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TECHNICAL REPORT

Enhancing Visualization with Frequency-based Transfer Functions

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Abstract

Transfer functions have a crucial role in the understanding and visualization of 3D data in the spatial domain. While exhaustive research has scrutinized the possible uses of one or multi-dimensional transfer functions in the visualization of the data in the spatial domain, to our knowledge no attempt has been done in the exploration of the use of transfer functions in the frequency domain. In this work we propose the use of transfer functions for the purpose of frequency analysis and visualization of 3D data. Frequency-based transfer functions offer the possibility to discriminate signals composed from different frequencies, to analyze problems related to signal processing, and to help understanding the link between the modulation of specific frequencies and their impact on the spatial domain. We demonstrate the strength of our technique by applying the frequency-based transfer function to synthetic and real-world medical data. The interactivity of the proposed framework allows the creation of complex filters and can also be used for structure or feature enhancement.

Keywords: Fourier Transform, Data Enhancement, Frequency Analysis, Transfer Function.

1 Introduction

Scientific visualization is focused on enabling and conveying a better and deeper insight about data and processes. In the last decades, unprecedented technological growth and development have contributed to the overall improvement of the visualization pipeline, in particular for the processes of data enhancement and visualization mapping. Special focus has been given to introducing advanced filtering and mapping techniques [12]. Direct volume rendering (DVR) is a powerful technique used in the visualization of data generated by computed tomography, magnetic resonance imaging (MRI), ultrasound scanning, and so on. DVR directly benefits from the concepts of data enhancement and mapping. It is based on the idea of mapping data properties to opacities and colors by means of transfer functions (TF). In many applications, first and second order derivatives are used to improve classification and visual perception [15], [24], [13]. In other ones, spatial and geometric features have also been considered in the design of transfer functions [6], [23]. The common objective of approaches that use transfer functions in their pipelines is the extraction and enhancement of features or structures of interest.

Motivated by the idea of transfer functions, in this paper we introduce a framework that enables the interactive modulation of 3D frequencies representing the signal (data). We define as frequency modulation the process of modifying the harmonics waves, which contribute to building the signal, by multiplication with a scalar in the frequency domain. Different from existing transfer-function techniques that operate in the spatial domain, our proposed frequency-based transfer function (FbTF) will be applied in the frequency domain. Since a change in the frequency domain results in a change in the spatial representation of the data, our FbTF can be considered as a part of the data enhancement step in the visualization pipeline.

The frequency domain is constantly in the center of interest in fields as signal processing and engineering. Many problems or events can be explained or interpreted only through frequency analysis. In communication theory, signals are decomposed into several simpler signals through filter banks [25]. In geology and oil industries the study of 3D seismic data is done in the frequency domain [26]. An entire field, called spectral decomposition and introduced by Partyka et al. in 1999 [20], deals with the analysis and evaluation of the frequency spectrum of stratigraphy and seismic data. In the brute force approach, conclusions are assessed by analyzing several mono-frequency volumes extracted from the original data. With our approach we introduce the possibility of interactively visualizing the different frequencies without the need of the serial analysis of these mono-frequency multi-volumes.

Our framework is designed to aid viewers in understanding complex or detailed geometric models through navigation in the frequency domain. Like images, volumes also have characteristic patterns in the frequency domain. Since frequency measures the rate of change of a signal in a particular direction, features like size and shape can be mapped to specific frequency bands. By using the FbTF we want to enable the visualization of the spatial response of specific frequency modulations, the highlighting of anomalies in medical datasets, and the enhancement of data by applying interactive noise removal.

The contributions of this work are: a) the introduction of frequency-based transfer functions as a data enhancement (preprocessing) step (Section 3), b) the usage of 1D transfer functions in the modulation of 3D frequencies based on 2D scatter-plots of frequency amplitude vs. radial-distance frequency (Sections 3 and 4), and c) the interactive (real-time) application of a FbTF in data exploration, frequency modulation and feature detection (Section 5).

2 RELATED WORK

Our framework can be considered as a bridge between research areas concerned with transfer functions, filter design and signal transforms. In this section we will provide information on existing work related to these fields and state the necessary links to our proposed work.

