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TECHNICAL REPORT

Information-based Transfer Functions for Multimodal Visualization

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Abstract

Transfer functions are an essential part of volume visualization. In multimodal visualization at least two values exist at every sample point. Additionally, other parameters, such as gradient magnitude, are often retrieved for each sample point. To find a good transfer function for this high number of parameters is challenging because of the complexity of this task. In this paper we present a general information-based approach for transfer function design in multimodal visualization which is independent of the used modality types. Based on information theory, the complex multi-dimensional transfer function space is fused to a well-known 2D transfer function with a single value and gradient magnitude as parameters. Additionally, a quantity is introduced which is used for achieving better separation of regions with complementary information. The benefit of the new method in contrast to other techniques is a transfer function space which is easy to understand and which provides a better separation of different tissues. The usability of the new approach is shown on examples of different modalities.

Keywords: Multimodal visualization, transfer functions, information-based classification, information theory, point-wise mutual information, complementary information.

1 Introduction

Volume visualization is a technique which enables physicians and scientists an insight into complex volumetric structures. In medical applications this helps to provide a diagnosis. Volume data sets acquired with different imaging modalities are used for different examinations. Currently, the trend towards information acquisition using data sets from multiple modalities is increasing in order to facilitate better medical diagnosis. As different modalities frequently carry complementary information, our goal is to combine their strengths providing the user with a consistent interface.

The different imaging modalities can be divided into two groups: modalities which show anatomical structures and modalities which show functional features. Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are examples for modalities which show anatomical structures. In contrast to these, e.g., Positron Emission Tomography (PET) shows functional features of the body. In general the spatial resolution of anatomical modalities is better than for functional modalities. Therefore a common combination of modalities is between anatomical and functional modalities. The functional modality provides the information about the processes inside the body and the anatomical modality is used to show the inner structure of the body. Also the combination of two anatomical modalities like CT and MRI is often used for diagnosis. Both of them show the inner structure of the body but have different contrast for different tissues. The brain, e.g., has a higher contrast in MRI whereas bones can be seen in CT.

Normally a side-by-side view is provided in medical applications for the inspection of the different modalities. A physician can simultaneously scroll through both registered modalities. This practice has two main drawbacks. One drawback is the failing of a direct visual combination of the data. A physician has to mentally overlap the two images to get the corresponding points of one modality in the other one. A second drawback is the restriction to a 2D visualization because in 3D it would be difficult to find corresponding regions in both data sets. These drawbacks can be eliminated by the direct fused display of both data sets together in a multimodal visualization.

The problem with such a multimodal visualization is the density of information in space. For each sample point, there is one value for each modality. Even for volume visualization of a single modality, it is hard to handle the dense information. Two steps are necessary in order to get an expressive visualization. First representative sample points are classified to reduce the density. In

a second step the values have to be mapped to optical properties which can be displayed. Both of these steps can be done at once by a transfer function. It defines optical properties, such as color and opacity, for certain values. The transfer function can be controlled by the user to change the appearance of the result image. The more input values are taken to classify a sample point and assign optical properties to it, the harder it is for the user to find a good transfer function. This is the main problem of multimodal visualization because there are at least two values involved. Additional derived quantities further increase the dimensionality of the transfer function domain.

In this paper, we introduce a novel concept for defining transfer functions in multimodal volume visualization. Our method aims to reduce the complexity of finding a good transfer function. A new transfer function space is provided which can be controlled by the user in an intuitive and familiar way. This is done by using the information contained in the distribution of values in both modalities. Based on this information, the values of both modalities are fused. This results in a fused transfer function space with a single value and a single gradient magnitude as parameters. A measure for the complimentary information of both modalities is used as additional parameter for more user control and a better separation of different tissues.

In Section 3 the new approach is described in detail. We show how the retrieved information of the value distribution can be used to generate the transfer function space. Section 4 briefly describes an efficient implementation of the new method. The usability of the new method is shown in Section 5 with some results generated from different modalities. Conclusions and ideas for further work are given in Section 6. First an overview over related works on this topic is given in the following section.

2 Related Work

The origin of multimodal volume visualization can be found in computer vision. In this research field techniques have been used for decades to generate a fused image out of two individual images from the same scene. The simplest image fusion method is to take the average of two input images. The penalty of this method is a reduction in contrast. To solve this problem Toet [18] introduced a fusion technique based on the Laplacian pyramid. One of the improvements of this technique, based on wavelet transforms, was introduced by Li et al. [13]. In general the goal of all image fusion techniques is to generate a fused result image which contains the most relevant parts of both images without redundant information.

For multimodal visualization the techniques from image fusion cannot be used directly because each change in one of the input images would result in the generation of new pyramids. So a small change in one of the transfer functions of one modality would require a new fusion. This would take too long to use this technique for an interactive visualization. Therefore different techniques for multimodal visualization have been developed.

All these methods for multimodal visualization can be classified - as described by Cai and Sakas [2] - according to the level in the rendering pipeline in which they are applied. In the illumination-model-level intermixing optical properties are assigned to a combination of values from the different modalities. The accumulation-level intermixing fuses the values after optical properties are assigned to each modality individually. In the image-level intermixing the fusion is done after a 2D image has been rendered for each modality.

The image-level intermixing is the simplest way for the fusion of two modalities, but it has the disadvantage that the 3D information is lost. Therefore this fusion technique is typically just applied on single slices of the volume. Several techniques have been developed for this purpose, such as alternate pixel display, linked cursor, and color integration procedures [15, 17, 19].

