactiferous ducts connected to the tumor are more important than the fat tissue, lobules, and mammary hyperplasia separated from the tumor. With the spreadsheets view, users can immediately select and refine the desired structures, and then generate a view which preserves the most important context. These results show the effectiveness of our space-aware segmentation procedure using the spreadsheets.

*Wrist.* The second experiment was conducted to demonstrate that our spreadsheets system allows users to intuitively explore the data. The wrist volume we used in this experiment is a 512x512x512x32bits data set. Our collaborators are interested in the bone structure and want to examine the erosion effect on the bone caused by wrist cancer. Usually, users have to fine-tune transfer function to visualize different layers of bones. In this data set, there are two layers (clusters) in the hand bone. If we assign them the same opacity, the outer layer will occlude the inner layer. The result is shown in Fig 3-(c). Using relation-aware spreadsheets, the "enclose" relation between layers can be easily revealed. Such information helps users set a higher opacity for inner structures than for outer structures. Fig 3-(d) shows the refined result.

## 7 Conclusion

This paper presents relation-aware spreadsheets for efficient volume segmentation and visualization based on region connection calculus. With the system, users can visually compare the segmentation results from various perspectives (using different visual attributes) and interactively refine them. A PET-guided segmentation procedure based on the spreadsheets is introduced for multimodal data segmentation. The current system supports only the merge and split refinement operations, which may not be sufficient for other complex image data sets. In the future, we plan to develop additional operations tailored to the needs of new applications. We also intend to conduct a user study with medical physicians and radiologists to improve this spreadsheet-based system according to our findings.

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