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• **MOOP** •

Rapid and High-quality 3D Fusion of Heterogeneous CT and MRI Data for the Human Brain

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Data obtained from computed tomography (CT) and magnetic resonance imaging (MRI) that describe the human brain are commonly used in medical research and diagnosis [1]. CT data are used to efficiently present high-density features, whereas MRI data are better suited for soft-tissue presentation [2]. The complementary functions of CT and MRI may be used to further develop medical care procedures and brain exploration. CT and MRI were combined to realistically depict the diagnostic, anatomic, and pathological information of the auditory and vestibular systems [3]. For brain tumor surgery, medical professionals often prefer to simultaneously visualize high-density structures (e.g., the skull structure) using CT and soft-tissue structures (e.g., the size and shape of tumors) using MRI to successfully determine the best craniotomy position [2].

1 Related Work

The technique of volume rendering includes three stages: data preprocessing, lighting model construction, and image generation.

The fusion accomplished in the data preprocessing stage is accurate but complicated because multiple types of data obtained from a single sampling point are merged, including the density values and computable gradients. Mutual information was used to obtain three-dimensional (3D) fusion information, which was then integrated into a common framework using extensive computation [4]. Based on the developed method, a fully automatic scheme for multimodal heterogeneous data visualization was successfully designed [5].

Fusion in light accumulation comprises two methods: fusion of the color and opacity of different heterogeneous data, followed by accumulation, and separate accumulation of heterogeneous data, followed by fusion. X. Liao et al. [6] proposed a 3D fusion algorithm for positron emission tomography (PET) and CT with a grayscale difference.

The simplest and most intuitive form of fusion is performed in the image-generation stage. Fusion is commonly achieved via color blending; however, traditional layered blending performed using color blending with transparency has certain limitations [7]; it can at most display only four layers. To ensure an accurate visual representation, Kuhne et al. [8] proposed a color perception method that blends two colors when the color tone changes.

2 Methods

Visualization of CT Volume Data. For the visualization of the CT volume data of the brain, tissues are usually divided into three layers: skin, muscle, and bone [9]. To minimize the overlap between

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two adjacent substances, the used transfer function can be described as a multiple trapezoid, each representing one of the tissue layers.

Visualization of MRI Volume Data. The visualization of MRI data is more complicated than that of CT data; we describe its main processing stages as follows.

(1) Separating the tissue

First, the data of the human brain are extracted using the brain extraction tool (BET)[1)], which automatically performs segmentation based on the active contour model and removes the non-brain tissue from the head image.

Second, image segmentation and tissue separation are performed. To spatially normalize the extracted brain by dividing the 3D image into different types of tissue, the Features from Accelerated Segment Test method is used. MRI data are divided into those representing the cerebrospinal fluid, the gray matter, and the white matter; then, the spatial intensity is corrected. To overcome the overlap in density intervals exhibited by some tissues, linear transformation is used to map three types of tissues to non-coinciding density intervals.

Finally, the above segmented tissues are fused . The center of gravity of the obtained three tissues is taken as the origin of the brain's center of gravity, and the position data are transposed to three axes, (x, y, z); then, each tissue is filled using a deformable surface model. Ultimately, the three types of local brain tissues are combined to obtain the MRI volume data values for the entire brain.

(2) Designing the MRI transfer function

Each trapezoid transfer function in the MRI datasets expresses one band or a layer of the segmented MRI brain data that has no overlapping region. The three bands correspond to the cerebral spinal fluid (CSF), white matter, and gray matter. Define the j-th $(j = 1, 2, \cdots, K)$ band as $C_j = [c_{j,0}, c_{j,1}, c_{j,2}, c_{j,3}]$ with a maximum opacity A_j and color T_j. Different bands correspond to different tissues; therefore, $C_m (C_m = [c_{m,0}, c_{m,1}, c_{m,2}, c_{m,3}]$ and C_{m+1} have no overlapping region. Herein, $m = 1, 2, 3$ and the sample point P_i has the opacity α_i as follows:

$$\alpha_i = \begin{cases} g(\frac{f_i - c_{m,0}}{c_{m,1} - c_{m,0}})A_m, & f_i \in [c_{m,0}, c_{m,1}], \\ A_m, & f_i \in [c_{m,1}, c_{m,2}], \\ [1 - g(\frac{f_i - c_{m,0}}{c_{m,1} - c_{m,0}})]A_m, & f_i \in [c_{m,2}, c_{m,3}]. \end{cases} \tag{1}$$

where $g(t) = t^2(3 - 3t)$ is the cubic function of the value in $[0, 1]$ and f_i is the scalar value corresponding to P_i on the viewing ray V. The color of P_i can be obtained from the maximum color T_m of the m-th layer, C_m, where $c_i = \alpha_i T_m$. The accumulated opacity and color can be obtained using the conventional ray-casting algorithm:

$$\begin{cases} c_i^* = c_{i-1}^* + (1 - \alpha_{i-1}^*)\alpha_i c_i, \\ \alpha_i^* = \alpha_{i-1}^* + (1 - \alpha_{i-1}^*)\alpha_i. \end{cases} \tag{2}$$

Three-Dimensional Fusion. 3D fusion includes the processes of unifying the data size, fusing the data, separating heterogeneous data, mixing transfer functions, and CUDA-based GPU ray-casting volume rendering. The specific process is described as follows:

(1) Unifying the volume data scale.