Due to the increasing speed of computers and graphics hardware volume rendering became more popular and, therefore, also the multimodal fusion could be done in the volume space. The first methods were based on surface models. Levin et al. [11] generated a surface model from an MRI scan and mapped the PET-derived measurement onto this surface. Evans et al. [3] generated an integrated volume visualization from the combination of MRI and PET. The mentioned and other works focused mainly on the combination of anatomical and functional images. A more general approach for the fusion of all combinations of modalities was introduced by Zuiderveld and Viergever [21]. For this method an additional segmentation of the volumes is necessary to decide which one to show at a given sample point. A more recent work by Hong et al. [4] describes how fusion techniques in this intermixing level can be efficiently implemented using the graphics hardware.

More sophisticated but more complex methods for multimodal visualization are directly applied in the illumination-model-level. The intermixing in this level directly generates optical properties from the combination of the values and additional properties of the two volumes at a single sample point. A case study for the rendering of multivariate data where multiple values

are present at each sample point was done by Kniss et al. [7]. In this work the idea of multi-dimensional transfer functions to assign optical properties to a combination of values was used. Akiba and Ma [1] used parallel coordinates for the visualization of time-varying multivariate volume data. Multimodal visualization of medical data sets by using multi-dimensional transfer functions was shown by Kniss et al. [10]. The classification is done on the basis of the dual histogram which is a combination of the values of one modality on one axis, and the values of the other modality on the other axis. The interpretation of a dual transfer function space based on this dual histogram is difficult because it is quite different to well-known histograms from a single modality. Therefore, it is also hard to find a good transfer function with trial-and-error. Kim et al. [5] presented a technique which simplifies the transfer function design by letting the user define a separate transfer function for each modality. The combination of them defines the two-dimensional transfer function. The problem with this technique is the loss of information by reducing the multi-dimensional transfer function to two 1D transfer functions.

As mentioned before, the assignment of optical properties in multimodal visualization is dependent on more than one value. When the whole information space is used then a multi-dimensional transfer function is needed. In general it is a non-trivial task to define a multi-dimensional transfer function because of its complexity. Nevertheless, multi-dimensional transfer functions are commonly used for volume visualization. 2D transfer functions were first introduced by Levoy [12]. In addition to the data value the gradient magnitude was used as second dimension to classify a sample point. Due to the fact that the design of a 2D transfer function is non-trivial, methods were developed, to support this task. Kindlmann and Durkin [6] introduced a semi-automatic approach for the visualization of boundaries between tissues. Pfister et al. [14] gave an overview on existing techniques to support the design task of transfer functions. The direct manipulation widgets introduced by Kniss et al. [8] can be used to find regions of interest in the multi-dimensional transfer function space in an intuitive and convenient way. In other work, Kniss et al. [9] describe a way to efficiently represent multi-dimensional transfer functions by Gaussian functions instead of storing a multi-dimensional lookup table.

For the definition of the multi-dimensional transfer functions, in addition to the values from the two volumes, further properties can be used to better distinguish between tissues. In this paper, these additional properties are retrieved by methods from information theory founded by Shannon [16]. He described how the probability of occurrence of a signal can be used to define the information content of the signal.

In imaging, information theory is used in different areas. Image registration is one of these areas. Wells et al. [20] maximized the mutual information to find a good registration position for two images or volumes. This idea is the basis for the information-based part of the new approach in this paper.

3 Information-based Transfer Functions for Multimodal Visualization

In this section we introduce a novel transfer function space for multimodal visualization. The aim of all steps described here is the design of a transfer function space which is as simple as possible but still is able to separate different tissues. The main contribution of the new approach is the use of methods from information theory for the design of this transfer function space. Figure 1 shows all necessary processing steps to classify a tuple of input values (f_1, f_2) in this new transfer function space, defined by f_{fused}, $\left|\nabla f_{fused}\right|$, and δ, with optical properties. The further sections describe these processing steps in detail.

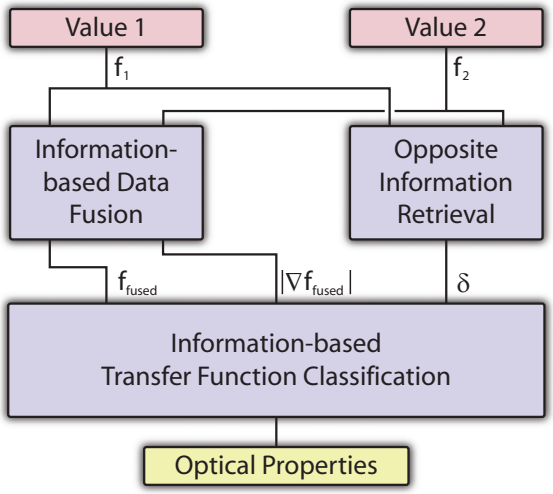


Figure 1: Processing pipeline for the classification of sample points in a multimodal visualization by an information-based transfer function.

In Section 3.2, we describe how the input values can be fused to get just a single value for each pair of input values. Section 3.3 introduces an additional property which

is used to refine the classification of different tissues through the transfer function. Finally, Section 3.4 describes how the fused values are used to define the new transfer function space and how the additional property is used to influence the classification. For Section 3.2 and Section 3.3, methods from information theory are used. For this we need probabilities for the occurrence of certain values. How these probabilities can be estimated is described in the following section.

