Optics and Lasers in Engineering 111 (2018) 50–57

Contents lists available at ScienceDirect

Optics and Lasers in Engineering

journal homepage: www.elsevier.com/locate/optlaseng

Evaluation of activity from binary patterns in dynamic speckle analysis

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A R T I C L E I N F O

Keywords:
Dynamic speckle
Correlation-based processing
Binary patterns
Speckle metrology

A B S T R A C T

Pointwise intensity-based statistical processing of dynamic laser speckle patterns formed on the surface of a diffusely reflecting object is perspective for monitoring of ingoing processes of physical or biological activity within the object. The output of the measurement is a two-dimensional map, which shows qualitatively regions of higher or lower activity on the object surface. In the paper, we have proposed transforming the captured 8-bit encoded speckle patterns into binary patterns by applying a pointwise threshold. Motivation behind this study is the need for an algorithm, which is robust to non-uniform illumination and offers lowered computational complexity as time and memory consumption. We showed by simulation and experiment that quality of the map obtained by processing of correlated binary patterns approached that achieved with 8-bit encoded patterns. We analyzed statistical behavior of the estimates built from binary patterns and proved applicability of a non-stochastic threshold as e.g. a constant intensity level at uniform illumination. The proposed algorithm was applied for processing polymer drop drying experimental data.

1. Introduction

The method known as dynamic speckle analysis for monitoring of processes relies on change in time of laser speckle patterns on the surface of diffusely reflecting objects under coherent illumination [1–3]. Speckle is due to surface roughness or, for the case of turbid media as e.g. human tissues, to different optical lengths of photons emerging at the object surface after they have undergone multiple scattering events in its bulk [4]. Statistical processing of speckle patterns can indicate the spatial regions of slower or faster changes or activity within the object, and different applications of the method have been reported in medicine, biology, industry and for food quality assessment [4–13].

In principle, non-destructive evaluation of activity in objects can be done by using different parameters of the speckle patterns as intensity, a phase in optically recorded digital holograms [14] or vortices [15]. Simple acquisition of the raw data and option for pointwise processing make the intensity-based algorithms the most preferable [2,16–21]. They produce a two-dimensional (2D) spatial contour map of a given statistical parameter as a measure of activity from a sequence of correlated in time speckle patterns. The map entry at each point is obtained by averaging over a sequence of intensities that correspond to the same pixel in the captured speckle patterns. By building maps in successive instants, one may characterize physical or biological activity in time for 3D objects.

As a whole, for the intensity-based algorithms, the 2D activity map qualitatively represents the regions of faster or slower intensity fluctuations and correspondingly of higher or lower speed of ingoing processes which cause change of the speckle pattern. Such properties of the map as contrast and spatial resolution are strongly affected by the speckle nature of the raw data. The limited number of the speckle patterns used for statistical estimation of activity leads to severe fluctuations of any pointwise intensity-based estimate across the map. The smaller the spread of fluctuations, the better the map quality [17]. Increasing the number of patterns improves sensitivity of the method by narrowing the probability density function (PDF) of the fluctuations. However, this means increasing computational complexity as time and memory consumption. The other important feature of the intensity-based approach is its vulnerability to non-uniform illumination or varying reflectivity across the studied surface in view of the signal dependent nature of the raw speckle data. Correct representation of activity in this case requires adequate normalization of the used estimates [18]. All these factors inspire constant search of algorithms with improved performance as accuracy and computational efficiency.

In this paper, we propose to solve the problem with non-uniform illumination and to alleviate computational complexity by transforming the acquired 8-bit encoded speckle patterns into binary patterns with only two levels. This is done by comparing the raw intensity data to a sign threshold. The statistical parameter chosen to describe activity is the temporal correlation function calculated at each point by processing the

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https://doi.org/10.1016/j.optlaseng.2018.07.020
Received 4 September 2017; Received in revised form 27 June 2018; Accepted 29 July 2018

binary sequences. The paper is organized as follows: in Section 2 we describe forming of binary patterns from speckle images, and the algorithm for evaluation of the activity map. We prove by simulation that the proposed approach successfully reveals activity at uniform and non-uniform illumination when the threshold is equal to the average intensity value at each point. We show that the proposed algorithm provides accuracy comparable to that of the standard correlation function. In Section 3 we study sensitivity of the algorithm to variation of the threshold and check the option of using non-stochastic threshold across the patterns. Discussion of efficiency of the developed approach in Section 4 is made by processing experimental raw data for a test object. The developed approach is used for detection of the drying process in a polymer water solution.

