Dynamic speckle analysis with smoothed intensity-based activity maps

Citation

Year
2017

Version
Publisher's PDF (version of record)

Link to publication
TUTCRIS Portal (http://www.tut.fi/tutcris)

Published in
Optics and Lasers in Engineering

DOI
10.1016/j.optlaseng.2017.01.012

Take down policy
If you believe that this document breaches copyright, please contact cris.tau@tuni.fi, and we will remove access to the work immediately and investigate your claim.
Dynamic speckle analysis with smoothed intensity-based activity maps

Elena Stoykova\textsuperscript{a,b}, Natalia Berberova\textsuperscript{b}, Youngmin Kim\textsuperscript{a,*}, Dimana Nazarova\textsuperscript{b}, Branimir Ivanov\textsuperscript{b}, Atanas Gotchev\textsuperscript{c}, Jisoo Hong\textsuperscript{a}, Hoonjong Kang\textsuperscript{a}

\textsuperscript{a} VR/AR Research Center, Korea Electronics Technology Institute, 8 Floor, 11, World cup haku-ro 54-gi, Mapo-gu, Seoul, Republic of Korea
\textsuperscript{b} Institute of Optical Materials and Technologies to Bulgarian Academy of Sciences, Acad. G. Bonchev Str., Bl 109, P.O.Box 95, 1113 Sofia, Bulgaria
\textsuperscript{c} Tampere University of Technology, Korkeakoulunkatu 10, 33720 Tampere, Finland

\textbf{A B S T R A C T}

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 underlying 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

\begin{footnotesize}
\textsuperscript{*} Corresponding author.
\textsuperscript{E-mail address: rainmaker@keti.re.kr (Y. Kim).}
\end{footnotesize}
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 N pixels
for time period T with the time interval Δt between the frames. A time
sequence of 8-bit encoded intensities \( I_{k,n} \) is formed at each point \((kΔ, lΔ)\), \( k = 1..N_k, l = 1..N_l \) of the acquired images as 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 \( \tau = mΔt \), where \( m \geq 0 \) takes integer values, from

\[
\hat{S}(k, l, m) = \frac{1}{N - m} \sum_{i=1}^{N-m} (I_{ki,l,i} - I_{ki+l,i+m})^2
\]  

The second estimator 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

\[
\hat{S}_{\text{mod}}(k, l, m) = \frac{1}{N - m} \sum_{i=1}^{N-m} |I_{ki,l,i} - I_{ki+l,i+m}|
\]

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, \( \sigma^2 \), of intensity fluctuations across the object. The
speckle intensity, \( I_{k,l,i} \), arising from a stationary process, is characterized
at each pixel \((kΔ, lΔ)\), \( k = 1..N_k, l = 1..N_l \) by a temporal autocorrelation function (ACF), \( R_{ii}(\tau = mΔt) \). The different time scales of activity across the
object surface are given as the 2D spatial distribution \( \tau_{ii}(kΔ, lΔ) \) of the temporal correlation radius of \( R_{ii}(\tau = mΔt) \). At \( \tau > \tau_{ii} \), correlation between the intensity values is weak. At uniform illumination and equal
reflectivity across the object, the ACF at pixel \((kΔ, lΔ)\) is given by

\[
R_{ii}(\tau) = \sigma^2 \rho_{ii}(\tau) \text{ with } \rho_{ii}(\tau) \text{ being the normalized ACF at this point; the value of } \tau_{ii}(kΔ, lΔ) \text{ is defined as } \rho_{ii}(\tau) = \rho_0 \leq 0.5. \text{ The choice of } \rho_0 \text{ is }
\]

task-specific. For activity induced by a stationary process, the SF at each
point is determined from \( \hat{S}_{\text{norm}}(k, l, m) = 2\sigma^2[1 - \rho_0(\tau)] \). The estimate given by

\[
\hat{S}_{\text{norm}}(k, l, m) = \frac{1}{N - m} \sum_{i=1}^{N-m} (I_{ki,l,i} - I_{ki+l,i+m})^2
\]

where \( \hat{S}_{\text{norm}}(k, l, m) \) is the variance estimate at \((kΔ, lΔ)\), \( k = 1..N_k, l = 1..N_l \) being the mean value at this point:

\[
\hat{S}_{\text{norm}}(k, l, m) = \frac{1}{N - m} \sum_{i=1}^{N-m} (I_{ki,l,i} - \hat{I}_{ki,l,i})^2, \hat{I}_{ki,l,i} = \frac{1}{N} \sum_{i=1}^{N} I_{ki,l,i}
\]