3.1 Probabilities in Volume Data

Information theory, which is used for the new information-based approach, is a concept which quantifies the information content of a message. This quantification is based on the frequency of data. An example for the quantity of data can be found in a language. Each language consists of characters. The frequency of these characters is not equal. Some characters occur more often than others. This frequency measurement is the basis for information theory.

To apply the methods of information theory on volume data sets we have to consider the value at a certain position inside the volume as discrete random variable. Hence, the occurrence of a certain value is associated with a probability. Similar to characters in a language not all values occur with the same frequency and, therefore, the probability of their occurrence is different.

The simplest way to estimate the probability of a certain value is done by counting its occurrence in the whole data set and by dividing this number by the total number of points in the volume. We assume the volume is given as a set of regularly arranged grid points. To do this for all values a histogram is generated. In a histogram the count of a bin is increased if a value falls in the range of this bin. When the counted numbers for all bins are divided by the total number of points in the volume, we get a probability distribution $P(f)$ which returns a probability of occurrence for each value f.

For retrieving the information content of the joint occurrence of two values from two modalities another probability distribution is needed. It returns a probability $P(f_1, f_2)$ for each tuple of values f_1 from modality 1 and f_2 from modality 2, also referred to as joint probability. Equally to the probability for the occurrence of only one value this probability distribution can also be estimated by a histogram. Due to the dependency of two values, the histogram is defined in 2D. This histogram is often referred to as dual histogram. Figure 2 shows an example of such a histogram. Dark regions in this histogram denote a higher probability as brighter regions

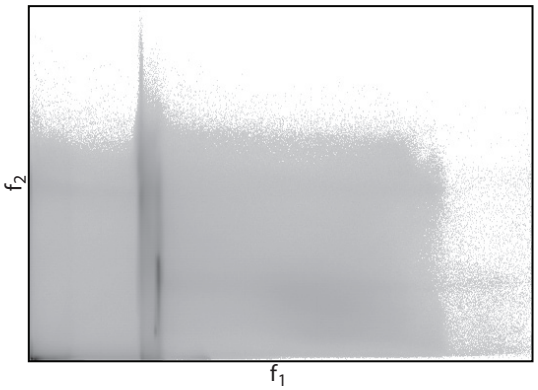


Figure 2: Example of a dual histogram which is needed to estimate the joint probability distribution.

and, therefore, these combinations of values occur more often.

In the context of the joint probability $P(f_1, f_2)$ the probability of just a single value $P(f_1)$ is referred to as marginal probability. These two types of probabilities are further used in the following sections to generate a new transfer function space based on the methods of information theory.

3.2 Information-based Data Fusion

At some point in a multimodal visualization pipeline the information from both data sets has to be combined, as each sample point can only have one color and opacity. The idea behind the information-based data fusion is a fusion which loses as little as possible information. Information can be measured concerning the quality or the quantity of the data. To be measured by the quality, user interaction would be necessary to decide which region is important in which modality. This would be a good measurement but it is a time-consuming process and has to be repeated for each new data set.

A second way to measure the information is based on the quantity, i.e. frequency, of the data. For this measurement the methods of information theory are used. The idea behind this measurement is that values which occur very often have less information than values which occur not so often. For medical data sets this can be interpreted that larger regions with the same value, such as the background, contain less information than smaller regions, such as border areas or small tissues. The information content can be expressed by the following equation:

$$I(f) = -log_2(P(f)) \tag{1}$$

The probability $P(f)$ in this equation returns a probability of occurrence for a certain value f. Through the log_2 function the information $I(f)$ is high for values with a low probability. This information content can be calculated for both values represented at a certain sample point. The fusion should then be done in a way to weight the value with more information content higher the value with less information content. The following equation describes a function which returns a single value which describes this weighting:

$$\gamma(f_1, f_2) = \frac{I(f_2)}{I(f_1) + I(f_2)} \tag{2}$$

The γ value is 0 when the second modality has no information. It is 1 if the first modality has no information. For a value of 0.5 both modalities contain the same amount of information for a given pair of values. Figure 3 shows an example where the γ value is calculated for two modalities according to Equation 2. The values in the matrix represent the calculated γ values for the given probability of both modalities, as shown on the left side and at the top. The background color indicates which modality has more information for a pair of values. Modality 1 has more information when the background is reddish, modality 2 when it is bluish respectively. The saturation of the color encodes the dominance of a modality.

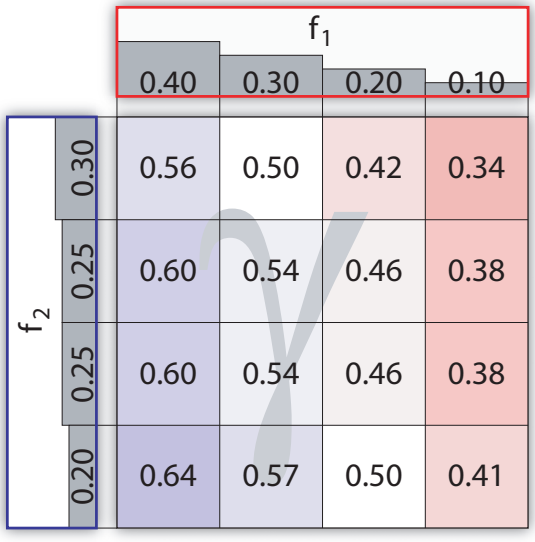


Figure 3: Diagram shows the relation between the probability of occurrence of a value in one modality and the γ value. The color in the diagram indicates which modality has higher information for a given combination of values.