The size of the data obtained using CT and MRI is inconsistent; this issue is addressed via interpolation, in which a new pixel is inserted between two neighboring pixels and assigned their average value. For CT data with a resolution of $512 \times 512 \times 23$ and MRI data with a resolution of $256 \times 256 \times 23$, the MRI data can be doubled in the x and y directions by interpolating new pixels.

(2) Volume data fusion.

The two heterogeneous datasets have different types and formats; however, the same essential information is stored by the datasets in the form of scalar values. For data fusion, the MRI tissue is filled in the blank part of the CT, where its value is equal to zero.

If $\mathrm{vol}(i, j, k)$ is the voxel value obtained at position (x, y, z) and $f(\mathrm{vol}(i, j, k))$ is the fused value at the same position, $g(vol(i, j, k))$ and $h(\mathrm{vol}(i, j, k))$ are defined as the values of CT and MRI at (x, y, z), respectively. Then, the fused volume data are expressed as follows:

$$f(\mathrm{vol}(i, j, k)) = \begin{cases} h(\mathrm{vol}(i, j, k)), & if\ g(\mathrm{vol}(i, j, k)) = 0. \\ g(\mathrm{vol}(i, j, k)), & else. \end{cases} \tag{3}$$

(3) Separating CT and MRI data

The voxel values representing different information in the CT and MRI coordinate systems; therefore, these values conflict if placed in a unique coordinate system. To solve this problem, a separation method based on the translation of volume data values is proposed for some tissue. The data values for MRI tissues are differentiated from those of CT using the following expression.

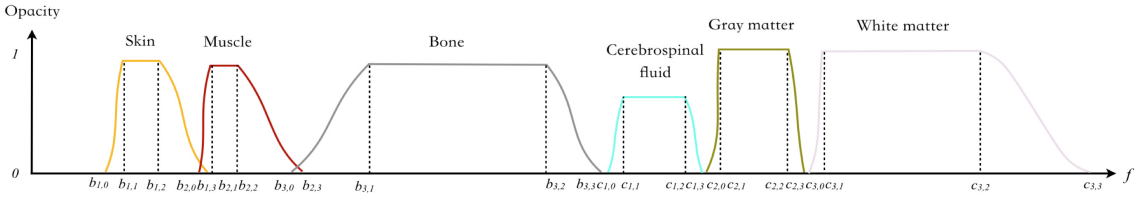
$$f(\mathrm{vol}(i, j, k)) = h(\mathrm{vol}(i, j, k)) + max(g(\bullet)), \quad if\ \mathrm{vol}(i, j, k) \in MRI. \tag{4}$$

Here, $max(g(\bullet))$ is the maximum value obtained by CT.

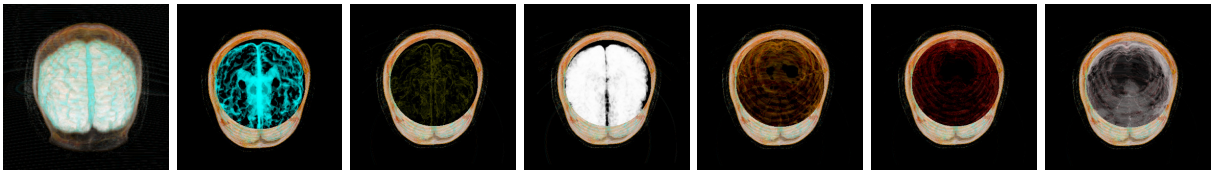
(4) Implementing a hybrid transfer function.

Three trapezoid transfer functions of MRI are translated to the next of CTs as shown in the last

1) http://poc.vl-e.nl/distribution/manual/fsl-3.2/bet/index.html



(a) Hybrid transfer function



(b) fused image (c) CSF (d) gray matter (e) white matter (f) skin (g) muscle (h) bone

Figure 1 Hybrid transfer function and results.

three bands of Figure 1(a), thereby creating a hybrid dataset. Scalar volume values are shown on the x-axis. The demarcation point between MRI and CT represents a boundary between data corresponding to a CT tissue and that corresponding to an MRI tissue, i.e., $max(g(\bullet))$ in Eq. 4.

(5) CUDA-based ray-casting volume rendering.

After the fusion volume data and the hybrid transfer function are transferred to the GPU texture buffer, the thread index needs to be determined in CUDA. If the viewing ray and the volume intersect, the volume is resampled. Before accumulating each sample point, the heterogeneous data belonging to the current sample must be determined; then, its opacity and color are obtained using the hybrid transfer function.

(6) Layered display.

To display inner tissue of the brain, a layer filter is defined and the volume dataset is divided into a region of interest (ROI) and non-ROI. ROI is a frustum intersection based on the projection plane and the entire volume dataset. The opacities of the selected and other layers are non-zero and zero, respectively. The non-ROI is drawn via a traditional GPU light transmission volume rendering.

The fused results are shown in Figure 1(b), and the different layers of the two heterogeneous datasets are displayed in Figures 1(c)(h).

A general evaluation of the proposed method was provided by Dr. Zhu et al. at Peking University Third Hospital. The proposed 3D fusion method was found to be particularly important for clinical judgments of the nature of diseases and the corresponding range of lesions. This method allows observing either the white matter or the gray matter, which is of great significance in the diagnosis and treatment of brain atrophy, hydrocephalus and other conditions. The fusion of the bone and brain tissue data is crucial to assess the fracture site and craniocerebral injury caused by cranial fracture. Also, the proposed method provides a good model for the teaching of brain anatomy.

Supporting information Videos and other supplemental documents. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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