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VISUAL ANALYSIS OF THE HUMAN BODY THROUGH VOLUME CLASSIFICATION

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Abstract

Computers are now embedded within an enormous variety of resources and works of art, and take on tasks in roughly all facets of our life, since we are becoming more linked and dependent on technology. Today, a variety of applications in the field of Computer science and engineering share the goal to track and understand human anatomy based on visual analysis. The interpretation of complex medical images is a difficult task which normally requires specialists with years of training. Modern scanning devices produce intricate data of large proportions, making it necessary to involve computational methods into the interpretation of this data. One of the more challenging aspects of this interpretation is the identification and representation of meaningful information, such as certain anatomical structures or tissue types. To this extent, in the paper we develop and use classification techniques based on transfer functions which operate on multiple value domains. These domains are constituted from various properties of the scanned data, such as density, gradients or spatial positioning. The images generated through this class of techniques allow for a more intuitive representation and interpretation of the underlying data.

Keywords: classification, medical imaging, transfer function, volume visualization

1. Human-computer interaction in our changing world

Major changes have aroused within the computer revolution, which cover all aspects of its role. The computer-aided applications in human life and behaviour are manifold. Although information systems and sciences in general have first and foremost been still on user interface design and the importance of human-computer interaction, over the last decades, the computing sciences have discussed on this matter [1]. The human-computer interaction emerged as a major discipline in computing, with the substantial support of engineering, education, behaviour, psychology, graphics [2]. In addition, the study of the connection involving humans and computers has rapidly develop into one of the most dynamic and significant fields of technical investigation. In spite of its short history, Computer science has brought fundamental contributions to

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Science and society, being a founding science of the contemporary era of human history characterized as the Information Age [3].

The rapid advancement of Science and technology, particularly in recent decades, has brought forth multiple benefits for mankind in terms of health, well-being and cognitive freedom. For example, researchers of Artificial Intelligence in education have been developing specific materials for adaptive learning in complex domains like programming languages, Mathematics, Medicine, Physics, industry, Electronics, etc. [4]. Performances in algorithmic music composition have been achieved in European concert music for centuries. However, once they have been implemented in computer software, these systems have expanded into systems of music representation and production [5]. Computers play a central role in response to demands of transport operations, including public dial-a-ride transportation services, shared-ride taxis, airlines, rail transport, etc. Computer aided engineering methods are already applied in kinematics and dynamics of mechanical systems [6], drugs design [7], manufacturing design [8], Medicine [9].

2. Computer-aided visual analysis of the human body

The field of medical imaging has benefited to a great extent from the development of computer technology. Non-intrusive imaging techniques such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) or ultrasound have proven indispensable for the proper diagnosis of multiple health conditions. Furthermore, modern scanning devices are not restricted to the medical field and have wide applicability in many other branches, such as industrial feasibility testing, fault detection in equipment and materials [10], or 3D seismography [11]. The modern versions of these devices generate complex data sets of large proportions, which contain a great deal of potentially useful information [12].

Traditionally, two-dimensional (2D) slices are produced from this data, which are individually analyzed by a specialist. However, this is in many cases a tiresome and time-consuming task, especially for large scans comprising hundreds of slices. Even with a smaller number of slices, expert training in radiology is still required for a proper interpretation, making the information contained therein inaccessible to the general public. As a solution to this problem, the field of volume graphics [13, 14] provides techniques for the direct, three-dimensional (3D) representation of this type of data. Normally, a radiologist analyzes individual 2D slices and mentally forms a complete picture of the originating object. When employing volume visualization techniques, images may be generated which approximate the shape and features of the scanned object or anatomical structure far more closely, while allowing for the visual separation of meaningful information through a careful manipulation of colour and opacity.

Detecting this information from the entire available data is a complex problem which has not been fully solved, given the wide variety of data sets and the large number of objects or structures which undergo scanning. The classification of this data therefore offers multiple challenges, especially when dealing with medical scans, due to the complexity of the human body and the small size and elusive nature of the features or structures which often need to be detected. The following sections describe various techniques for the classification of volume data originating from medical scans. We show how multiple criteria can be used for feature separation, and employ various types of so-called *transfer functions* to generate colour and opacity from the originating data, based on these criteria.