2. Dynamic speckle measurement with binary patterns

2.1. Pointwise binarization of speckle patterns and the processing algorithm

For convenience, we briefly describe intensity-based pointwise dynamic speckle measurement. Capture of speckle patterns, forming of temporal sequences of intensities for pointwise processing and an activity map as an output of this processing are shown schematically in Fig.1. Different colors within the map correspond to different activity. A CMOS camera with a pixel interval Δ is adjusted to focus the object illuminated by the laser beam. The optical axis of the camera is normal to the object surface. The set-up is positioned on a vibration-insulated table. A sequence of N correlated speckle images of size $N_x \times N_y$ pixels are captured for the time 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 for each pixel $(k\Delta, l\Delta), k = 1..N_x, l = 1..N_y$ of the acquired images. A pointwise estimate of a given statistical measure is built from these data by averaging over T or over N intensity values respectively. The intensity obeys the speckle statistics [1] at each point. For a stationary process, variation of the speckle intensity in the sequence, $I_{kl,\ n}$, at each pixel $(k\Delta, l\Delta), k = 1..N_x, l = 1..N_y$is characterized by a temporal correlation function,$R_{kl}(\tau = m\Delta t)$, where $\tau = m\Delta t$is the time lag between the measured intensity values and $m \geq 0$ takes integer values. Activity may have different time scales across the object surface and can be described by the 2D spatial distribution of the temporal correlation radius $\tau_c = \tau_c(k\Delta, l\Delta)$ of $R_{kl}(\tau = m\Delta t)$. At $\tau < \tau_c$ correlation between the intensity values is strong and vice versa. At uniform illumination and equal reflectivity across the object, $R_{kl}(\tau) = \sigma^2 \rho_{kl}(\tau)$ is fulfilled with $\rho_{kl}(\tau)$being the normalized correlation function (NCF) at $(k\Delta,\ l\Delta)$ and $\sigma^2$is the constant variance of intensity fluctuations. At non-uniform illumination, the variance varies with the mean intensity. The value of $\tau_c(k\Delta,\ l\Delta)$ is defined as$\rho_{kl}(\tau_c) = \rho_0 \leq 0.5$. The choice of $\rho_0$is task-specific. The interval between the speckle patterns, Δt, should be several times shorter than the minimal temporal correlation radius across the object in order to build an adequate temporal correlation function. The choice of the acquisition time $T = N\Delta t$is based on controversial requirements. On one side, the temporal resolution of the method is given by T in view of averaging over a sequence of N values to calculate the estimate of activity. On the other side, T must be long enough to ensure high ratio $T/\tau_c$for representative statistical data.

Effective retrieval of activity data can be done by correlation-based algorithms whose response reflects correlation between the speckle patterns at a given time lag. In pointwise processing, the 2D distribution of the correlation estimate is related non-linearly to the 2D distribution of $\tau_c$at the instant of the measurement. The time lag introduces selectivity that improves the contrast of the produced activity map. Building activity maps for a set of time lags allows for determination of short-scale activity.

We propose to estimate correlation between binary patterns which are formed by comparing each intensity value in the temporal sequence $I_{kl,n}, n = 1..N$ at the point $(k\Delta,\ l\Delta)$to the mean value, $\hat{I}_{kl}$, at this point according to the algorithm

$$\Phi_{kl,n} = \begin{cases} 1 & if \quad I_{kl,n} \geq \hat{I}_{kl} \\ -1 & if \quad I_{kl,n} < \hat{I}_{kl} \end{cases}, \qquad \hat{I}_{kl} = \frac{1}{N}\sum_{i=1}^{N} I_{kl,i} \tag{1}$$

