Diffusion Tensor Visual Analysis of the Human Brain

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1. Introduction

1.1. Diffusion Tensor Magnetic Resonance Imaging

Magneto-Resonance (MR) Imaging allows retrieving information about tissues by emitting a magnetic pulse and measuring the electro-magnetic radiation as emitted from hydrogenium atoms. Depending on the structure of this magnetic pulse, different hydrogenium atoms are selected and diverse properties of the tissues, in particular depending on the content of water, can be highlighted. In a more elaborated version, a sequence of signals can be combined with a strong gradient magnetic field to retrieve information about the motion of water molecules along the direction of this gradient. This diffusion of water in tissues is not isotropic in general, and especially neuronal fibers constrain diffusion along their orientation. Thus this image acquisition technique yields best results in brain tissues where the density of neuronal fibers is very high. In its most simple form, anisotropic diffusion is modeled by a symmetric tensor field, i.e. a symmetric 3×3 matrix given at each point in a volume as built from six independent measurements. As there are six times more quantities given *per point* as in a standard MR image, the question rises how to visually best represent these data.

1.2. Reduction to Scalar Fields and Fiber Tracking

Various quantities can be extracted computationally from a diffusion tensor field and be displayed as a usual image (i.e., as grayscale image or via artificial color coding to enhance details), similar to MR or CT data. However, there is no unique way to reduce the six available quantities to a single one, and several such measures have been proposed. Among them is the widely used fractional anisotropy (FA) which indicates the strength of water diffusion in dominantly one direction. Alternative indicators are the shape factors as introduced by Westin et al., 1997. There are three such shape factors indicating whether diffusion occurs dominantly in one, two or three directions. The respective indicators are called the linear, planar or spherical shape factors. They are computed from the eigenvalues of the diffusion tensor field and dependent on each other. A large spherical shape factor indicates isotropic diffusion, for instance in ventricle filled with fluid. A large linear shape factor indicates diffusion constrained to one direction and may be interpreted as areas with high density of aligned neuronal fibers.

A common approach is to try extracting the structure of the neuronal fibers from the diffusion tensor data. This is done by determining the dominant eigenvector of the diffusion tensor, and tracking a neuronal fiber by computing an integration line that is tangential to the dominant eigenvectors. This approach yields three-dimensional line structures that resemble the textures known from anatomical dissections of brain tissue. However, this straightforward approach is numerically unstable, as the dominant eigenvector is only uniquely defined where diffusion is highly linear. In planar or isotropic regions, the dominant eigenvector becomes undefined and the computed fibers are sensitive to numerical artifacts. Various approaches have been proposed to stabilize the approach of fiber tracking, e.g. the method of tensorlines (Weinstein, Kindlmann, Lundberg; 1999).

2. Visualizing Using the Method of Tensor Patterns

In our approach presented here we seek to display the full information content of a diffusion tensor field, without reduction to a single quantity, and robust with respect to numerical artifacts (Benger et al, 2006).

The six quantities of a diffusion tensor may be represented as an ellipsoid at each data point. The extent of this ellipsoid in each direction in space indicates the amplitude of water diffusion in this direction. However, ellipsoids are not a good visual representation, as they occlude each other and small variations in the diffusion properties are hard to glimpse. In the method of Tensor Patterns we employ Gabor Patches to represent the six quantities of the diffusion tensor. The concept of a Gabor Patch originates from vision research theory and provides an optimal visual stimulus (Gabor, 1946). It is represented as a two-dimensional disc that is transparent at its rim (transparency defined via a Gaussian function) and a linear texture adding a sinusoidal pattern on top of this disc. We may orient the disc in three dimensions according to the two dominant eigenvectors of the diffusion tensor, and the linear texture parallel to the most dominant eigenvector.

