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Dynamic speckle analysis with smoothed intensity-based activity maps

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ABSTRACT

Pointwise intensity-based algorithms are the most popular algorithms in dynamic laser speckle measurement of physical or biological activity. The output of this measurement is a two-dimensional map which qualitatively separates regions of higher or lower activity. In the paper, we have proposed filtering of activity maps to enhance visualization and to enable quantitative determination of activity time scales. As a first step, we have proved that the severe spatial fluctuations within the map resemble a signal-dependent noise. As a second step, we have illustrated implementation of the proposed idea by applying filters to non-normalized and normalized activity estimates derived from synthetic and experimental data. Statistical behavior of the estimates has been analyzed to choose the filter parameters, and substantial narrowing of the probability density functions of the estimates has been achieved after the filtering. The filtered maps exhibit an improved contrast and allowed for quantitative description of activity.

1. Introduction

Dynamic laser speckle is a method for non-destructive detection of physical or biological activity through statistical processing of speckle patterns captured for a diffusely reflecting object. The method is sensitive to microscopic changes of the object surface over time [1–3]. Various applications have been reported for monitoring of processes in medicine, biology, industry and food quality assessment [4–11]. In principle, information retrieval can be done from different parameters of the captured speckle patterns, e.g. using phase in optically recorded digital holograms [12] or applying vortex determination of activity [13]. The most popular, however, are the intensity-based algorithms due to simple acquisition of the raw data and ability for pointwise processing [1,14–19]. The latter relies on a sequence of speckle patterns correlated in time and creates a 2D spatial contour map of a given statistical measure. By building maps in successive instants, one may follow the undergoing processes in time.

Speckle nature of the raw data combined with finite acquisition time leads to strong fluctuations of any pointwise intensity-based estimate across the activity map. The spread of fluctuations within the map depends on the applied algorithm. Thus, the probability density function (PDF) of an estimate is crucial for the choice of an algorithm [15]. However, even if an algorithm with a narrower PDF is chosen, the latter can be rather wide as to make variation of activity barely distinguishable. This worsens sensitivity of the method and results in qualitative evaluation by simply indicating regions of higher or lower activity across the object surface. Separation of these regions is strongly alleviated by low spatial correlation of the estimates that is related to the average speckle size [16–19]. That's why, quantitative evaluation is preferably done by statistical parameters which describe activity by a single value [20] or function [21]. As such parameters are obtained through spatial averaging over a comparatively large number of pixels, spatial characterization of activity is lost.

In this paper, we propose to improve quality of any intensity-based activity map by applying a smoothing filter to its fluctuations. What makes this task non-trivial is the signal-dependent nature of the fluctuations as their spread depends on activity and is expected to vary across the map. Therefore, we firstly analyze statistics of pointwise intensity-based estimates in dynamic speckle measurement and then demonstrate efficiency of smoothing by processing synthetic and experimental data. There are two mutually related goals to be achieved by filtering: i) to increase the map contrast and thus to enhance its visualization and ii) to obtain quantitative description of activity. Analysis is done on the example of three pointwise algorithms for estimation of the temporal structure function that have been introduced in [15,16]. These algorithms need less computation time compared to other popular algorithms [19] at the same quality of the activity map. The paper is organized as follows: in Section 2 we describe acquisition

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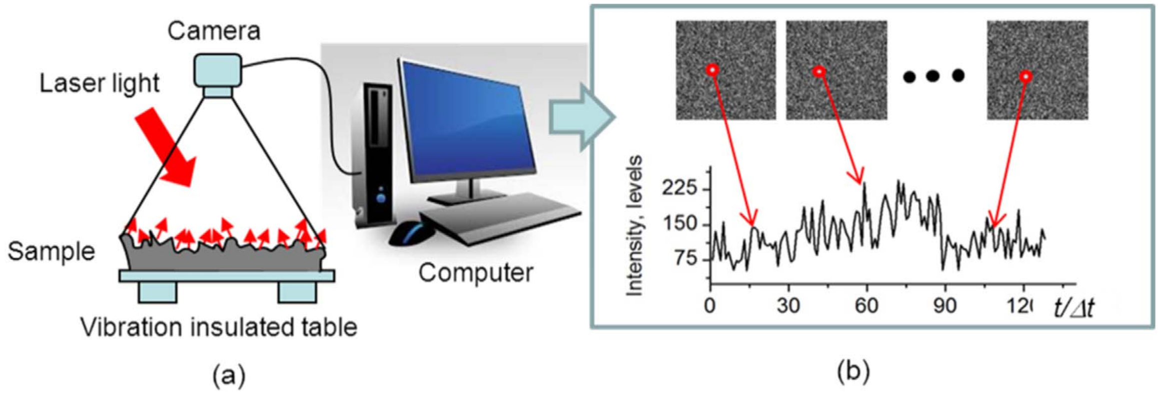

Fig. 1. Experimental set-up for capture of dynamic speckle patterns (a); pointwise processing of the capture speckle patterns (b).

of real and generation of synthetic data and the algorithms. In Section 3 we analyze the PDFs of fluctuations within a map built for a synthetic object and achieve quantitative characterization of activity by applying a proper filter. Discussion of efficiency of the developed approach in Section 4 is made by processing experimental data.

2. Dynamic speckle measurement with pointwise intensity-based processing

2.1. Dynamic laser speckle measurement

The measurement is depicted schematically in Fig. 1(a). A CMOS camera with a pixel interval Δ is adjusted to focus the object under laser illumination. The optical axis of the camera is normal to the object surface. The set-up is positioned on a vibration-insulated table. The camera records a sequence of N correlated images of size $N_x \times N_y$ pixels for time period T with the time interval Δt between the frames. A time sequence of 8-bit encoded intensities $I_{kl,n} \equiv I(k\Delta, l\Delta, n\Delta t)$, $n = 1..N$ is formed at each point $(k\Delta, l\Delta)$, $k = 1..N_x$, $l = 1..N_y$ of the acquired images as is shown in Fig. 1(b). These data are used to build a pointwise estimate of a given statistical measure over T.