3. A scientific case study against visual analysis of the human body through volume classification

3.1. Volume data sets and classification techniques

A 3D medical scan originating from various scanning devices may be assembled into a volume data set, which may then be subjected to reconstruction and visualization techniques that produce a volume object [15]. Such an object is constituted from atomic elements referred to as *voxels*, the 3D equivalents of pixels [16]. Therefore, a volume data set may be seen as a 3D volumetric representation of an object. By applying projection transforms, a 2D image may be generated from this data, which is then represented on screen for visual analysis. However, not all voxels are part of interesting or useful information. From the entire data set, only certain features or structures may be of interest, such as, for instance, blood vessels, certain types of tissues, etc. Therefore, proper classification of the data is required, which involves the detection and separation of useful voxels, while discarding the rest. Most commonly, the useful information contained within a volume constitutes a rather small percentage of the entire available data. This point is illustrated in Figure 1. A rendering of a 3D medical scan is shown, along with a bounding box which circumscribes the entire data set. The visible structures are in the centre and it can be easily calculated that they constitute about 23% of the whole data set. Therefore, 23% of the voxels in this image are opaque or semi-transparent, while the rest are invisible. The information which presents interest has been visually separated from the rest of the data based on differences in opacity. Furthermore, colour and various degrees of transparency are used to highlight various structures within the visible object: bone is visually separable from skin and other tissue types.

Figure 2 illustrates a simple case of volume classification: assign certain levels of opacity and colour to meaningful information, and eliminate the rest by making it transparent.

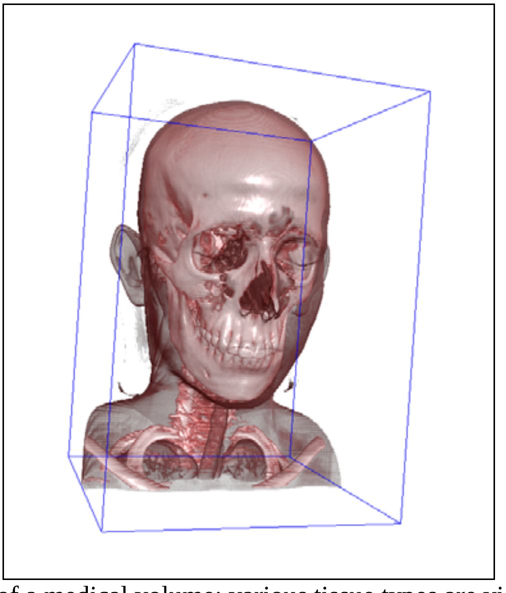

Figure 1. Rendering of a medical volume; various tissue types are visible, while the bounding geometry encompasses the entire data set.