The frequency of this linear texture is now related to the linear shape factor of the diffusion tensor such that this texture vanishes in regions where the linear shape factor vanishes as well. In such regions, the Gabor patch reduces to a disc with radially symmetric Gaussian transparency falloff towards its rim. In such regions diffusion happens in the plane represented by this Gaussian disc. The overall transparency of the Gabor patch is also related to the spherical shape factor such that it becomes transparent when the spherical shape factor is large, indicating isotropic diffusion with no directional preference at all. Regions of isotropic diffusion are thus visually suppressed by this approach, whereas anisotropy is enhanced. Additionally, we may colorize the Gabor patches to emphasize linear versus planar regions. We use red to depict planar regions and green to depict linear regions.

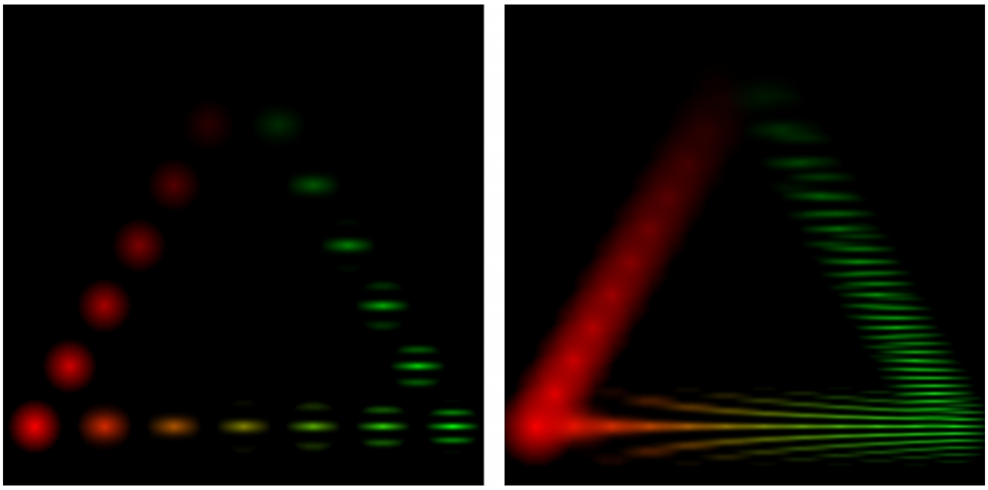

Figure 1: Artificial dataset representing the parameter space of diffusion - planar (lower left vertex), linear (lower right vertex) and spherical (upper central vertex). Each data point is represented by a so-called Gabor patch. Appropriate scaling - as demonstrated in the right image - yields a visually smooth appearance.

Figure 1 demonstrates the visual representation of the most extreme cases of anisotropic diffusion. The linear, planar and spherical shape factors depend on each other equally to the barycentric coordinates within a triangle. In the lower right vertex of this artificial tensor field as defined on the edges of a triangle, the planar and spherical shape factor are zero, the linear shape factor is one. The tensor field is represented by an ensemble of green "needles" pointing into the direction of the dominant eigenvector (which, in this setup, is oriented parallel to the lower edge of the triangle). The lower left vertex represents vanishing linear and spherical shape factor with large planar shape factor, rendered by a red disc in the plane of the two dominant eigenvectors. The upper central corner relates to an isotropic region of no dominant eigenvector and is rendered transparent. This visual representation allows a smooth transition covering various values of the shape factors. Scaling these Gabor patches such that they overlap each other yields a visual impression as if they were connected into lines (as demonstrated in the right image of Figure 1). However, this impression is just perceptual, an effect known in perception theory as association field (Field, Heyes, Hess; 1993). Unlike numerically computed integration lines, they are not vulnerable to accumulating numerical errors because they are always build from a local representation of the tensor field. Moreover, these perceptual lines have a variable width that is able to convey the influence of the second eigenvalue, and thus directly visualize the uncertainty of the dominant eigenvectors.