We used three algorithms for pointwise processing of the acquired speckle patterns. The first estimator of activity was a temporal structure function (SF) [16] determined at a time lag $\tau = m\Delta t$, where $m \geq 0$ takes integer values, from

$$\hat{S}(k, l, m) = \frac{1}{N-m}\sum_{i=1}^{N-m}(I_{kl,i} - I_{kl,i+m})^2 \tag{1}$$

The second estimate was the modified structure function (MSF) introduced in [15]; it is obtained by replacing the square in Eq. (1) with the absolute value of the difference $I_{kl,i} - I_{kl,i+m}$:

$$\hat{S}_{\mathrm{mod}}(k, l, m) = \frac{1}{N-m}\sum_{i=1}^{N-m}|I_{kl,i} - I_{kl,i+m}| \tag{2}$$

The estimates (1) and (2) give correct output at uniform intensity distribution within the illuminating laser beam and equal reflectivity all over the object. The intensity obeys the speckle statistics [2]. Therefore, these conditions are equivalent to the same mean value and hence the same variance, σ^2, of intensity fluctuations across the object. The speckle intensity, $I_{kl,n}$, arising from a stationary process, is characterized at each pixel $(k\Delta, l\Delta)$, $k = 1..N_x$, $l = 1..N_y$ by a temporal autocorrelation function (ACF),$R_{kl}(\tau = m\Delta t)$. The different time scales of activity across the object surface are given as the 2D spatial distribution $\tau_c = \tau_c(k\Delta, l\Delta)$ of the temporal correlation radius of $R_{kl}(\tau = m\Delta t)$. At $\tau > \tau_c$ correlation between the intensity values is weak. At uniform illumination and equal reflectivity across the object, the ACF at pixel $(k\Delta, l\Delta)$ is given by $R_{kl}(\tau) = \sigma^2\rho_{kl}(\tau)$ with $\rho_{kl}(\tau)$ being the normalized ACF at this point; the value of $\tau_c(k\Delta, l\Delta)$ is defined as $\rho_{kl}(\tau_c) = \rho_0 \leq 0.5$. The choice of ρ_0 is task-specific. For activity induced by a stationary process, the SF at each point is determined from $S_{kl}(\tau) = 2\sigma^2[1 - \rho_{kl}(\tau)]$. The estimate given by Eq.(1) is an unbiased estimate of $S_{kl}(\tau)$.

Robust estimation of activity at non-uniform illumination, when the variance of intensity fluctuations varies from point to point, is achieved by normalization. We used the normalized SF (NSF) introduced in [21]:

$$\hat{S}_{norm}(k, l, m) = \frac{1}{(N-m)\hat{\upsilon}_{kl}}\sum_{i=1}^{N-m}(I_{kl,i} - I_{kl,i+m})^2 \tag{3}$$

where $\hat{\upsilon}_{kl}$ is the variance estimate at $(k\Delta, l\Delta)$, $k = 1..N_x$, $l = 1..N_y$ with $\hat{I}_{kl}$ being the mean value at this point:

$$\hat{\upsilon}_{kl} = \frac{1}{(N-1)}\sum_{i=1}^{N}(I_{kl,i} - \hat{I}_{kl})^2,\ \hat{I}_{kl} = \frac{1}{N}\sum_{i=1}^{N}I_{kl,i} \tag{4}$$

The main advantage of the estimates (1)–(3) is selectivity introduced by the time lag, τ, which increases the activity maps contrast. Apart from that, the SF estimates have another two positive features. First, they offer a set of activity maps at increasing time lags and hence an option for evaluation of short-time activity scales across the object. Second, they are computed with only one summation and therefore need less time than the other popular estimates as a generalized difference [17] and a weighted generalized difference [19]. The SF and MSF algorithms provide the same quality of processing as the weighted generalized difference and substantially outperform that of the generalized difference [15].

2.2. Generation of synthetic data

To study the intensity based estimates as input data to a smoothing filter, we used also synthetic data. They were generated for a specially designed test object composed by four equal rectangular regions Z_1, Z_2, Z_3 and Z_4 of different constant activity. The capture of speckle patterns was simulated for a He-Ne laser at uniform illumination and reflectivity. Activity was described by the 2D array $\tau_c = \tau_c(k\delta, l\delta)$,$k = 1...2N_x$, $l = 1...2N_y$ with $\delta = \Delta/2$. The simulation included generation of a sequence of 2D delta-correlated in space random phase distributions $\phi(k\delta, l\delta, i\Delta t)$, $k = 1..2N_x$, $l = 1..2N_y$, $i = 1..N$ on the object surface starting from an initial 2D array of random delta-correlated phase values uniformly distributed from 0 to 2 π. Time evolution in these phase distributions was introduced as is described in Ref. [22] to obtain the normalized ACF $\rho_{kl}(\tau) = \exp[-\tau/\tau_c(k, l)]$. The complex amplitude of the light reflected from the object was $U_S = \sqrt{I_0}\exp\{-j\phi(k\delta, l\delta, i\Delta t)\}$ at the instant $i\Delta t$ for the illuminating beam with intensity I_0. The complex amplitude of the light falling on the camera array was $U_{cam} = FT^{-1}\{H{\cdot}FT\{U_S\}\}$ where H is the coherent transfer function of the registration system and $FT\{\cdot\}$ denotes Fourier transform (for a diffraction limited $4f$ system H is reduced to a *circ* function [23]). Integration by the camera pixels with size Δ was