The main advantage of the estimates (1)–(3) is selectivity intro-
duced by the time lag, \( \tau \), 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 Z1, Z2,
Z3 and Z4 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 \( \tau_{ii}(kΔ, lΔ) \), \( k = 1..N_k, l = 1..N_l \) with \( \delta = \Delta/2 \). The simulation in-
cluded generation of a sequence of 2D delta-correlated in space random
phase distributions \( \phi(kΔ, lΔ, \omega) \), \( k = 1..N_k, l = 1..N_l, \omega \) = 1..N on the
object surface starting from an initial 2D array of random delta-
correlated phase values uniformly distributed from 0 to 2 \( \pi \). Time
evolution in these phase distributions was introduced as is described in
Ref. [22] to obtain the normalized ACF \( \rho_{ii}(\tau) = \exp[-r/\tau_{ii}(k, l)] \). The complex amplitude of the light reflected from the object was

\[
U_{\text{norm}} = \sqrt{I_{0}} \exp[-r/\tau_{ii}(k, l) + i\phi(kΔ, lΔ, \omega)]
\]

The complex amplitude of the light falling on the camera array was

\[
U_{\text{norm}} = FT^{-1}[H.[FT\{U_{\text{norm}}\}]] \text{ where } H \text{ is the coherent
transfer function of the registration system and } FT \cdot \text{ denotes Fourier
transform (for a diffraction limited 4f system } H \text{ is reduced to a circ
function [23]). Integration by the camera pixels with size } \Delta \text{ was
}
modeled by summation of intensity regions $|I_{\text{act}}|^2$ in a window of size $2 \times 2$ pixels. The obtained arrays of $N_t \times N_z = 256 \times 256$ pixels were saved as bitmap images with 256 Gy levels. The simulated patterns were divided into four rectangular regions of size $64 \times 256$ pixels each with $t$, taking values of $10\Delta t$, $20\Delta t$, $40\Delta t$ and $80\Delta t$, i.e. the correlation radius was increasing in geometric progression (Fig. 2(a)). The MSF estimate spatial distribution obtained at $t = 4\Delta t$ and $N = 64$ is shown as a contour map and a 3D surface in Fig. 2(b) and (c).

3. Visualization enhancement of pointwise intensity-based activity maps

3.1. Probability density functions of activity estimates

Any pointwise intensity-based estimate shows severe fluctuations within the activity map (Fig. 2) due to i) pointwise calculation of estimates from speckle patterns; ii) finite acquisition time. Statistics of these estimates is affected by the speckle intensity statistics through the applied algorithm and depends on the ratio, $T/\tau$, which measures information capacity of a time sequence of intensities at each point of the map. The larger the value of $T/\tau$, the narrower the PDF of the built estimate. This ratio varies a lot in the four regions $Z_1$, $Z_2$, $Z_3$ and $Z_4$; at $N = 16$, $T/\tau$ is 1.6 in $Z_1$ and 0.2 in $Z_4$ whereas at $N = 512$ it is about 50 in $Z_1$ and about 6 in $Z_4$. Hence, at fixed acquisition time, accuracy of any estimate varies across the activity map.

To illustrate this point, we built the SF, MSF and NSF maps for the synthetic object at $t = 4\Delta t$ and then the histograms of the estimates as a measure of their PDFs in the four regions $Z_1$, $Z_2$, $Z_3$ and $Z_4$ for $N$ from 16 to 512. Variation of histograms with $N$ is given as a set of contour plots in Fig. 3. The number of points for each histogram is 16,384. All three estimates rise with activity and exhibit different spread of fluctuations in the four regions. For each estimate, the histograms in the four regions overlap. This means that one may observe the same value of an estimate in two neighboring spatial regions where activity and hence the estimate should be different. Note that the SF and MSF estimates are composed from 8-bit encoded intensities and occupy different intervals of values.