3. Diffusion Tensor Field of a Brain Tumor

Fiber tracking is used to investigate possible connectivity between certain regions in the human brain. Such is of particular interest in conjunction with functional MR imaging. However, due to the aforementioned uncertainties in fiber tracking this field of tractography is still subject to ongoing research and considered an experimental technique (see also S.Deoni, 2005).

Contrary to tractography, the investigation of the influence of brain tumors on their surrounding tissues requires local information rather than global connectivity. Here we show results of applying the technique of Tensor Patterns upon a DT-MRI dataset as provided by H.Kitzler, Uniklinikum Dresden, as acquired from a patient with a tumor. Figure 2 demonstrates rendering as a scalar field with color-coding, where the trace of the diffusion tensor was selected as representative indicator for the absolute value of diffusion velocity (green: small values, red: large values). Anatomical features such as the eye (lower left) and cortex are easily identifiable. The tumor itself shows up in the center of the image with higher diffusion velocity, suggesting edema-like properties of the tissue in its periphery. Major parts of the brain however appear homogeneous. The diffusion tensor image rendered using the aforementioned tensor pattern technique yields details in just those regions (right image in figure 2).

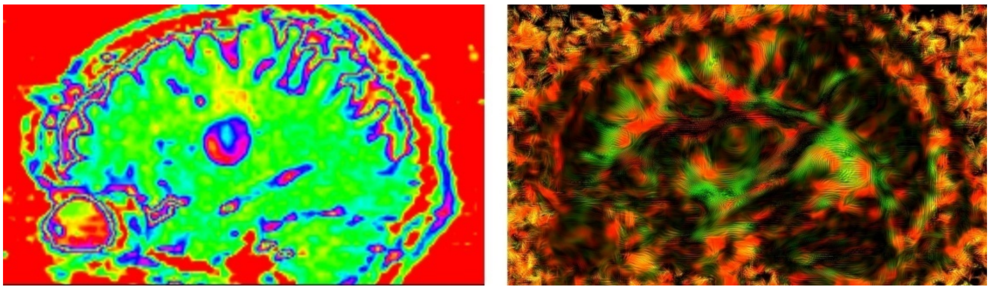

Figure 2: Scalar (left) and tensor (right) visualization of a DT-MRI dataset containing a brain tumor.

The diffusion tensor image is very rich in information and requires to be viewed at high resolution, as the color scheme by itself only indicates the predominant diffusion properties. Green regions indicate white matter with linear diffusion along bundles of neuronal fibers. The spatial resolution of DTI is orders of magnitudes above the size of a single neuronal fiber - one volume point (at the size of about 1-

2mm) contains about 1000 fibers. The average signal of two bundles of fibers crossing (or, a single bundle bending within one volume element) yields a planar diffusion signal. Such features are visible with appropriate resolution, as depicted in figure 3. Transparent regions, which show up dark in figure 3, represent averaged isotropic diffusion, which can be due to ventricles, gray matter or volume elements where three directions of fiber bundle tracts cross. The tumor in the center is more isotropic than the surrounding tissue; it is remarkable to find that the neuronal fibers appear to bend around this central region. This influence of the tumor's pressure is only visible by visualizing the directional information of the diffusion tensor. The complexity of the visual representation however requires some training to comprehend the huge information content.