With Equation 2 we get a number for each pair of values which can directly be used for the weighing in the fusion step. The fusion of two values, f_1 and f_2, is simply done by the following equation:

$$f_{fused} = (1-\gamma) * f_1 + \gamma * f_2 \tag{3}$$

The fused value f_{fused} is close to the value of one modality when this modality contains more information than the other modality. Therefore, points with high information content in just one modality are only slightly modified in contrast to their original value. This property makes it easier to find such points in the new transfer function space because they have almost the same value as they would have in volume visualization of this modality alone. For points with almost the same information content in both modalities a new value is calculated which lies between the two original values.

The gradients of both modalities are fused in the same manner as the values:

$$\nabla f_{fused} = (1-\gamma) * \nabla f_1 + \gamma * \nabla f_2 \tag{4}$$

The fusion of the gradients is needed for the shading calculation as well as for classification by the transfer function based on gradient magnitude. The result of the fusion is a single value for each sample point like for the visualization of a single volume. This fused value together with the magnitude of the fused gradient can be used for the classification by a transfer function. Unfortunately some tissues are overlapping in this fused transfer function space. Therefore an additional parameter is introduced in the following section which supports the transfer function design for a better separation of different tissues.

3.3 Opposite Information Retrieval

In the previous section, with the γ value, a quantity was calculated which indicates which of the two values has more information. In this section we will define a quantity which indicates the information contained in the joint occurrence of two values rather than the information contained in the occurrence of a single value. This new quantity will be used as another attribute for the classification of a sample point with optical properties. The goal of the new attribute is to extract regions with high opposite information content from regions with almost the same information content in both modalities. For the classification with optical properties this property can be used for a better separation of different tissues.

For image and volume registration the maximization of the mutual information is a common tool to find a good registration position. In this context the best registration position is found when the mutual information is at a maximum. This means that in this position both data sets contain the lowest possible opposite information. The mutual information is a quantity for the whole data set. In contrast the point-wise mutual information (PMI) is a quantity for the mutual information for a certain combination of points. It is defined by the following equation:

$$PMI(f_1, f_2) = log_2\left(\frac{P(f_1, f_2)}{P(f_1) * P(f_2)}\right) \tag{5}$$

The PMI is 0 when a pair of values occurs exactly as frequently as one would expect by chance. This is the case when both values are statistically independent from each other and the joint probability $P(f_1, f_2)$ is exactly the product of both marginal probabilities $P(f_1)$ and $P(f_2)$. If they occur together more frequently as one would expect by chance then the result of the calculation is greater than 0. Conversely, the value is lower than 0 if a pair of values occurs less frequently as one would expect by chance. By the definition of Shannon this case contains more information than a result value greater than 0 because the occurrence is less frequent. For a joint probability $P(f_1, f_2)$ of 0 the PMI is by definition 0. For all other probabilities the PMI can be normalized to a value between 0 and 1 by subtracting the lower bound ($P(f_1) = 1$ and $P(f_2) = 1$) from the PMI and dividing it by the difference between the upper bound ($P(f_1) = P(f_1, f_2)$ and $P(f_2) = P(f_1, f_2)$) and the lower bound:

$$PMI_{norm}(f_1, f_2) = \frac{PMI(f_1, f_2) - log_2(P(f_1, f_2))}{log_2(\frac{1}{P(f_1, f_2)}) - log_2(P(f_1, f_2))} \tag{6}$$

If this equation returns a value close to 0 then the pair of values has more information than if it would return a value close to 1. To get a high value for pairs of values with high information content we define a new quantity δ as an inversion of PMI_{norm}:

$$\delta(f_1, f_2) = 1 - PMI_{norm}(f_1, f_2) \tag{7}$$

Figure 4 illustrates two slices of two different modalities. The different regions, labeled with capital letters, have different colors to symbolize regions of different values in both modalities. The red crosses are sample points for which the δ value should be calculated. For the sample point S_1 the involved marginal probabilities ($P(f_1)$ and $P(f_2)$) are rather low because only a small area (C_1 and C_2) has the same value in both modalities. For the sample point S_2 the marginal probability in the second modality is higher because the sample point lies in a larger area B_2. The joint probability $P(f_1, f_2)$ is the same for both sample points because the combination of C_1 and C_2 occurs exactly as often as the combination of D_1 and B_2. By calculating the δ values with these probabilities we, however, get a smaller value for the sample point S_1 than for the sample point S_2.

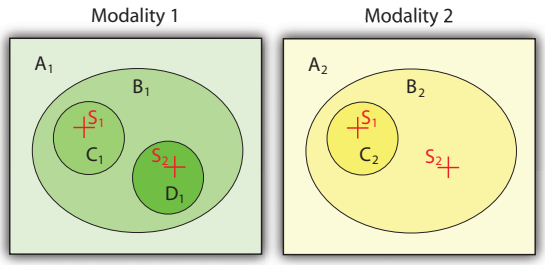


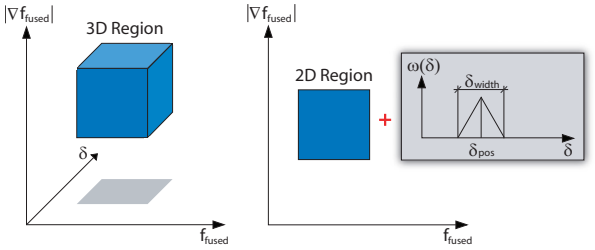
Figure 4: Example of slices of two different modalities to explain how the δ value is affected by the value distribution. The regions with different colors indicate regions with different values in the modalities. S_1 and S_2 are sample points for which the δ value is calculated.

