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Studying Pulsatile Flow with Fractal Analysis of Speckle Images

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Abstract: The scattering of coherent light from an evolving system bears the signature of the basic physical phenomenon. The characteristic properties of these speckle patterns fluctuate depending upon when the image is captured during the process. There is thus a rapid change in the properties of the images including the fractality of the images. The speckle images can be analyzed to extract the parameters of flow using this. In this paper we report the results of experiments done to study pulsatile flow with speckle images. *Copyright © 2016 IFSA Publishing, S. L.*

Keywords: Scattering, Speckle, Statistical optics, Turbid media.

1. Introduction

The transmission or reflection of coherent light through diffuse media gives rise to a granular intensity pattern called speckle. The different optical path lengths traversed by coherent light in a medium leads to constructive or destructive interference in the image plane. The image is therefore full of bright or dark spots of varying sizes and intensity. Laser light illuminating a rough surface is an ideal scenario for generation of speckle. This is noise for most imaging applications, but carries valuable information about the medium. By studying the changes in the speckle pattern the time evolution of the medium can be observed. In case the object as a whole moves or parts of it move, changes can be seen in the speckle pattern which are correlated to the motion for a certain time frame, till the speckle pattern decorrelates completely. This offers a unique opportunity to study changes in a medium without direct imaging by simply quantifying the decorrelation in the speckle pattern.

The coarseness in granularity of the spatial intensity distribution of the speckle patterns make them a good candidate for a study of fractality [1]. The random spatial distribution of bright and dark spots in a speckle image displays the self-similarity, scaling, and statistics which we are familiar with in fractals [2]. Fractal statistics is also very relevant in studying biological systems. In a living sample, a level of complexity of the system is considered normal and other behavior can indicate disease [3]. In most physiological processes, the measured values usually fluctuate in time and this can also be studied for fractal behavior. This has been investigated in studies like that of cardiac inter-beats for healthy volunteers and patients [4]. Optical techniques are used in biomedical imaging because important information can be obtained in a non-invasive manner. The techniques can range from point or line scans for instance in optical coherence tomography or full field imaging techniques. The imaging techniques have their own complex requirements due to the equipment and data processing required. Laser speckle imaging is currently being studied as a method to extract biomedical parameters without direct imaging [5-7]. Biomedical imaging in live conditions always has the complication of relative motion between the imaging system, the illumination and the subject. This is more relevant when imaging dynamics like flow in a living medium. Speckle based techniques have been shown to be quite robust for such case [8-9]. In most cases the sample is illuminated by a laser light and the scattered light is collected by a camera. Due to interference of light diffracted by the scatterers in the diffuse media a grainy speckle image is created. In case the sample is subject to motion or contains moving particles, the dynamics of the complex scattering medium can be extracted from the time evolving speckle patterns. The complexity of these signals is mainly due to fluctuations caused by moving red blood cells and appears to be pretty random in a scattering medium such as skin with an underlying capillary network. The standard technique of studying these dynamic series of speckle patterns is based on spatial or temporal implementations of laser speckle contrast analysis. Fractal statistics is being used to study speckle images [1, 10-11] in many recent studies. Analyzing the speckle data with fractal statistics provides a measure of the fluctuations of an evolving process at different temporal resolutions. This reveals the self-similarity and order which underlies the apparent chaotic changes in the signal. This behavior where statistical properties of smaller parts are proportional to statistical properties of the whole can be addressed using power law scaling in fractal statistics.

In this paper, we report on a study of pulsatile flow using speckle images. Using differential box counting approach, for fractal analysis, we have measured the changes of fractal dimensional over time for speckle images. This data was also analyzed using standard speckle contrast analysis.