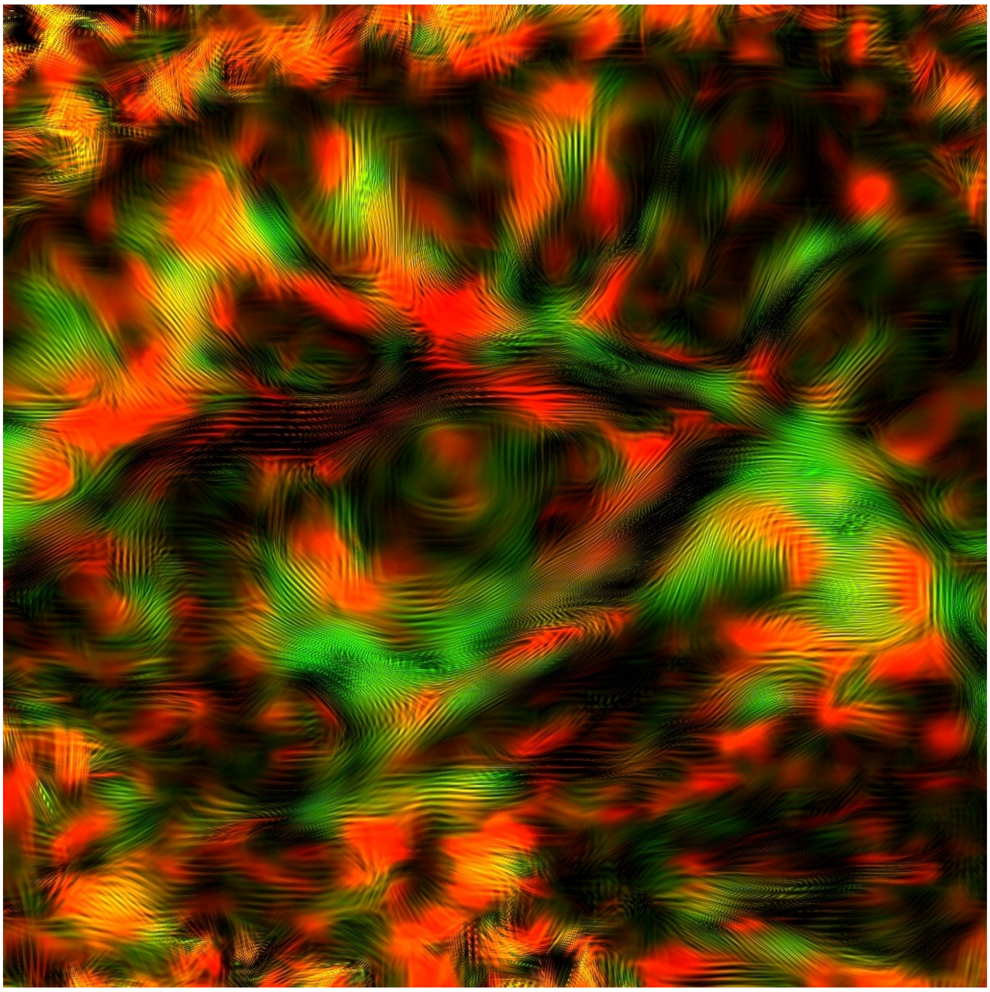

Figure 3: Detailed overview of the diffusion tensor image, indicating the pathways of neuronal fibers around the brain tumor.

While figure 2 and 3 merely display a top view of a slice through the actually volumetric data set, all information is intrinsically three-dimensional. A VR environment with stereographic projection capabilities supports communicating the full information content. It is very well possible to combine the transparent tensor patterns with other three-dimensional geometric representations, such as demonstrated in figure 4, using an orthogonal slice representing a scalar field. The tensor patterns itself may also be used within a volume rather than just a slice; this fully volumetric representations are hard to analyze. Nevertheless by appropriate choice of parameters controlling transparency, this approach may well be used for data mining purposes of a six-dimensional dataset over a three-dimensional data volume.

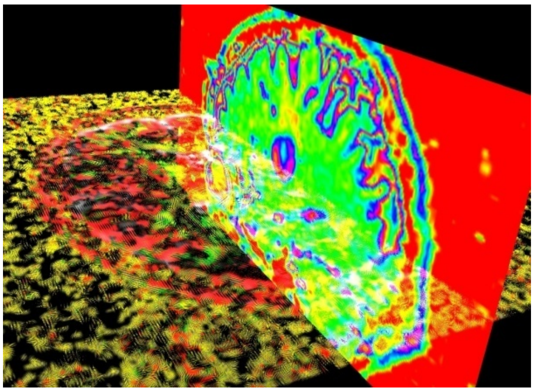

Figure 4: Combination of a horizontal slice of transparent tensor patterns with a vertical slice of a complementary scalar field visualization.