This example can be interpreted in a way that for sample point S_1 both modalities contain correlated information whereas for S_2 modality 1 complements the information of modality 2 because the region D_1 is only represented in modality 1. This means that the δ value responds with a high value for regions with high opposite information content. So this value can be used to separate tissues which only show up in one modality from tissues which are present in both modalities. It can be seen as a quantity which indicates the difference of information content in both modalities at each sample point. Noise in the data sets does not influence the δ value. It flattens the probability distribution function but the relation between the probabilities does not change and, therefore, the δ value is not affected. The following section describes how this property can be integrated in the classification process.

3.4 Information-based Transfer Function Classification

In the previous two sections we described how methods from information theory can be used to generate a fused value and fused gradient as well as an additional property δ which indicates the opposite information. These values together will be used now for the assignment of optical properties.

Due to the existence of three values (f_{fused}, $|\nabla f_{fused}|$, δ) for each sample point the classification could be done in a 3D space. For every triple of values optical properties would be assigned. This approach is shown in Figure 5(a). The problem with this approach is the complexity of the transfer function design. A 3D region for the assignment of certain optical properties is defined by a 3D position as well as an arbitrary 3D shape. With this degree of freedom for the definition of a 3D region it is hard to find a good transfer function.



(a) 3D transfer function space

(b) 2D transfer function space and δ windowing function

Figure 5: Transfer function space is converted from 3D (a) to 2D (b). Additionally, a simple windowing function for the δ value is used to modify the optical properties of each 2D region.

Therefore, we reduce the degree of freedom by defining a region only in the 2D transfer function space (f_{fused}, $|\nabla f_{fused}|$). This task is easier because the 2D space is already well-known from volume visualization of only one volume. Additionally, for each region a simple windowing function is defined for the δ value. The selection of a windowing function for this task results from the fact that the δ values for points of one tissue are in a certain value range. To extract this tissue only points with a δ value in this range should be selected. A windowing function is easy to adjust to a certain value range and, therefore, is perfect for this purpose. The windowing function can be expressed by the following equation:

$$\omega(\delta) = max\left(\left|1 - \frac{\delta - \delta_{pos}}{0.5 * \delta_{width}}\right|, 0\right) \qquad (8)$$

The parameters δ_{pos} and δ_{width} define the position and shape of the windowing function $\omega(\delta)$. In Figure 5(b) an example of a windowing function can be seen. The windowing function returns a value between 0 and 1. The original opacity α, assigned according to a 2D region in the transfer function space, is multiplied with this value to fade out points with a low return value of this windowing function. In Figure 5(b) the separation in a 2D region and a corresponding windowing function is shown.

The definition of a transfer function can be done in two steps. In a first step a region in the transfer function space is defined. In a second step the windowing function for the δ value can be adapted for a better separation of the tissue of interest. With this two-step approach the complexity of the transfer function design is reduced. The definition of a region in the fused 2D transfer function space is similar and thus well-known to the design of a 2D transfer function for single volume visualization.

In the following section some aspects of the implementation are briefly described. Section 5 presents results to explain the benefits of the new method in contrast to an already existing technique for multimodal visualization.

4 Implementation

For a fast and efficient volume rendering it is necessary to do as many calculations as possible in a pre-process. The most time-consuming part of the whole process is the generation of the dual histogram and the two individual histograms of both modalities for the estimation of the probabilities. This can be done before the rendering because the histograms are static for two given volume data sets and do not change during the rendering process. The histograms are used to calculate the γ and δ values as described in the previous section. Each of these values can be stored in a 2D lookup table. They also do not change for two given volume data sets.

Figure 6 shows the processing steps for each sample point during the rendering process. The processing steps with a bluish background are lookups and the processing steps with a reddish background are calculations. As first step lookups in the a priori generated γ and δ lookup tables are done. The γ value is used to fuse the two input values as described in Section 3.2. With the fused value and the magnitude of the fused gradient a lookup in the lookup tables of the transfer function is done. One lookup table stores the color c and opacity α for each point in the transfer function space. The second lookup table stores the parameters δ_{pos} and δ_{width} of the windowing function. The color c of the 2D transfer function is directly used for further processing steps, such as shading. The opacity α is modified by the windowing function according to the parameters δ_{pos} and δ_{width} as well as the δ value. As output of this calculation step we get a modified opacity α_{mod}.