2. Methods

2.1. Laser Speckle Contrast Analysis

Study of dynamics in diffuse media using time varying speckle patterns arising due to laser illumination, has the advantage of being full field and relatively inexpensive. A speckle pattern generated by a sample which contains moving scatterers gets increasingly blurry as the integration time of pattern increases. Finally the patterns decorrelate completely. Crucial information about the evolution of media can be obtained by analyzing the time fluctuation dynamics of speckle images. Laser speckle contrast, which was first introduced by Briers and Webster [12] is a parameter which can be used to quantify the changes in the medium being studied. The speckle contrast (K)

$$K = \frac{\sigma}{< I >} \tag{1}$$

is defined as the ratio of the standard deviation (σ) over the average intensity fluctuation (< I >), in the image. This parameter can be evaluated for the entire image at once or using a sliding spatial window of (n × n) camera pixels [13]. Pulsatile flow can be studied using speckle contrast by recording a time series of speckle images. The speckle contrast is then calculated for the entire image in total or using a sliding spatial window. The resulting contrast time series are then Fourier transformed to obtain the frequency spectrum. This frequency spectrum has information about all the fluctuations arising in the flowing media for the entire duration of each measurement. This is also a function of the camera exposure time and acquisition rate.

2.2. Fractal Analysis of Speckle Images

The fractal dimension of an image mainly corresponds to the perception of roughness and also describe the scaling seen in it mathematically. The fragmentation of the image resembles a structure where smaller pieces can reproduce the statistical properties of the entire image. This can be explained using a scaling law, where an image is a union of N distinct, non-overlapping copies of itself. The copies have been scaled down by a ratio r = M/s where M is the image size and s is the size of the length scale of the composing copies. The number N is related to the ratio by

$$N(s) \cong r^{-D}, \tag{2}$$

where the non-integer exponent D is the fractal dimension. Fractal dimension has been shown to be a useful tool to study the complex systems. The estimation of the fractal dimension (FD) of an image can be done using several techniques, Fourier power spectrum of image intensity [14], using triangular prisms, or the reticular cell counting method [15-16]. All of these can be classified under three main categories of box counting, fractional Brownian motion and the area measurements [17]. The study of certain properties that do not change as an object undergoes continuous deformation is described by topological dimension. This is represented by Koch snowflake where the topological dimension stays the same even as the curve gains more complexity [18]. However, the fractality of the curve can reveal another dimension which mainly reflects the properties of the evolving curves and characterizes their texture. This is a good measure of how structure or coarseness is distributed in a surface area and can be clearly related to the spatial distribution measured in a speckle pattern. The time evolution of this in the area under observation is very useful in studying dynamical systems. The original term fractals was used to describe objects whose Hausdorff-Besicovich dimension exceeded their topological dimension. However, Mandelbrot applied this term for all sets of objects which were self-similar, self-affine, or quasi-self-similar [19]. The self-similarity cannot be only attributed to space but also time. The essential properties of fractals are often seen in speckle images. In a speckle image, a large number of wavelets contribute to form a dark or bright spot in the image plane. The contributing waves have encountered various path lengths on the surface or inside the medium.

This method computes the fractal dimension by subdividing the speckle image with multiple boxes of a specific size, Fig. 1, and estimating how many of them are required to cover the whole object [20]. This process is repeated for a range of sizes. If N(s), number of boxes, is estimated across a range of s, then there should be linear relationship between log(N(s)) and log(1/s), where the measure slope is an indication of the fractal dimension. The fractal dimension can be written as:

$$FD = \lim_{s \to 0} \frac{\log(\mathrm{N}_s)}{\log(1/\mathrm{s})} \tag{3}$$

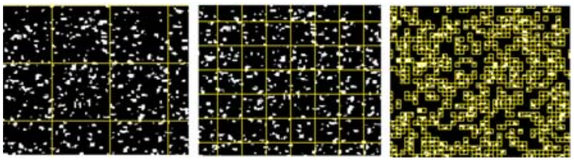
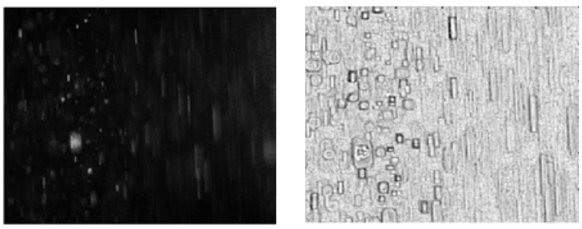


Fig. 1. Box counting for a typical speckle image which has been converted to a fractal image. Three different values of box size are shown.