The shape factors represent only relative information about the dominance of the direction of diffusions, but do not convey information about the absolute diffusion velocity. A possible choice is to map the absolute velocity, given by the trace of the diffusion tensor, to the color saturation, as demonstrated in figure 5. Whitish and pale regions thus represent regions of fast diffusion. The corpus vitreum is apparent as brightly white region. The tumor tissue becomes grey, indicating high diffusion velocity, in addition to the isotropy. The fast and isotropic diffusion might be due to an edema.

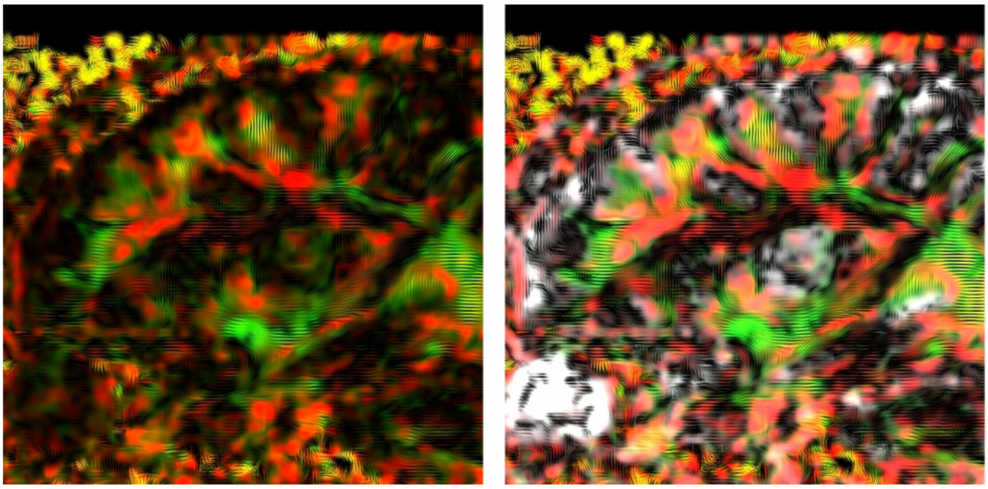

Figure 5: Adding color saturation to tensor patterns to represent absolute diffusion velocity.

The approach to visual represent a tensor field by colored Gabor patches is well supported by vision research theory. Mojsilovic et al., 2000, investigated the perception of color patterns. They identified a five-dimensional parameter space that determines how we recognize regions of similarity. They found the property of "equal patterns" (orientation and regularity) to be the most relevant rule. This observation supports well the perceived continuity of association fields even through regions of different colorization. The "overall appearance" (colorization and orientation) of a pattern is of subordinate relevance. The current technique of Tensor Patterns does not fully utilize the full parameter space of color pattern similarity. Table 1 summarizes the mapping of diffusion tensor quantities to their visual representation. Further ongoing research may explore the capabilities of utilizing even more of the perceptual parameter space to display additional quantities on top of the tensor field, or tensor fields of higher order. Additional quantities of interest are in particular alternative MRI measurements such as T1 and T2 images, as these provide additional information about the tissues. There also exist experimental data acquisition techniques that allow to measure more than six diffusion directions. These might be used as a validation tool to assess the quality of the retrieved data, or to implement a model of diffusion beyond using a tensor of second order.

Tensor Property	*Quantities*	*Visual Representation*
Max Eigenvector direction	2	Major orientation
Median Eigenvector	1	Minor orientation
Isotropy (Spherical shape factor)	1	Transparency
Planar vs. Linear shape factor	1	Texture frequency and red/green colorization
Absolute Velocity (trace)	1	Color saturation
Full tensor	***6***	***Tensor Pattern***

Table 1: Mapping of tensor quantities to graphical representation

4. Acknowledgements

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5. Literature

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