The design of transfer functions is an active research area. Transfer functions can be classified as image-centric and data-centric. Most data-centric approaches attach transfer functions to voxel properties related to intensity and gradient [21]. Gradient [14] and curvature information [13], [15] has been used for enhancing classification through transfer functions. Röttger et al. [23] have included spatial information for adding insight to the histogram of a volume. Correa and Ma [6] introduced size-based transfer functions for volumetric classification based on the local size of features of interest. Caban and Rheingans [4] used several statistical properties derived through data analysis for assigning color and opacities. Bruckner and Gröller [3] introduced style-based transfer functions for enhancing illustrative visualization. Sereda et al. [24] introduce LH histograms to enhance volume classification through better detection of boundaries. Our FbTF, being derived from the amplitude histograms in the frequency domain, is a data-centric approach.

Filtering is a well-established step in the visualization pipeline. Depending on the data types and on the requirements prior to volume rendering, noise removal, low-pass, high-pass and band-pass filters are applied. Much work has been done for enhancing rendering and visualization through filtering [10], [11]. Luft et al. [16] focus on enhancing depth perception by unsharp masking the depth buffer. Ritschel et al. [22] introduce a local scene enhancement by unsharp masking over arbitrary surfaces under any form of illumination. Filters can be classified, based on their domain of application, i.e. spatial or frequency filters. When applied in the frequency domain filters show a global behavior and no local spatial assessment of their effect can be conducted directly. In visualization it is more common to specify a filter in terms of the smoothness of the resulting reconstructed function and the spatial reconstruction error. Still, when the kernels of the local filters become very complex and with wider support (i.e., kernel size), applying these filters in the spatial domain becomes unfeasible [18]. In our framework we can interactively design complex filters in the frequency domain guided by the effects or modifications we want to see in the data.

Several transforms such as the Fourier, the Cosine, the Sine and Wavelet transforms give a wide range of possibilities to represent signals in different domains according to the application requirements [19], [17], [8]. The main disadvantage of using global methods as the Fourier transform, is the loss of spatial information in the frequency domain. Wavelets, Gabor and Short Time Fourier transforms (STFT) offer a possibility to window the signal and hence to provide spatial (or temporal) information for the frequency response of the signals [8]. For a 1D signal the respective STFT is a 2D signal, for a 3D signal the response is a 6D signal, and so on. The visualization or interactive analysis of such data becomes unfeasible. In our framework we use the Fourier transform for estimating the frequency representation of the 3D data we want to analyze. The main motivation for this selection is that the Fourier representations are well studied and several algorithms for their fast implementation are available.

3 Frequency Analysis

The Fourier transform is a useful theoretical tool for the analysis of signals. Its importance stems from the fact that the frequency domain representation can provide a wealth of crucial information for the study and characterization of signals.

The discrete Fourier transform (DFT) can be used represent finite sequences in the frequency domain. There are several existing approaches for computing the DFT coefficients. The most popular and efficient in terms of complexity is known as the fast Fourier transform (FFT). We denote the discrete Fourier transforms of a finite extent 3-D sequence, $V(x,y,z)$, where $0 \leq x < N_x$, $0 \leq y < N_y$, $0 \leq z < N_z$, as $\mathscr{F}(k_1,k_2,k_3)$. The complex numbers $\mathscr{F}(k_1,k_2,k_3)$ are called the DFT coefficients. Two important characteristics are related with the DFT coefficients: the amplitude and the phase. While the amplitude refers to the magnitude of the frequency oscillations, the phase is concerned with their angular position [2]. Denoting with $\Re_{k_1,k_2,k_3}$ and $\Im_{k_1,k_2,k_3}$ the real and imaginary part of the Fourier coefficient $\mathscr{F}(k_1,k_2,k_3)$, we define the amplitude $A(k_1,k_2,k_3)$ as follows:

$$A(k_1,k_2,k_3) = \sqrt{\Re^2_{k_1,k_2,k_3} + \Im^2_{k_1,k_2,k_3}} \qquad (1)$$

Designing a one-dimensional transfer function in the spatial domain is related with the assignment of opacity and colors to specific densities. In the frequency domain, the 3D volume is represented by the complex entries for each frequency, i.e., $\Re$ and $\Im$. Choosing a modulation factor based on the values of these entries would have an unpredicted effect on the spatial domain, since we do not know which frequencies we are modulating. On the other side, different from the spatial domain representation, the position (x,y,z) of each entry in the frequency domain has a special meaning. Each position represents the frequency ($\frac{2\pi x}{N_x}$, $\frac{2\pi y}{N_y}$, $\frac{2\pi z}{N_z}$) of the volume. Hence, in order to modulate specific frequencies we should construct our transfer function based on the position-triplets (x,y,z). We assume that the zero-frequency component (the DC component) is at the center of the volume, and we denote its position with (x_{DC},y_{DC},z_{DC}). In our transfer function we will decide the modulation factor for a specific frequency based on the relative distance from the zero-frequency component, or more specifically in the triplet $(x-x_{DC},y-y_{DC},z-z_{DC})$. In order to overcome the non-trivial process of using a 3D transfer function, we introduce the concept of radial-distance frequency (RDF). For each entry (x,y,z) the $RDF(x,y,z)$ is defined as follows:

$$RDF(x,y,z) = \sqrt{(x-x_{DC})^2 + (y-y_{DC})^2 + (z-z_{DC})^2} \qquad (2)$$

From the geometrical point of view selecting to modulate frequencies that have the RDF equal to a specific value r, means selecting all the points on the surface of a sphere with center at the zero-frequency point and radius r.

4 FREQUENCY-BASED TRANSFER FUNCTION

4.1 Constructing the FbTF

In one-dimensional transfer functions density histograms are attached to the transfer function editor in order to help deciding the setting of opacities and colors. In the same fashion we make use of 2D scatter-plots of frequency related statistics, in our case, amplitude vs. RDF. Each entry $H(i,j)$ in the scatter-plot is equal to the number of frequencies that have $RDF = j$ and the amplitude equal to i.

After setting the opacities for specific radial-distance frequencies with our FbTF, we modulate by those opacities both the real and imaginary part of the Fourier coefficients. More details about the range of the frequency opacity will be given in the section related with implementation issues.

4.2 Building the framework

In Fig. 1 we show the flow of our framework. As stated in the introduction, the frequency modulation is applied as a data enhancement step prior to direct volume rendering. By changing the frequency-based transfer function we modulate the Fourier coefficients and after applying an inverse Fourier transform we obtain and render the spatial representation of the modulated data. The interactivity allows us to search for the best FbTF setting that enhances the structures, details or features that the user is interested in.

In Fig. 2 we show a screen-shot of our framework where two renderings of the original dataset (top left) and the modulated dataset (top right) are displayed. The two transfer functions are used for setting the opacity and color mappings to densities in the spatial domain (top) and the frequency-modulation factors in the frequency domain (bottom). In the shown example the frequencies are modulated with a linear function that starts with a value of one at the lowest part of the frequency spectrum and diminishes gradually to zero. The output can be interpreted as a smoothed version of the input data. The modulation of frequencies causes a change in the value-range of the data in the spatial representation. For display purposes normalization is applied to bring the values in the same range.