So differential box counting has been carried out on the speckle images to transform the speckle data to fractal dimension. An example of the speckle data recorded with pulsatile flow is shown along with the transformed image in Fig. 2.



(a) (b)

Fig. 2. (a) Raw speckle image of pulsatile flow on the left. (b) The speckle image converted to corresponding fractal image, on the right.

This method was first proposed in 1994 by N. Sarkar and Chaudhuri [21]. Here, a speckle image is considered as a 3D spatial surface where two coordinates are the spatial coordinates of the pixel and the third one is the gray level. The original speckle images are transformed to the fractal images. For differential box counting for an image of size M divided in 3D space into blocks $s \times s \times s'$ where s is the size of the square and s' is gray level of the block. If the total gray level of the image is G then we can write G/s' = M/s. To determine the required thickness of the blanket needed to cover the image surface we need to know that the minimum gray level falls in the box number k and the maximum gray level falls into box number l. Then the thickness of the blanket coverage on the grid (i; j) is:

$$n_s(i, j) = l - k + 1 \tag{4}$$

The total number of boxes is calculated for different values of s as:

$$N_s(i, j) = \sum_{\substack{1 \le i \le M/s \\ 1 \le j \le M/s}} n_s(i, j) \tag{5}$$

The fractal dimension was calculated for each image from the slope of the linear regression line fit to the log plot of total number of boxes N_s versus the dimension scale or the box size s. This approach is mainly used in medical setting for feature extraction [22]. To study dynamics, a time series of fractal dimension has been used to determine the corresponding frequency spectrum.

3. Experimental Setups

In this section, an overview of different parts of the setup will be given. The experimental setup, Fig. 3, is simple and can be decomposed into three main parts: illumination, detection and phantom with scattering fluid.

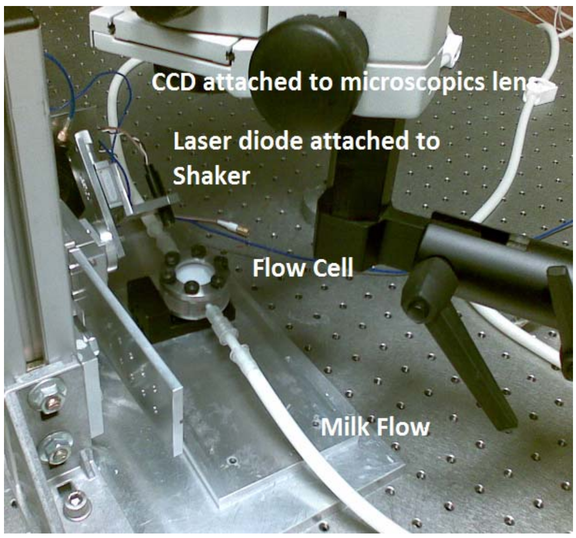


Fig. 3. The experimental setup which has been used for the experiments. The flow cell can be fitted with different top membrane to introduce static scatterers. The insert into the flow cell mimics a homogeneous thin layer of flow.

3.1. Static Scatterers

These experiments were carried out using a semi rectangular channel phantom. The flow cell consists of a semi-rectangular channel with a length of 20 mm and a depth of 1 mm to represent a homogeneous, thin layer of flow. The top membrane of the cell can be interchanged to be glass or a non-transparent skin phantom made of Delrin® (polyoxymethylene, POM) to mimic the scattering properties of skin [23]. In this experiment, we used a roller pump (Minipuls® 3) to generate a pulsatile flow with a controlled frequency in our sample. As a scattering fluid, we used a bulk scattering medium, milk to mimic the blood flow, as the fat particles in milk scatter light similar to red blood cells (RBC's) in blood [24-25]. The measurements aimed to observe the influence of a top membrane and consider the effect of additional static scatterers besides the scattering along the flow on the dynamic speckle images. The three configurations considered included a top membrane of glass, Delrin with 1 mm thickness and 2 mm thickness. The dynamic speckle images were then analyzed and the results of the time series can be seen in Fig. 4. The analysis using the standard speckle contrast can be seen in Fig. 4(a, b, c) and using the fractal dimension of the images can be seen in Fig. 4 (d, e, f).