We calculated also the mean values of the estimates by spatial averaging within $Z_1$, $Z_2$, $Z_3$ and $Z_4$. The results are depicted in Fig. 4. The mean values reflect the fact that activity varies in the four regions. The SF and MSF mean values show very weak dependence on $N$; the SF mean value practically coincide with $S_0(\tau) = 2\sigma^2[1 - \mu_0(\tau)]$ at $t = 4\Delta t$. Therefore, these algorithms yield unbiased estimates and are good for quantitative evaluation. The NSF varies theoretically from 0 to 2; its mean value is given as a set of contour plots in Fig. 4. The estimate remains positively biased even at $N = 512$. The bias is clearly seen also in Fig. 3. At small number of the processed images, the bias substantially decreases the contrast of the NSF activity map.

To characterize fully the distributions in Fig. 3, we found their skewness, kurtosis and full-width-at-half-maximum (FWHM). These parameters are given in Fig. 5 as a function of $N$. The kurtosis and skewness decrease with $N$ for the SF and MSF algorithms approaching respectively 3 and 0 for the Gaussian distribution whereas for the NSF they have different behavior. The FWHM values become close in the four activity regions for all estimates above $N = 256$; for the MSF estimate they are practically equal at $N \geq 256$. The MSF estimate demonstrates the most symmetric PDFs and the smallest relative spread determined as a ratio between the FWHM and the mean value of the estimate. At $N = 256$, the MSF relative spread is 0.35 in $Z_1$ and 0.6 in $Z_4$. The relative spread does not fall below 0.5 for the NSF estimate even in $Z_1$ at $N = 512$.

Quantitative characterization of sensitivity of algorithms can be done by using the parameter $\alpha$ introduced in Ref. [19]:

$$\alpha = \frac{A_4}{A_1} \times 100\%$$

where $A_1$ and $A_4$ are the areas under histogram curves for two adjacent activity regions with equal number of points and $A_1$ is the area of overlap of both curves. The smaller the value of $\alpha$, the higher the sensitivity and spatial resolution provided by a given algorithm. Fig. 6 shows $\alpha$ as a function of $N$ for the three algorithms at $t = 4\Delta t$. The parameter $\alpha$ was evaluated by comparing the histograms in $Z_1$ and $Z_2$, $Z_2$ and $Z_3$, $Z_3$ and $Z_4$. The parameter $\alpha$ should be around 20–25% to have good sensitivity [19]. Such values are observed at very large $N$ for the SF and MSF estimates which give close results, and the NSF estimate is the best. The values of $\alpha$ are considerably higher for the normalized estimate, and sensitivity of the NSF algorithm is very low at small ratios $T/\tau$.

3.2. Visualization enhancement of the activity map by a smoothing filter

Increasing the acquisition time $T$ is not an effective way to reduce the spread of fluctuations within an intensity-based activity map. The temporal resolution worsening at larger $T$ is not justified by the rather small gain in spread reduction, as is seen in Fig. 3. Our proposal is to enhance quality of such a map by applying a filter to the 2D array of the estimate values. The filter is expected to narrow the PDF of the estimate and to improve the map contrast. Actually, any PDF narrowing leads to visualization enhancement of the map. The problem is that the different parts of the map, that have been obtained at a given time lag, exhibit different spread of fluctuations – a wider PDF in a high activity region and a narrower PDF in a low activity region (Fig. 3). So, one may assume that the measured value of activity is buried in a signal-dependent noise.

We checked the efficiency of the proposed idea for the synthetic test object characterized with sharp edges between the different activity zones on its surface. The light propagation to the optical sensor...
introduces spatial correlation within the average speckle size that only slightly smears the edges of these regions and they remain well defined on the map. The filter should preserve these edges.