The transfer function editor for the 2D transfer function is based on the work of Kniss et al. [8]. The user can

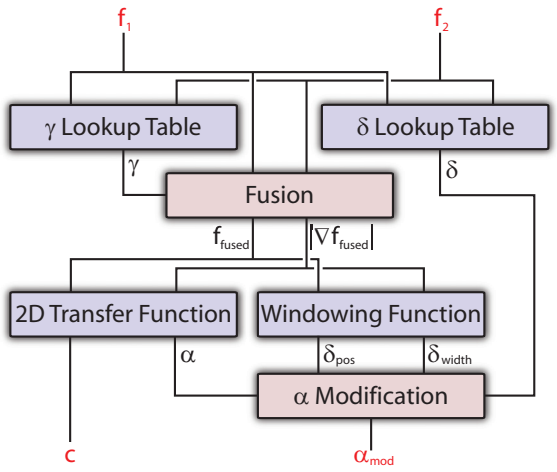


Figure 6: Overview over the processing steps for each sample point during the rendering process. Nodes with a reddish background are calculation steps and nodes with a bluish background are lookups. The output of the processing pipeline is a color c and an opacity α.

define regions in the transfer function space and assign a color and opacity to these regions. The parameters for the windowing function for each region can be modified with an intuitive mouse interaction. The δ_{pos} value is changed by the movement of the mouse in vertical direction and the δ_{width} value by a movement in the horizontal direction. For each change of a region the lookup table for the transfer function and the windowing parameters have to be updated to directly see the result of the modification in the rendering result.

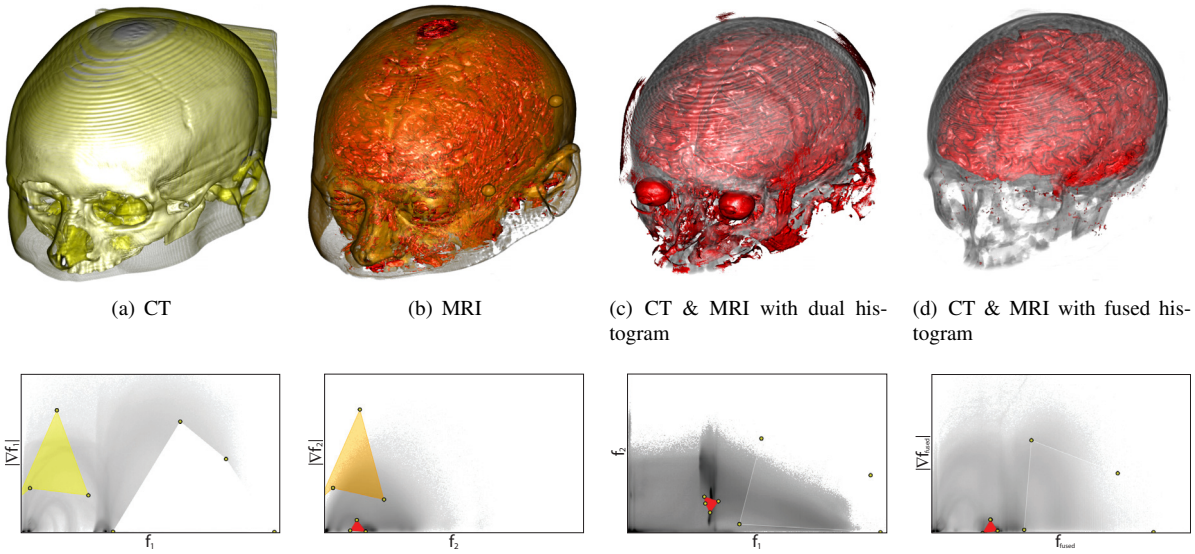
5 Results

As mentioned in the introduction, modalities can be generally classified into two groups: functional and anatomical modalities. In the result section the focus lies on the combination of two different anatomical modalities. The combination of anatomical and functional modalities has already been shown in many works before. The most common anatomical modalities are CT and MRI. CT is typically used to show bone structures. Soft tissues have a low contrast in CT data sets and cannot be displayed very well. For an MRI scan it is the other way around. Soft tissues, such as the brain, have a high contrast whereas bones cannot be seen. In Figure 7(a) a visualization of a CT scan is shown and in Figure 7(b) the visualization of an MRI scan. Both visualizations can be useful for special examinations but it can also be seen that both data sets contain some joint information. Furthermore some regions with less information, such as the tissue around the brain in the MRI scan, are hiding regions with more information, such as the brain itself.

The goal of a multimodal visualization is to combine relevant tissues from both modalities and show them together to provide additional context. The relevance of a tissue is dependent on the kind of examination. In a combination of CT and MRI of a head the brain could be the relevant part of the MRI scan and the bones could be the relevant parts of the CT scan. Figure 7(c) shows the rendering results of a traditional multimodal visualization. The dual histogram space was used to define regions which assign optical properties to sample points. Both relevant tissues, the brain and the bones, are visible but also a lot of artifacts are visible in the result. This follows from the fact that the brain cannot be better separated in the transfer function space based on the dual histogram. Figure 7(d) shows the result generated by the new method. In comparison to the result generated with the traditional multimodal visualization technique the brain is clearly separated from other tissues and only a few artifacts are visible.

Figures 7 (e) to (h) show the corresponding histograms for the visualizations in Figures 7 (a) to (d). The regions which were used to classify sample points with optical properties, such as color and opacity, are also shown on top of these histograms. It can be seen that the regions for classifying the brain tissue and the bones in the new fused transfer function space, as shown in Figure 7(h), are highly related to the individual regions in the single modality visualizations, as shown in Figure 7(e) and Figure 7(f). The regions for the multimodal visualization, based on the dual histogram, are shown in Figure 7(g). The position and shape of the regions in this transfer function space are completely different in comparison to the regions for the single modality visualization. This makes it much harder for the user to define regions for the transfer function because the knowledge from the single modality visualization cannot be used.