The effects of changes in velocity of the scatterers and the changes in particle density in the pulsatile fluid signal leaves a different imprint on the contrast and fractal dimension of the images. This can be seen clearly in Fig. 4. The frequency spectrum of the time series data in Fig. 4 is shown in the Fig. 5. In the absence of static scatterers in the Fig. 4(a, d) we can see that the time series data is similar, though, the bulk scattering in the milk does make the time series of the fractal dimension more noisy. The frequency spectra seen in the Fig. 5(a, d) are very similar. The addition of the extra static scattering layer adds to complexity but the time series data with laser contrast analysis can still monitor the pulsating flow. In comparison the fractal dimension of the images changes more rapidly with the thickness of the layer of static scatterers, to be able to monitor the pulsating flow. This also reflected in the frequency spectra of the respective time series, though both techniques could determine the primary frequency of pulsation of the pump which was at 1.25 Hz.

4. Results and Discussions

The multiscale analysis of time series of light scattered from a sample can be a useful tool for better understanding the complex underlying mechanisms of the medium. In this paper, we studied the fractal dimension change of speckle images of pulsatile flow and compared it to speckle contrast analysis. We address the result of measured fractal dimension for the case of pulsatile flow using different membranes on top of the bulk scattering fluid. We observe that in case of a 2 mm thick layer of Delrin as the top membrane, which has a high number of static scatterers, the fractal dimension does not reflect the pulsation and changes in flow. Whereas the laser speckle analysis can still capture the changes in the pulsatile flow.

The fractal dimension is a more sensitive measure than speckle contrast since it can measure the texture of image. It is also extremely responsive to rapid changes in the texture and this can be exploited to study the time evolution in more complex media just by observing the scattering from it.