To guarantee more or less symmetric PDFs of the estimates, the time $T$ was chosen to exceed the maximum observable $\tau_c$ of the processes in the object. This allowed usage of a spatial Gaussian filter, $GF \{\cdot\}$, or a bilateral filter, $BF \{\cdot\}$ with Gaussian spatial and range kernels as follows [24,25]:

$$GF \{\hat{S}_p\} = \sum_{q \in \Omega_p} G_{\alpha_c}(\|p-q\|)\hat{S}_q$$

$$BF \{\hat{S}_p\} = \frac{1}{W_p} \sum_{q \in \Omega_p} G_{\alpha_c}(\|p-q\|)G_{\sigma_d}(\|\hat{S}_p - \hat{S}_q\|)\hat{S}_q$$

where $\hat{S}_p$ denotes any of the SF, MSF and NSF estimates, $p$ gives the pixel position in the 2D activity map, $\Omega_p$ is a local window with size $(2w + 1) \times (2w + 1)$ around the pixel $p$ of the activity map and $\|\|$ denote $L_1$ and $L_2$ norms respectively, $G_{\alpha_c}(x)$ is a 2D Gaussian kernel

$$G_{\alpha_c}(x) = \frac{1}{2\pi \omega^2} \exp\left(-\frac{x^2}{2\omega^2}\right)$$

and the normalization factor $W_p$ is determined from the formula

$$W_p = \sum_{q \in \Omega_p} G_{\alpha_c}(\|p-q\|)G_{\sigma_d}(\|\hat{S}_p - \hat{S}_q\|)$$

Both Figs. 5 and 6 proved that the PDFs of the estimates become fairly symmetric at $N \geq 128$ with comparable FWHM values in the different activity zones. That's why we smoothed the SF, MSF and NSF activity maps starting from $N=128$. We chose a $(2w + 1) \times (2w + 1) = 9 \times 9$ pixels spatial window to apply both filters at parameter, $\sigma_d$, of the spatial Gaussian kernel equal to 3 pixels. The large spread of PDFs combined with low spatial correlation within the activity map indicates that the range parameter, $\sigma_r$, of the bilateral filter should be set equal to the largest among the FWHM values obtained at a given $N$ for effective smoothing. We checked efficiency of such an approach by processing synthetic data. Despite the rather large range parameter, which makes the results for both filters very close, the bilateral filter provided better edge preservation. So we present the

Fig. 3. Contour plots of the histograms of the SF, MSF and NSF estimates in the four regions $Z_1$, $Z_2$, $Z_3$ and $Z_4$ as a function of the number of the processed speckle patterns at $\tau = 4\Delta \tau$ (the color scales give the number of counts).

Fig. 4. Mean values of the SF, MSF and NSF estimates in the four activity regions of the synthetic object as a function of the number of processed speckle patterns $a t \tau = 4\Delta \tau$. 

58
results obtained only with this filter.

Substantial decrease in both FWHM and $\alpha$ for the three algorithms as a result of smoothing is shown in Fig. 7 (see for comparison Figs. 5 and 6). The values of $\alpha$ are comparatively high only for the normalized estimate when comparing $Z_1$ and $Z_4$ at $N < 256$. Fig. 8 depicts the histograms of the estimates in the four zones after the filtering. The non-normalized estimates ensure better contrast but the NSF map is also of good quality. The filter changes at less than 0.5–1% the PDFs modes and the mean values of the non-normalized estimates at $N \geq 128$. This strongly facilitates quantitative characterization of activity.

Efficiency of the normalized estimate at non-uniform illumination has been proven elsewhere [16,26]. However, for completeness of this study, we processed also speckle patterns acquired for the synthetic object at illumination with a Gaussian beam with intensity distribution $I_k(\kappa \Delta, \Delta \Delta) = A_0 \exp\left\{ -\frac{\Delta^2}{2} \left( (\kappa - k_0)^2 + (\ell - \ell_0)^2 \right) \right\}$ with amplitude $A_0 = 30$ levels, $(\kappa_0, \ell_0) = (128, 128)$ and $\Delta = 150\Delta$. The exemplary speckle patterns at uniform and Gaussian illumination are shown in Fig. 9. The histograms of fluctuations of the NSF estimate that have been obtained for the Gaussian illumination in the four zones of the synthetic object after applying the bilateral filter to the activity map at $\tau = 4\Delta\tau$ and $N = 256$ are also given. The filter parameters are as in Fig. 8. Although Gaussian illumination causes varying spread of intensity fluctuations across the speckle patterns, the NSF gives reliable results. Filtering of the activity map obtained for Gaussian illumination results practically in the same histograms in the four zones of the synthetic object as for the uniform illumination case in Fig. 8.