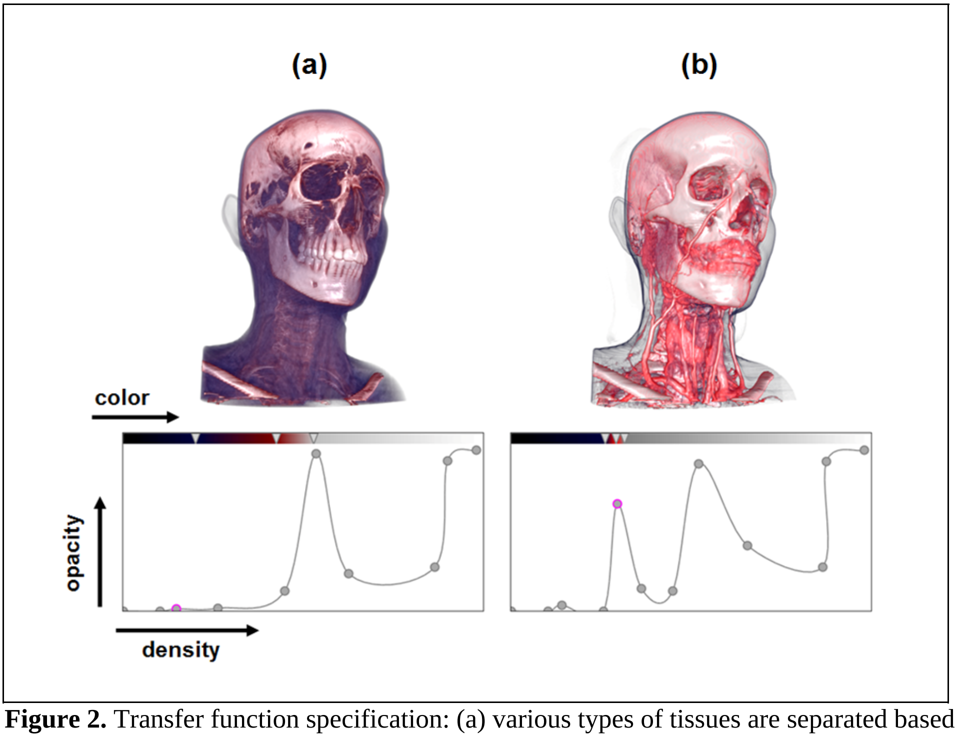

Figure 2. Transfer function specification: (a) various types of tissues are separated based on differences among their densities; (b) a more feature-centric approach clearly highlights specific tissue types, specifically, blood vessels.

Classification is an important step in the volume rendering pipeline and it has to be implemented explicitly since volume data does not in itself contain information on structures, features or anatomical parts. A data set is in fact a three dimensional array of scalar values, which each such scalar value corresponding to a voxel from the volume. Therefore, each voxel has an associated number, which is a rough indicator of the physical properties of the material from the corresponding scanned object. The values often indicate the density of the material, thus, voxels with lower scalar values are typically part of lower density areas from the volume (such as softer tissue, cavities etc), while higher scalar values indicate higher density regions (bone tissue, metal). Furthermore, the initial data does not provide any optical information (colour, opacity), which is needed for the generation of images. It is up to the developers to implement proper classification techniques which allow the identification of useful information, while at the same time assigning colour and opacity to each voxel so that they may be represented on a display.

Volume classification techniques mostly fall within two categories:

- **segmentation**, which typically takes place in a pre-processing step and identifies one or several distinct objects within the data. Each voxel is assigned an object ID that indicates which of the identified objects it belongs to. Segmentation algorithms are typically decoupled from the rendering stages; therefore, each identified object may be represented via its own rendering method. When generating a final, on-screen image, objects may overlap or occlude each other, which creates the situation where pixels colours result from a combination of one or multiple object [17, 18].
- **transfer functions** constitute a broad category of classification methods, which involve the use of various mapping functions to assign colour and opacity to the voxels inside a volume, based on one or multiple criteria. Usually, a transfer functions assigns colour and opacity (RGBA values) to a subset of voxels sampled from the volume. Subsequently, the colours of the on-screen pixels are assembled from the RGBA values of the sampled voxels [19].

In this paper, we focus on transfer function-based classification, specifically, on the various domains in which transfer functions may operate. We define these domains based on various voxel properties, such as scalar value, gradient magnitude, curvature or spatial position. These properties are, in fact, criteria for classification; with each added criterion, increasingly complex and hard-to-detect features may be identified and represented. Transfer functions are an important component of the volume rendering process and are the main factor which decides the colours of the resulting image. As mentioned, volume data itself does not contain information on colour and opacity, which is required for the simulation of light interaction and the implementation of shading and rendering algorithms. A transfer function (T_f) therefore bridges the gap between non-optical voxel properties $v_1,...,v_n$ and the optical characteristics (*RGBA* quadruplets) required for visual representation (Equation 1).

$$T_f : R^n \to R^4$$
$$T_f(\upsilon_1, \upsilon_2, \ldots, \upsilon_n) = RGBA \quad (1)$$

3.2. Data-based transfer functions

The most basic transfer functions directly operate on the scalar values of the voxels from the originating data set. Each voxel has one such value, and the range of these values constitutes the domain of the transfer function [20]. The scalar values commonly indicate the density of the corresponding media. For each density level, a data-based transfer function specifies certain colour and opacity values. Various structures and shapes may therefore be isolated from the full data set by virtue of the fact that their densities are distinct from other, surrounding elements. Figure 2 illustrates the specification and use of a data-based transfer function. We have implemented a manual means of defining the transfer function, as shown at the bottom of Figure 2. The shape of the function is clearly visible and adjustable in the interface: the horizontal axis contains density levels (which correspond to the values from the original data set), while the vertical axis represents opacity. The circular controls are used to define the opacity, while the triangular ones specify colour values. Certain elements of interest such as bone or blood vessels are assigned a higher opacity and distinctive colours, making them easily identifiable from the rest. The shape of the transfer function may be adjusted as needed, so as to highlight meaningful anatomical structures.

The transfer function is generated from the control points via Catmull-Rom interpolation [21], for a smooth transition between domain values. The shape depicted in the interfaces from Figure 2 determines the distribution of opacity values among density levels. Lower density material such as skin is assigned lower opacity so that it does not occlude other anatomical structures located toward the centre of the volume.