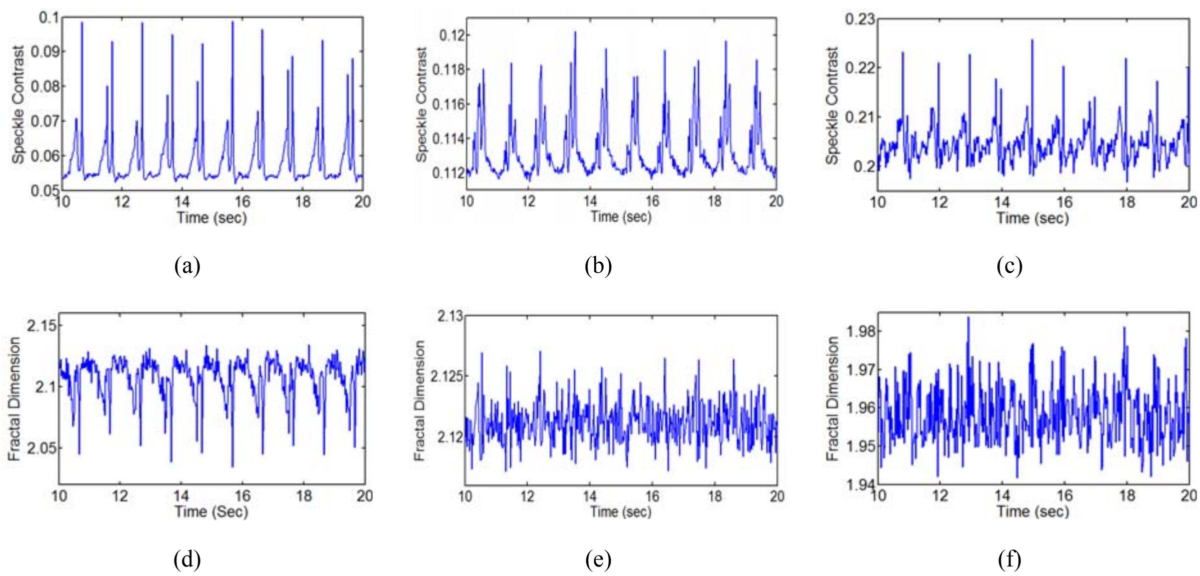


Fig. 4. The time series signal measured for pulsatile flow in the rectangular flow channel with different top membrane. a) Glass membrane, images analyzed, with speckle contrast. b) 1 mm thick Delrin membrane, images analyzed, with speckle contrast. c) 2 mm thick Delrin, images analyzed, with speckle contrast. d) Glass membrane, images analyzed, with fractal dimension. e) 1 mm thick Delrin membrane, images analyzed, with fractal dimension. f) 2 mm thick Delrin membrane, images analyzed, with fractal dimension.

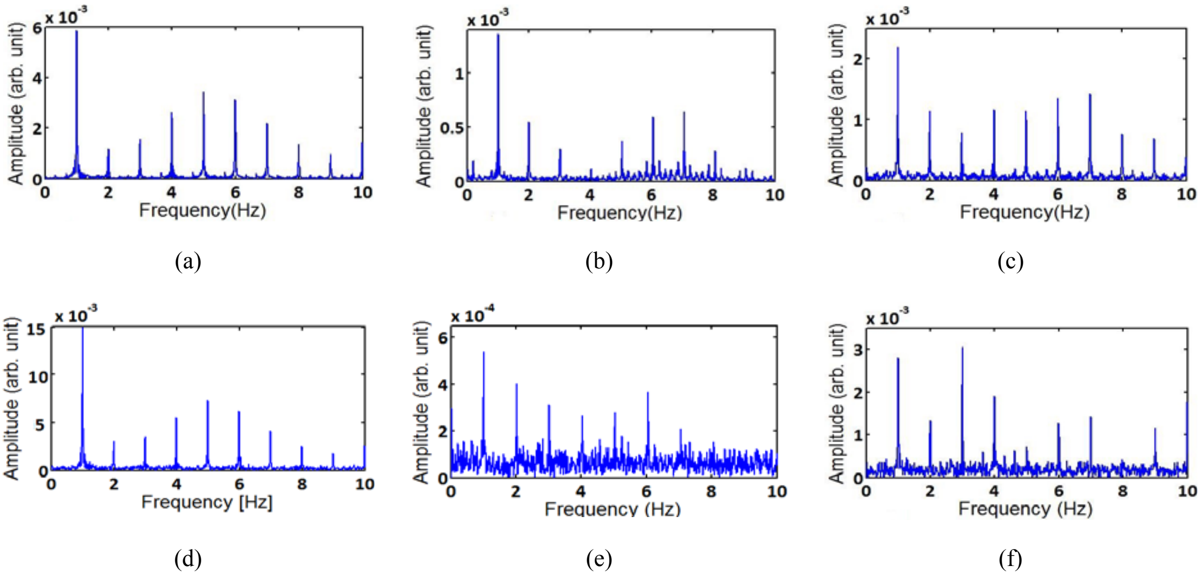


Fig. 5. The spectral analysis of the time series measured for pulsatile flow in the rectangular flow channel with different top membranes. a) Glass membrane, images analyzed, with speckle contrast. b) 1 mm thick Delrin membrane, images analyzed, with speckle contrast. c) 2 mm thick Delrin, images analyzed, with speckle contrast. d) Glass membrane, images analyzed, with fractal dimension. e) 1 mm thick Delrin membrane, images analyzed, with fractal dimension. f) 2 mm thick Delrin membrane, images analyzed, with fractal dimension.

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