An activity map is usually deciphered in a qualitative manner as regions of lower or higher activity due to the pointwise fluctuations within the map that seriously interfere with quantitative evaluation. We checked whether the smoothing of the unbiased SF and MSF estimates could provide determination of short time scales of activity. The problem is that spread of fluctuations increases with the time lag [15,16]. For the purpose the maps at $m$ varying from $1$ to $m = M$ were built for the synthetic object. The histograms of the MSF estimates for the maps before and after smoothing are presented in Fig. 10 as contour plots for the four activity zones. We chose this algorithm because of its best performance. The histograms from $m = 1$ to $m = 20$ are normalized to the maximum observed number of counts. The points in which there are no entries to a given histogram are depicted in a white color in order to indicate clearly the range of values taken by the MSF estimate. In this way one may interpret the plots in Fig. 10 as 100% confidence intervals for the MSF estimate. To smooth the activity map at a given lag, $\tau$, we set the range parameter of the bilateral filter to be equal to the FWHM value determined from the histogram in $Z_1$ at this $\tau$, i.e. the range parameter became a function of the time lag $\sigma^{Z_1}(\tau) = \text{FWHM}(Z_1, \tau)$.

As it can be seen in Fig. 10, filtering narrows considerably the
Fig. 7. FWHM (a) for $Z_1$ (black line), $Z_2$ (red line), $Z_3$ (green line) and $Z_4$ (blue line) and the parameter $\alpha$ (b) for comparing $Z_1$ and $Z_2$ (black line), $Z_2$ and $Z_3$ (red line), $Z_3$ and $Z_4$ (blue line) for the filtered estimates as a function of the number of speckle patterns at $\tau = 4\Delta t$; the bilateral filter parameters are $w = 4$, $\sigma_d = 3$, $\sigma = \text{FWHM}(Z_1)$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 8. Histograms of the non-filtered (top) and filtered (middle) fluctuations in the four activity zones $Z_1$, $Z_2$, $Z_3$ and $Z_4$ of the synthetic object and activity maps (bottom) obtained with the SF, MSF and NSF algorithms for this object; filtering is done with a bilateral filter at $w = 4$, $\sigma_d = 3$, $\sigma = \text{FWHM}(Z_1)$ for each of the algorithms; $\tau = 4\Delta t$, $N = 256$. 
histograms. The parameter $FWHM$ for the filtered maps that is a measure of accuracy of determination of a given activity value remains small even at large time lags. This makes possible rather accurate determination of the MSF as a function of the time lag across the object surface as well as to attach different values to two neighboring spatial regions with close activity values. Without smoothing these regions are indistinguishable. Although, no analytical formula relates the MSF to the temporal ACF, $\rho_{kl}(\tau)$, of intensity fluctuations at point $(k\Delta l, l\Delta)$, the MSF dependence on $\tau$ can be empirically derived for a given model of the ACF and used for quantitative description. Filtering is performed in the spatial domain and inevitably restricts the detectable spatial frequency of activity variation across the object, but decrease of spatial resolution seems not to be a rather serious issue in most of the practical cases which are suitable for dynamic speckle inspection.

4. Smoothing raw data – discussion

In order to make discussion of the obtained results more efficient, we applied the developed filtering procedure to the raw data. For the experiment we used a He-Ne laser emitting at 632.8 nm and specially designed circular metal object divided into four co-centric flat regions – one inner circle and three annular regions. The circle and one of the annular regions were hollow regions of the same depth. The object was positioned on a sheet of paper and covered with a transparent polyester paint to form a flat layer. Thus, the hollow regions contained larger quantity of paint than the flat surface of the other two annular regions. This produced a difference in the speed of paint drying on the object surface, and regions with abruptly changing activity were formed at laser light illumination. One of the captured speckle patterns for this object is shown as a bitmap image in Fig. 11(a) and as a color surface in Fig. 11(b). Severe intensity fluctuations within the speckle pattern are clearly seen.