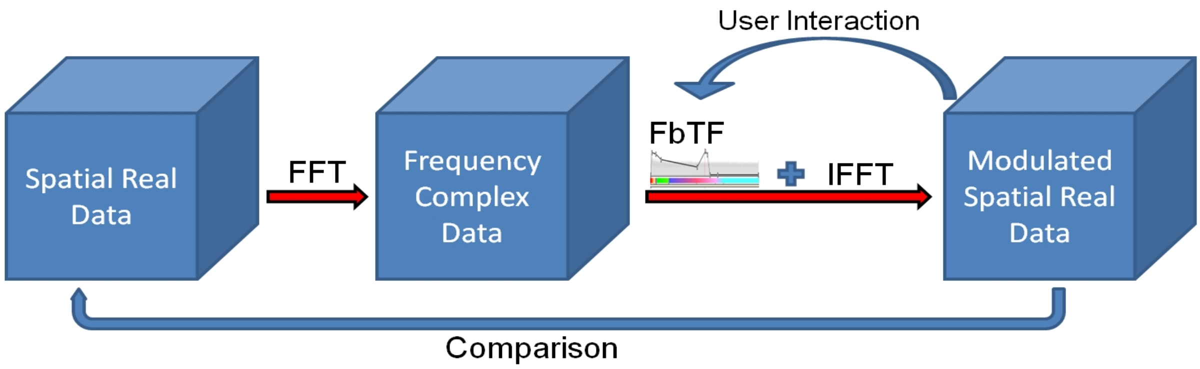


Figure 1: Conceptual scheme of frequency based modulation. A 3D signal (dataset) is transformed to the frequency domain through a Fourier transform, and based on a scatter-plot of the amplitudes vs. radial-distance frequencies we modulate specific frequencies of interest. The output then is transformed back in the spatial domain with an inverse Fourier transform.

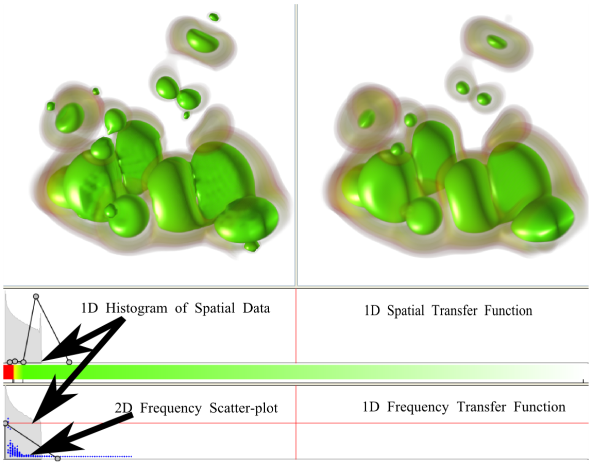


Figure 2: Interface of our frequency-based visualization framework.

5 Implementation and Results

Our test platform is an Intel Dual Core 2.70 GHz processor machine with 8GB of RAM equipped with an NVidia GeForce GTX 2600 graphic card. For the direct volume rendering we have implemented a GPU-based raycaster and used GLSL as a shading language.

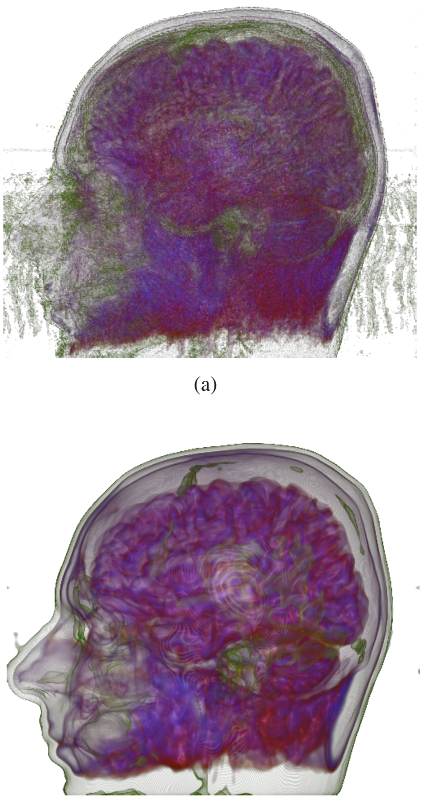
The filters are applied in the frequency domain, hence the implementation of these filters requires a forward and inverse Fourier transform. For the implementation of the Fourier transform we have used the FFTW library for the CPU-based implementation [9] and the CUFFT CUDA library for the GPU-based implementation [7]. The times concerning the Fourier transform depend on the dimensions of the dataset and hence influence the real-time response of our framework. We investigated and compared the performance of these two libraries. The FFTW has a better performance for very small datasets, but starting from $64 \times 64 \times 64$ datasets the performance of the CUFFT is up to ten times faster for a $256 \times 256 \times 256$ dataset.