Thus, instead to 8-bit encoded speckle patterns, processing is applied to binary images with only two levels. In principle, different correlation-based algorithms can be used, but we proceed with the estimate

$$\hat{P}(k\Delta, l\Delta, \tau = m\Delta t) \equiv \hat{P}(k, l, m) = \frac{1}{N-m}\sum_{i=1}^{N-m} \Phi_{kl,i}\Phi_{kl,i+m}, \tag{2}$$

which is an estimate of a correlation function which will be called a polar correlation function (PCF). It is clear from Eq. (2) that one can calculate the PCF estimate at different time lags $\tau = m\Delta t, m = 1, 2...M < N$ and to obtain a set of activity maps or to build the PCF as a function of the time lag at each pixel. It is also clear from Eqs. (1) and (2) that the level "−1" is introduced to take into account the contribution of all intensities in a given temporal sequence that are below its average value, i.e. the binary sequence consists of "+1" and "−1" values and not of units and zeros. Note that in the case of even N the sum in Eq. (2) is always even for even m and odd for odd m respectively. At the limited number of the captured speckle patterns, the estimate of the mean value $\hat{I}_{kl}$ strongly fluctuates from point to point, i.e. it may have a rather wide PDF. This means that the threshold in Eq. (1) is a stochastic quantity. Choosing the threshold in this manner is justified by the fact that the estimates of the mean intensity value or of the mode value for a given time sequence $I_{kl,n}, n = 1..N$ effectively divide the intensities in this sequence in two more or less equal groups.

To study the new algorithm, capture of correlated in time speckle patterns was simulated for a He–Ne laser at uniform illumination and reflectivity. In simulation, temporal variation of intensity fluctuations at each point $(k\Delta,\ l\Delta)$ of the patterns was given by the input NCF $\rho_{kl}(\tau)$ or in other words by the correlation coefficient between images captured at a time lag $\tau = m\Delta t, m = 1, 2...M < N$. Simulation was based on the model in Refs. [22] that described correlation coefficient $\rho_{kl}(\tau = m\Delta t) = \exp(-\sigma^2\{\Delta\phi_m^{kl}\})$ as exponentially decreasing with the variance, $\sigma^2\{\Delta\phi_m^{kl}\}$, of the phase change, $\Delta\phi_m^{kl}$, which occurred for the images separated with the time lag $\tau = m\Delta t$. This exponential decrease is valid for the case of normally distributed phase change due to variation of the height of the scattering centers in normal direction to the surface at the assumption of mutually independent amplitudes and phases at each scattering center and between any two centers. The dependence $\rho_{kl}(\tau = m\Delta t) = \exp(-\sigma^2\{\Delta\phi_m^{kl}\})$ can be used for setting the variance, $\sigma^2\{\Delta\phi_m^{kl}\}$, of the phase change in simulation from the known NCF. Note that an arbitrary NCF can be used for describing decrease of correlation as e.g. exponential or non-exponential decay. In this paper, we generated intensity fluctuations for exponentially decreasing correlation, i.e. with the NCF $\rho_{kl}(\tau) = \exp[-\tau/\tau_c(k, l)]$ at a given 2D distribution of the temporal correlation radius. The chosen NCF belongs to the class of monotonically decreasing functions, observed for many processes as e.g. a drying process. It allows also to determine the standard deviation of the phase variation between successively captured images as $\sigma\{\Delta\phi_{m=1}^{kl}\} = \sqrt{1/\tau_c(k, l)}$.

Simulation started from an initial 2D array of random delta-correlated phase values uniformly distributed from 0 to 2π and generated a sequence of 2D delta-correlated in space random phase distributions $\phi(k\delta, l\delta, i\Delta t), k = 1..2N_x, l = 1..2N_y, i = 1..N$ with $\delta = \Delta/2$on the object surface. The time variation between two consecutive phase distributions was introduced as $\phi(k\delta, l\delta, i\Delta t) = \phi[k\delta, l\delta, (i-1))\Delta t] + \sqrt{1/\tau_c(k, l)}N(0, 1); k = 1..2N_x, l = 1..2N_y, i = 1..N$, where $N(0,\ 1)$ is a normally distributed random number with zero mean and unit variance. Refreshing of $N(0,\ 1)$is required at each new speckle pattern. For the illuminating beam with a constant intensity, I_0, the complex amplitude of the reflected light at the object surface was $U_S = \sqrt{I_0}\exp\{-j\phi(k\delta, l\delta, i\Delta t)\}$ at the instant $i\Delta t$. The complex amplitude at the camera array plane was determined from $U_{cam} =$