We chose a section in the captured speckle images that satisfied the requirement for equal reflectivity and uniform illumination. The processed section in one of the images is shown in Fig. 12(a). The intensity fluctuates in the same manner all over the section; the histogram of intensity fluctuations is given in Fig. 12(b). Different activity within the object is revealed only after statistical processing as is seen in Fig. 12(c) which represents the activity map for the MSF algorithm at $\tau = 6\Delta t$ and $N = 256$. Activity is the lowest within the hollow regions and shows a slight rise on the paper surface; it is much higher on the flat object surfaces. Let us consider the part of the MSF map encircled by the rectangular region in Fig. 12(c) that exhibits constant activity. Fig. 13 gives the distributions of the estimate inside

![Fig. 9. Speckle patterns for the synthetic object with four activity zones $Z_1$, $Z_2$, $Z_3$ and $Z_4$ at uniform (a) and Gaussian illumination (b); histograms of the NSF estimates (c) for processing the patterns under Gaussian illumination after bilateral filtering at $w=4$, $\sigma_d=3$, $\sigma_{\text{FWHM}}=F_{\text{FWHM}}(Z_1); \tau = 4\Delta t$, $N = 256$.](image)

![Fig. 10. Contour plots of the normalized histograms of the MSF estimate in the four activity zones of the synthetic object as a function of the time lag at $N = 256$ before (top) and after (bottom) filtering of the MSF activity maps with a bilateral filter at $w=4$, $\sigma_d=3$, and $\sigma_{\text{FWHM}}=F_{\text{FWHM}}(Z_1, \tau)$; the white color indicates zero entries to the histograms. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)](image)
this region as color surfaces at $N = 32$ and $N = 256$. Generally speaking, the $S_{\text{mod}}(k, l, m)$ distribution resembles a speckle pattern with numerous outliers and low spatial correlation. At larger $N$, the estimate is less fluctuating but the map is still far from the uniform distribution corresponding to constant activity. We built the histograms of $S_{\text{mod}}(k, l, m)$ within the rectangular region as a function of $N$ at two time lags. They are depicted in Fig. 13(c) and (d). The PDFs are long-tailed with spreads increasing with the time lag and decreasing with the acquisition time. The rise of $N$ makes the PDFs more symmetric.

Fig. 14 shows the SF, MSF and NSF histograms for the rectangular region at $N = 32$, 256 and 512. As in simulation, processing of more patterns is not very effective for the PDFs narrowing with exception of the NSF estimate due to more accurate determination of the variance and the mean value at larger $N$. The PDFs modes and the mean values of the non-normalized estimates are practically independent on $N$. The positive bias of the NSF estimate is especially strong at a small number of the processed patterns. This is clearly seen in Fig. 16(b) which depicts the NSF estimate at two points as a function of the time lag. Both curves are smooth but exhibit different slopes. The difference is due to spatial fluctuations of intensity and hence of the estimate. Filtering decreases the difference between the two curves and allows for more precise determination of the true MSF. The histograms obtained for the raw and filtered maps are shown as contour plots in Fig. 16(c) and (d). Similarly to Fig. 10, the histograms for the raw maps are very wide. As in the case of simulation, filtering leads to substantial narrowing for all time lags. However, the slight variation of the mean intensity within the chosen spatial region is expressed as widening of histograms. After the filtering, the temporal MSF curves in all points are restricted by a much narrower region of possible values shown in Fig. 16(d) and accuracy of determination of the time scale of the paint drying for this part of the area.

We smoothed the activity maps obtained for the experimental object by bilateral filtering. We used $w = 6$ and $\sigma_d = 4$, and chose the range parameter to be approximately equal to the largest $FWHM$. The MSF result is shown in Fig. 15 where Fig. 15(c) depicts the MSF estimate variation along the dashed line in Fig. 15(a) and (b). Note that the drop of the estimate value at pixel 380 and the rise at pixel 600 are due to really existing drop and rise on the activity map.