For modulating frequencies in our FbTF we map the height h of the transfer function at a specific point, through the function $f : h \rightarrow 4h^2$,where h takes values in the range $[0,1]$. When h is in the interval $[0,0.5]$ the amplitudes of the respective frequencies are minimized, and when h is in the interval $[0.5,1]$ the amplitudes are maximized.

5.1 Complex Filtering

Filtering is a useful procedure in signal processing that can be used as an enhancement or restoration step. The data enhancement in the frequency domain is straightforward. We simply compute the Fourier transform of the data, multiply the result by a filter, and take the inverse transform to produce the enhanced data. By reducing high frequency components we blur the data, and vice-versa by increasing the magnitude of the high frequencies we sharpen the data.

One of the most desired data-enhancing effects of filtering is the noise smoothing or noise removal. In spatial domain noise removal can be achieved by the convolution of data with smoothing kernels of different size and structure. Special attention must be made to an excessive smoothing effect, since it can corrupt the data and with that also the features/structures we are trying to enhance. In our framework we can interactively tune our FbTF until a good balance is achieved between the removed noise and the preservation of our structures/features. In Fig. 3 we show an example from a human head MRI where a lot of noise is present in the original data. Through our FbTF we can clearly enhance the visual appearance of the data without blurring the structures. The achievement of the same result through spatial convolution would be non-trivial, since it would require the construction of a complex filtering kernel and would be more time consuming.



(a)

(b)

Figure 3: Renderings of MRI head dataset obtained from the: a) original dataset and b) dataset modulated with a smoothing filter.

In Fig. 4 we show several renderings from the Hydrogen dataset obtained from different filtering settings. In Fig. 4 the results are obtained from applying a Gaussian low-pass (Fig. 4(b)) and a high-pass filter (Fig. 4(c)). The cut-off frequency is depicted interactively based on the desired output. By interactively changing our FbTF we can better understand the linking between the modulation of specific frequencies to the response in the spatial domain.

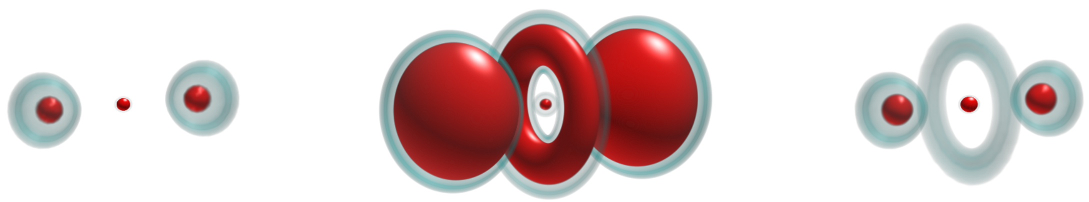
5.2 Selecting Single-frequencies

In signal processing very often is required the detection or selection of specific frequencies. With transfer functions operating in the spatial domain it would be impossible to detect or highlight material or parts of a signal (or data) that only consists of specifics frequencies. With our FbTF if a signal consists of specific frequencies, it is very easy to detect and hence to segment those frequencies. In Fig. 5 we show a synthetic dataset consisting of three principal frequencies. In our 2D scatter-plot the spectrum of the dataset is represented by three entries, so it is trivial to discriminate between them. Achieving the same result with a transfer function operating in the spatial domain would be non-trivial, since the data is created by the sum of three 3D sine waves, hence the spatial density histogram consists of several minima and maxima.

In the same way we believe that our work can give an efficient solution to problems like spectral decomposition. Spectral decomposition is based on the concept that a reflection from a thin bed has a specific and characteristic expression in the frequency domain that indicates of the temporal bed thickness [5]. The most concern regarding spectral decomposition is the necessity to visualize and interpret several mono-frequency volumes created from a single input dataset. As shown in the previous example this can be achieved quite easily with our proposed framework.