While this approach offers great flexibility when classifying volume data, it also comes with drawbacks. Specifically, it is unable to separate anatomical structures or tissues which share the same density. Any set of voxels which contain the same scalar values are treated as belonging to the same object, though this may not always be the case. This necessitates the use of other classification criteria, as elaborated upon in the following sections.

3.3. Gradient-based transfer functions

The gradient vector (or gradient, in short) is a measurement of the variation of scalar values from the volume data set. Considering that the volume is described by a function $V : R^3 \to R$, which assigns a scalar value to each position from a region in 3D space, the gradient is a three-component vector composed of the partial derivatives of V along the three directions, x, y, z (Equation 2).

$$grad(V) = \nabla V(x,y,z) = \begin{pmatrix} \partial V(x,y,z)/\partial x \\ \partial V(x,y,z)/\partial y \\ \partial V(x,y,z)/\partial z \end{pmatrix} \tag{2}$$

The direction of the gradient shows a variation of scalar values, which may suggest meaningful surfaces in the volume. The gradient magnitude indicates the degree or significance of the change, thereby pointing out the amount of difference between the materials located on either side of a bordering surface [22]. In practice, we approximate the gradient using central differences. For any position in the volume, we sample pairs of voxel values on either side of that position, one pair for each axis. The differences among the three pairs closely approximate the components of the gradient. Considering that the samples are taken at distance *d* from the target position, the gradient is computed as shown in Equation 3.

$$\nabla V(x,y,z) = \frac{1}{2d} \begin{pmatrix} V(x+d,y,z) - V(x-d,y,z) \\ V(x,y+d,z) - V(x,y-d,z) \\ V(x,y,z+d) - V(x,y,z-d) \end{pmatrix} \tag{3}$$

Gradient-based transfer functions operate on gradient magnitudes, rather than densities. We use these functions to classify data and identify structures that could not be isolated using data-based means alone. The images in Figure 3(a) and Figure 3(b) are generated using data-based and gradient-based classification, respectively. While data-based classification can easily separate high density material such as teeth, it makes it difficult to highlight various other features located in the vicinity of the skull cavity. These have density values similar to other occluding structures. However, they are identifiable using a gradient-based approach, which excels at determining the borders between different media. Figure 3(b) shows how, using gradients, other more problematic structures can be identified, such as the sinus cavity or the metencephalon.

Two or more structures with overlapping density ranges have, in most cases, different surface properties, making them good candidates for gradient-based classification. While they have densities similar to their neighbours, their outlining surfaces make them unique.

3.4. Curvature-based classification

Curvature values quantify the flatness of a surface or region. The flatter the surface in a specific spot, the lower the curvature for that spot. Conversely, where valleys and ridges are present, or where the surface is highly irregular, curvature values are correspondingly high. Traditionally, the computation of local curvature relies on complex convolution operations, which involve the computation of the second derivative of the volume function [23]. Other methods are tailored for ray casting-based direct volume rendering approaches and involve the approximation of curvature values along projected rays [24]. Once curvature values are obtained, their range may constitute the domain of transfer functions, wherein opacity and colour are assigned based on the level of deformation of the local surface.

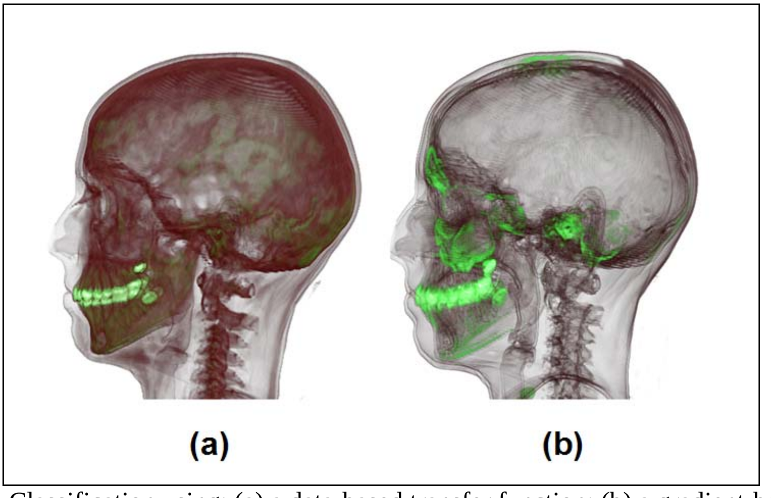

Figure 3. Classification using: (a) a data-based transfer function; (b) a gradient-based transfer function. The latter excels at detecting meaningful surfaces as opposed to solid structures and is capable of revealing additional features.