We applied the bilateral filter also to the rectangular region in Fig. 12(c) for a set of activity maps obtained at $m$ from 1 to 20. The MSF spatial distribution within this region at $N = 512$ and $\tau = 6 \Delta t$ is shown in Fig. 16(a). The activity map looks almost smooth and flat, i.e. $S_{\text{mod}}(k, l, m = 6)$ is approximately the same in all points. Note that the values of $S_{\text{mod}}(k, l, m)$ for $m = 1..20$ are highly correlated when being determined from a temporal sequence in a single point. This is clearly seen in Fig. 16(b) which depicts the MSF estimate at two points as a function of the time lag. Both curves are smooth but exhibit different slopes. The difference is due to spatial fluctuations of intensity and hence of the estimate. Filtering decreases the difference between the two curves and allows for more precise determination of the true MSF. The histograms obtained for the raw and filtered maps are shown as contour plots in Fig. 16(c) and (d). Similarly to Fig. 10, the histograms are normalized to the maximum observed number of counts for $m = 1..20$ and the bins with zero entries are depicted in a white color. The histograms for the raw maps are very wide. As in the case of simulation, filtering leads to substantial narrowing for all time lags. However, the slight variation of the mean intensity within the chosen spatial region is expressed as widening of histograms. After the filtering, the temporal MSF curves in all points are restricted by a much narrower region of possible values shown in Fig. 16(d) and accuracy of determination of the time scale of the paint drying for this part of the area.

Fig. 11. Speckle pattern on a surface of a metal object covered with a transparent polyester paint (a); the same pattern depicted as a color surface (b). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 12. Section of a speckle pattern (a) and a histogram of intensity fluctuations within the section (b); activity map of the MSF estimate at a time lag $\tau = 6 \Delta t$ and $N = 256$ (c).
Fig. 13. Distribution of the MSF estimate at a constant activity at $N=32$ (a) and $N=256$ (b) within the rectangular region on the activity map in Fig. 11 (c); histograms of the MSF estimate as a function of the number of the processed speckle patterns at $\tau = 6\Delta t$ (c) and $\tau = 12\Delta t$ (d).

Fig. 14. Histograms of SF, MSF and NSF estimates for the rectangular region in Fig. 11(c) at $\tau = 6\Delta t$ and $N = 32, 256, 512$.

Fig. 15. MSF activity maps for the experimental test object at $\tau = 6\Delta t$ and $N = 256$ before (a) and after (b) bilateral filtering with $w=6$, $\sigma_d=4$, and $\sigma_F=FWHM(Z)$; MSF estimate along the dashed line in the figures (a) and (b).
object surface is increased. It is important to stress that evaluation of the time scale can be done using only a few points.

5. Conclusions

The paper considers quality enhancement in 2D determination of physical or biological activity in diffusely reflecting objects from changing speckle patterns on their surface. We focused on dynamic laser speckle measurement with intensity-based processing which enables pointwise estimation and needs a simple experimental set-up. We proposed visualization enhancement of the output 2D activity map to be done by filtering. To choose the filter, we studied statistics of fluctuations within the maps built for three algorithms for estimation of a temporal structure function. We proved the signal-dependent character of fluctuations by showing that their spread depends on activity even at uniformly distributed variance of speckle intensity across the studied object. We especially stress upon the latter fact because the signal-dependent behavior of fluctuations of intensity-based estimates should not be confused with the well-known signal-dependent nature of the speckle noise. Statistics of the estimates was evaluated at different time lags and increasing number of the speckle patterns. We processed synthetic and experimental data acquired for objects with well-defined regions of different activity on their surface. We applied bilateral filters with Gaussian kernels to activity maps. To ensure comparable full-widths at half maximum of the probability density functions of the estimates at different activity, the acquisition time exceeded the maximum observable temporal correlation radius of intensity fluctuations. Filtering decreased substantially these widths and allowed for much better detection of activity. Besides the improved contrast and resolution of the activity map, filtering alleviates to a large extent 2D quantitative determination of the short-time scales of activity. This result is the most promising as, to the best of our knowledge, only qualitative interpretation of the activity maps has been reported up to now. The developed procedure can be applied to activity maps built with other algorithms. The important task we plan to solve in future is to improve the temporal resolution of the 2D pointwise estimation by proper filtering and estimation of activity time scales for the case of a small number of speckle patterns.

Acknowledgment

This research was supported by Ministry of Science, ICT and Future Planning (MSIP) (Cross-Ministry Giga KOREA Project GK16D0100).

Natalia Berberova acknowledges the World Federation of Scientists, Switzerland, for financial support.

References