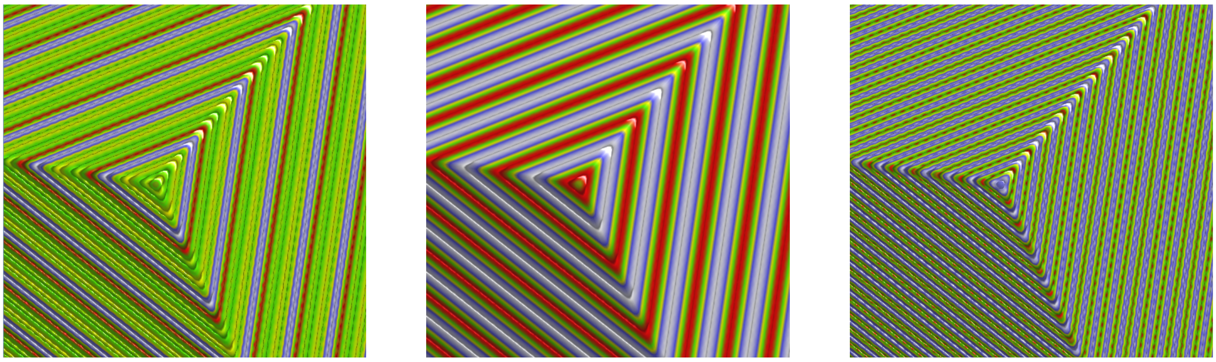
5.3 Feature detection

The frequency response of a signal represents the rate of change of the signal. Fast changes contribute to high frequencies and vice-versa. Gradient information can be deducted from the upper part of the frequency spectrum (i.e., the high frequencies). In the other hand, structures with similar or constant density contribute to the lower part of the frequency spectrum. With a tuned bandpass filter, structures of different sizes can be detected. This idea is similar to the approach presented by Correa and Ma [6], where analysis and size-based feature enhancement is done through multi-scale Gaussian filtering. In Fig. 6 we show results of an Aneurism dataset. By amplifying the frequencies of a specific frequency band (manually tuned), we are able to detect the aneurism. For display purposes we apply an image blending of the result we have from the bandpass amplification with the rendering from the original data.



(a) (b) (c)

Figure 4: Renderings of Hydrogen dataset obtained from: a) original dataset, b) dataset modulated with low-pass filter, and c) dataset modulated with high-pass filter.



(a) (b) (c)

Figure 5: Renderings of a Synthetic dataset from: a) original dataset consisting of 3 principal frequencies, b) modulated dataset consisting only of one frequency (lowest), and c) modulated dataset consisting only of one frequency (highest).

6 Conclusion and Future work

We presented an interactive framework that extends the common visualization pipeline by including frequency modulation as a data enhancement step. The DFT implemented with CUDA provides a fast and interactive way of analyzing 3D signals in the frequency domain. We showed different scenarios related to: the construction of complex filters, the enhancement of structures and detection of features of interest. The interactivity of our framework creates possibilities for the better exploration of the signals in the frequency domain and for the linking to the spatial domain representation of those signals.

We observed that changing specific frequencies may lead to the undesired changes or the corruption of the overall structures of the data. In our future work we plan to put more emphasis in the scientific linking between the modulation of specific frequencies and the impacts on the spatial data representation. One other possible way to extend our framework is by including spatial local information to the frequency data. We plan to achieve this by using a Short Term Fourier Transform [8] and devote special focus on how to overcome the problem of dealing with dimensions two times higher in the STFT domain.

We showed that important information can be extracted from the frequency spectrum. In addition further investigation will be pursued in understanding the impact of frequency modulation in structures and features of interest. We will consider the usage of Fourier descriptors in the representation and enhancement of features of interest [1]. Considering spectral decomposition one of the fields that directly benefits from our framework we also plan to coordinate with experts from geology studies in

(a) (b) (c)

Figure 6: Renderings of an Aneurism dataset obtained: a) from the original dataset, b) from the dataset after applying a global low-pass filter in the frequency domain, and c) from image blending the image in *a)* with the rendering output from the aneurism dataset obtained after applying a band-pass amplification in the frequency domain.

order to develop the framework in symbiosis with their needs.

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