As described in Section 3.4 the definition of a transfer function is done in two steps. In Figure 7(h) only the regions are shown which assign a color and non-zero opacity to sample points. Furthermore for each of these regions a windowing function for the δ value is defined. This function is used to refine the separation by the transfer function. In Figure 8(a) the rendering result is shown which is generated without the usage of a windowing function for δ. The region which is used to assign optical properties to the brain is the same as used for Figure 7(d). It can be seen that the result contains a lot of artifacts. In comparison to that Figure 8(b)

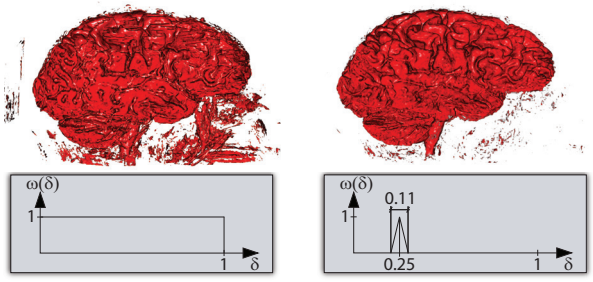


(a) CT (b) MRI (c) CT & MRI with dual histogram (d) CT & MRI with fused histogram

(e) CT histogram (f) MRI histogram (g) Dual histogram (h) Fused histogram

Figure 7: The images show single volume visualizations of CT data (a) and MRI data (b) in contrast to multimodal visualizations by using the dual transfer function space (c) and the fused transfer function space (d). Histograms (e)-(f) with the colored 2D regions for the assignment of optical properties correspond with the above visualizations. The green points in the histograms symbolize the vertices of the 2D regions.

shows a result which is generated by the additional usage of a windowing function for δ to modify the opacity. Through the refinement of the classification with the windowing function most of the artifacts are gone and the brain is clearly separated.

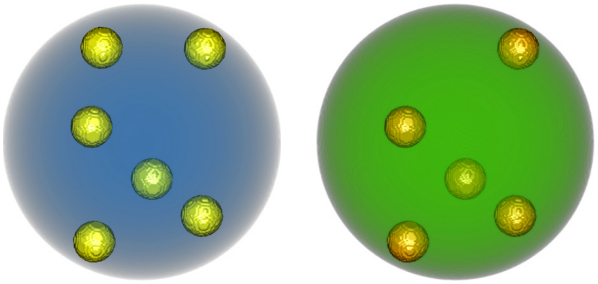


(a) Without usage of δ windowing function (b) With usage of δ windowing function

Figure 8: The two results show the effect of the usage of δ to modify the optical properties of a 2D region in the transfer function space. For both results exactly the same 2D region was used.

Besides the reduction of artifacts the strength of the additional δ value is the ability to find regions with high differences in both data sets. This can be very helpful for several applications, such as the finding of a tissue which only shows up in one modality. Due to the properties of δ as described in Section 3.3 regions with opposite information in both data sets have a high δ value. Figure 9 shows the response of the δ value for the combination of two example data sets. In Figure 9(a) and Figure 9(b) two data sets are shown which only differ at one region where in modality 1 a sphere exists and in modality 2 not. Figure 9(c) shows the corresponding distribution of δ values for the two modalities. In the region where the sphere is represented in only one modality the δ value is the highest because this region contains a lot opposite information.

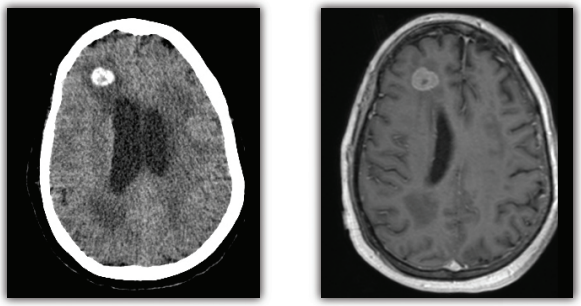
This property can be used to easily find regions with a lot of opposite information in the two modalities. An example where this is useful is the detection of tumors in the brain. A tumor is a region which shows up with a high contrast in the MRI. The contrast in the CT scan is lower. Therefore, the region of the tumor contains a lot of opposite information. Figure 10(a) and Figure 10(b) show slices from a CT and MRI scan of a data set with a tumor in the brain. The tumor is the bright region in the top-left area of the brain. Due to the opposite information in this region the δ value is high. This can be used to easily find this region in the multimodal visualization by defining a region over the whole fused transfer function. The windowing function for δ is then adjusted in a way to show only points with a high value. When a region



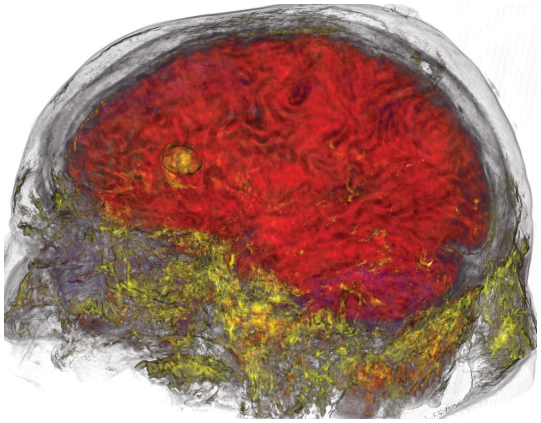
(a) Modality 1 (b) Modality 2

(c) δ distribution

Figure 9: The image in (c) shows the distribution of δ in volume space. It is highest in regions with the largest difference. In this case the largest difference occurs where in modality 1 (a) a sphere exists and in modality 2 (b) not.