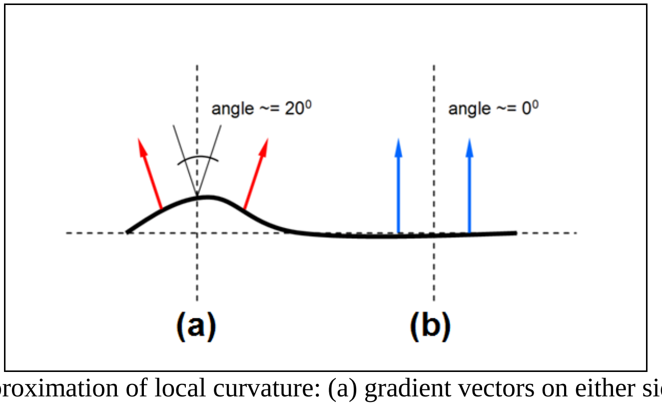

Figure 4. Approximation of local curvature: (a) gradient vectors on either side of the target position form an angle, thus indicating a "bump" in the local surface; (b) when gradient vectors are nearly parallel, the local surface is almost flat.

We calculate curvature values based on an approximation method. Specifically, for any arbitrary position in the volume, we evaluate the local curvature by computing the differences between the angles of neighbouring gradient vectors. Since gradients indicate the orientation of local bordering surfaces, the greater the angle between consecutive gradients, the greater the curvature in the immediate neighbourhood (Figure 4).

Similar to the approaches used in Section 3.2., we sample neighbouring gradient pairs along each axis and evaluate the angle in-between the gradients in each pair. The result is a three component vector; the local curvature is indicated by its magnitude. This is illustrated in Equation 4, where the curvature value *k* in position *(x, y, z)* is the magnitude of the vector formed by the dot products of gradients sampled at distance *d* and normalized.

$$k(x,y,z) = \left\| \begin{pmatrix} \nabla V(x+d,y,z)_n \cdot \nabla V(x-d,y,z)_n \\ \nabla V(x,y+d,z)_n \cdot \nabla V(x,y-d,z)_n \\ \nabla V(x,y,z+d)_n \cdot \nabla V(x,y,z-d)_n \end{pmatrix} \right\| \tag{4}$$

Figure 5 shows a rendered image where local curvature is used to identify regions according to their level of deformation. In the darkest spots, the depicted surface forms narrow angles, thus the corresponding curvature value is high. Such areas which exhibit high curvature are useful for highlighting significant contours around irregular anatomical features. The identification of such contours is important for isolating regions with similar surface characteristics.

Figure 5. Volume rendering where local curvature is shown though greyscale levels (darker regions have a greater degree of irregularity and higher curvature values).

3.5. Distance-based classification

In previous sections, the transfer function domains have so far been based on or derived from the scalar values from the data set. Conversely, distance-based classification accounts fro the spatial positioning of the voxels. This constitutes an additional, independent means of separating regions in the volume. The main idea is that the voxels should be classified according to their distance from a focal region. Such regions may be constituted from a single point in volume space, or an entire pre-identified substructure from inside the volume [25]. Distance-based transfer functions operate on a domain constituted from the pre-computed distances between each voxel and the chosen focal region. We used distance based classification alongside the more classic, data-based transfer function, to render a more complete picture of the dataset; thus, the color and opacities assigned as a result of scalar value-based classification are modulated by a distance-based transfer functions, thereby revealing regions not easily classifiable using data-based means alone.

The approach first involves the establishment of a focal region. We exemplify by selecting a point roughly in the middle of the volume. Distances from the point to every voxel are then pre-computed and stored in a distance volume. A distance-based function is defined, which operates on the values stored in the distance volume, as opposed to the original scalars generated by the scanning device. The opacity values of voxels are then tweaked using this new criterion, i.e. voxels which are at certain distances from the focal point have certain opacities. Figure 6 depicts the usage of distance-based classification. The image in Figure 6(a) is rendered using a traditional data-based transfer function, which assigns opacity and colour. In Figure 6(b) a secondary, distance based transfer function is used to modulate the opacity around the centre of the volume (the focal point), which is adjusted so that the area in the vicinity of the centre is visually removed. This reveals additional structures and details within the volume, while preserving the opacity of the outer 'shell', which constitutes context information.