(a) CT slice (b) MRI slice



(c) Multimodal visualization of a CT and MRI data set

Figure 10: The multimodal rendering in (c) highlights a tumor in the brain, shown in the CT (a) and MRI (b) slice. Through the δ value the segmentation of the tumor is made easy because this region has a higher δ value than other surrounding parts.

of interest is detected then the 2D region in the transfer function space can be minimized until it only covers the points with a high δ value. Figure 10(c) shows a result of the multimodal visualization which was generated in this way. The yellow blob inside the brain is the tumor as shown in the slices above. The artifacts in this image result from the very bad registration of the two data sets in some regions. Nevertheless, the new technique is able to highlight the tumor without the need of a segmentation.

The results so far used only anatomical modalities for the multimodal visualization but it is also common to combine anatomical modalities with functional modalities. This combination brings together the benefits from anatomical modalities, such as high spatial resolution and anatomical structures, with the benefits of functional modalities, such as depicting functional processes inside the body. For this combination already a lot of research has been done. Most of these approaches provide a 2D visualization where the anatomical information is overlaid with the functional information. Also 3D visualizations have been presented which clearly show the regions of high activity in contrast to the anatomical modality. Figure 11 shows a result of a multimodal visualization for the combination of these two modalities generated by the new approach. It shows a CT scan of the head together with a PET scan. The regions of high activity inside the brain and at the tumor in the neck were defined by 2D regions in the fused transfer function space together with a windowing function for δ and are visualized in yellow.

The different results have shown how the new approach can be used for multimodal visualizations in different ways. In our experiments, the fused transfer function space has proven to be an intuitive space for the design

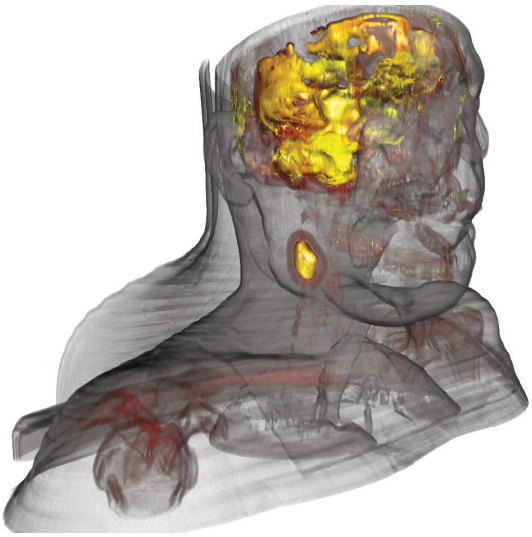


Figure 11: Multimodal visualization of a CT and PET scan. The yellow color symbolizes regions of high activity such as in the brain area and in the tumor on the neck.

of a transfer function because it is similar to the transfer function space of single volume visualizations. Furthermore the widowing function for the δ value is an interesting tool to better separate different tissues from both modalities and it can also be used to find regions with a lot of opposite information.

6 Conclusion and Future Work

In this paper we have shown a novel approach for the definition of transfer functions for multimodal visualization. The initial idea was to define a user-friendly transfer function space, which makes it easy to find an expressive transfer function in order to visualize certain tissues of both modalities. Through the fusion of the data values, based on the information content, a 2D transfer function space is defined which is similar to the well-known 2D transfer function space of single volume visualization with value and gradient magnitude as the two dimensions. Therefore, the distribution of points in this transfer function space is easier to understand by the user. A δ value, which describes the opposite information contained in a pair of values, is used for a better separation of different tissues. The δ value would extent the transfer function space by one dimension to a 3D space. Optical properties could be assigned in this transfer function space by defining 3D regions. Due to the complexity of this task in three dimensions, we introduced a two-step approach where a region is only defined in the 2D transfer function space over the fused value and the magnitude of the fused gradient. In a second step a simple windowing function is adapted for each 2D region to refine the selection and better separate different features. This separation in two steps reduces the complexity of the design task because the degree of freedom is reduced.

In comparison to other approaches, which are used for multimodal visualization, the benefit of the new approach is the conversion of the classification problem to a problem which is already known from classification in single volume rendering. Most of the other approaches, such as the dual histogram, represent the distribution of values in a completely new space which is difficult to interpret by the user. It is hard to find structures in these distributions because one distribution is strongly related to certain data sets. For another data set, acquired with the same combination of modalities, the distribution can already differ a lot from. This variation makes it difficult to find structures. With the new approach structures in the volume can be seen in the 2D histogram of the fused values. These structures are a combination of the structures which are visible in the individual 2D histograms of both data sets. This gives the user a clue where to initially place regions in the transfer function space, especially when the user is already experienced with the 2D transfer function space for single volume rendering.

In the result section we have shown that with the new fused transfer function space it is easier to define a transfer function. Also different tissues can be better separated in comparison to the dual transfer function space. The main reason for this better separation is the additional usage of the δ value which is used to refine the classification.

For the generation of the transfer functions always two modalities as input sources were used in this paper. Therefore, exactly two values are existent at every sample point. An idea for further work is to develop a more general approach out of the described method. The general approach should be able to visualize a combination of an arbitrary number of modalities. The dimension of the transfer function space should not increase with the increasing number of involved values at every sample point. So the data fusion has to be extended to fuse more than two values to a single new value. The calculation of the opposite information has also to be adapted to return a single value which represents how complementary the information is for the combination of more than two values at a certain sample point.

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