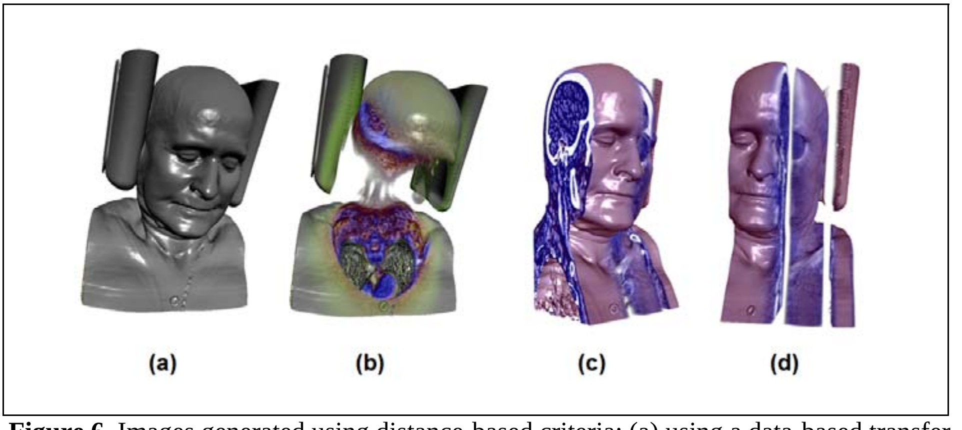

Figure 6. Images generated using distance-based criteria: (a) using a data-based transfer function; (b) adding distance allows for the removal of voxels around the centre of the volume; (c) and (d) two different views of the same volume generated via focal plane-based distance.

Distance based classification need not be restricted to focal points. Indeed, virtually any geometry can be used. In the simplest case, the distance values can be computed in relation to a focal plane, which may have any arbitrary orientation. The constituents of the volume are then separated based on their distance from the plane. A result of this approach is visible in Figure 6(c) and (d), where, as previously, data-based and distance-based transfer functions are used to visually separate and group voxels into volumetric slices.

This approach has an effect similar to the use of multiple clipping planes [14], but with several advantages. First, setting up and manipulating multiple clipping planes can become tedious; a distance transfer function can recreate the same effect from a single user interface element, similar to the one from Figure 2. The use of a transfer function generated via smooth interpolation allows for certain areas to transition smoothly from fully opaque to fully transparent. In Figure 2, sharp slices through the volume, toward the left side, are simultaneously generated alongside smoother transitions near the centre-right. The effect is achieved from the same transfer function; no further clipping algorithms are necessary.

7. Conclusions

In this paper we have so far explored the use of multiple criteria for the isolation of meaningful information from medical scans. This presented a number of challenges, due mostly to the complex nature of the data involved. Through the use of volume rendering techniques, a scanned object may be represented as a 3D construct, while most of the relevant information can be represented in a single image. One of the most important aspects of this process was the classification stage, where relevant information as isolated from the rest of the data. This was achieved through the use of transfer functions, which assigned colour and opacity to the constituents of the volume, while being capable of operating on multiple domains. The first such domain was generated from the range of initial scalar values. This allowed for the isolation of various anatomical features such as bone and blood vessels based on differences in density. However, additional criteria were needed when this form of classification had reached its limitation. We then used gradients and curvature values to further refine the classification process. While gradient magnitudes proved useful for revealing significant surfaces, the computation of curvature yielded the possibility to identify features such as valleys, ridges, and, generally speaking, surface components which exhibited deformations and irregularities. Finally, accounting for the spatial distance of volumetric structures from an explicitly-selected focal geometry offered an additional strong criterion for classification. Removing the voxels around a specified focal point revealed additional anatomical structures in the immediate neighbourhood, while adjusting opacities based on the distance from a focal plane allowed the efficient emulation of clipping geometry.

Such techniques, along with multiple others from within the field of volume visualization allow for the generation of high quality images for the efficient and intuitive visual analysis of the underlying data. Future, subsequent developments in this area will focus on refining developing further classification methods based on additional, more complex criteria, such as visibility, occlusion or user-centric information which involve semantics or more advanced, intelligent and reactive visualization pipelines.

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