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Smart photonic wristband for pulse wave monitoring

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Section 1: Theoretical background of specklegram

In general, the intensity of each speckle is different, but the total intensity of the speckle pattern must be constant. The number of modes transmitted in the multimode optical fiber is defined as M, which is determines the number of speckles[S1], given by Eq. (S1).

$$M = \frac{V^2}{2}, \text{with } V = \frac{2a\pi\sqrt{n_{\mathrm{co}}^2 - n_{\mathrm{cl}}^2}}{\lambda} . \tag{S1}$$

In Eq. (S1), a is the core radius of the multimode optical fiber, λ is the wavelength of the laser source, and n_{co} and n_{cl} are the refractive indices of the core and cladding, respectively.

By analyzing the speckle pattern, external perturbations applied to the multimode optical fiber affect the propagation conditions, such as mode-coupling and phase modulation, thus affecting the speckle pattern. When a multimode optical fiber is subjected to external perturbations, the propagation constant of each mode changes, resulting in a phase translation. Moreover, mode coupling also plays a significant role in the modulation of the speckle field. Similarly, the multimode optical fiber is subject to external perturbations, and different waveguide modes will couple, resulting in a change in the mode power distribution. The power change of the m-th mode (ΔP_m) is expressed by Eq. (S2):

$$\Delta P_m = \sum_{n=0}^{M-1} h_{mn}(P_m - P_n) , \tag{S2}$$

where P_m and P_n are the initial power values of the m-th and n-th modes, respectively and h_{mn} is the coupling coefficient of the m-th and n-th modes, which is a function of the propagation constant of each mode and the optical fiber length[S2].

Notably, the model determines the relationship between speckle pattern changes and measurable perturbations $F(t)$[S3]. In particular, the intensity of each speckle I_i is obtained by integrating the spatial intensity function over the speckle area as follows:

$$I_i = A_i\{1 + B_i[\cos\delta_i - F(t)\,\varphi_i \sin\delta_i]\} , \tag{S3}$$

where A_i is the result of the mode of self-interaction, and $F(t)$ represents the external perturbation to the system. A_i, B_i, φ_i, and δ_i are constant values for any given i. Therefore, by tracking and processing the light intensity of each scattered spot, important vital sign information can be identified and recorded.

Section 2: Different speckle processing methods

In this supplement, several different speckle processing methods present in this work are described in detail.

A: Normalized inner-product coefficient

In addition to the intensity information of the speckle patterns, the spatial correlation between images is also a significant characterization value. Francis et al.[S4] proposed using the normalized intensity inner-product coefficient (NIPC) for speckle field analysis, as shown below:

$$NIPC(i) = \frac{\iint I_{\mathrm{o}}(x,y) I_{\mathrm{i}}(x,y)\mathrm{d}x\mathrm{d}y}{\left(\iint I_{\mathrm{o}}^2(x,y)\mathrm{d}x\mathrm{d}y \iint I_{\mathrm{i}}^2(x,y)\mathrm{d}x\mathrm{d}y\right)^{1/2}} . \tag{S4}$$

Eq. (S4) combines the speckle position information with intensity information and evaluates the normalized correlation between speckle intensity $I_{\mathrm{i}}(x, y)$ and reference $I_0(x, y)$ corresponding to the current state. When $I = I_0$, $NIPC = 1$, and the NIPC method decreases with the deviation of the speckle pattern. In this way, it is possible to use the NIPC method to quantify the relative change with high sensitivity.

B: Zero-mean normalized cross-correlation

To avoid the effect of the intensity fluctuations of the speckle pattern, a modified processing method, ZNCC, can be used to characterize the speckle pattern changes. Compared with the conventional cross-correlation analysis, the ZNCC method adopts the method of subtracting the local average intensity of the reference and current speckle patterns (see

Eq. (S5)), thus compensating for the change in intensity of the obtained pictures and making them more robust[S5]. The ZNCC method for the i-th frame is given by the following relationship:

$$ZNCC\,(i) = \frac{\iint (I_\mathrm{o}(x,y)-\bar{I}_\mathrm{o})\,(I_\mathrm{i}(x,y)-\bar{I})\mathrm{d}x\mathrm{d}y}{\left(\iint (I_\mathrm{o}(x,y)-\bar{I}_\mathrm{o})^2(I_i(x,y)-\bar{I})^2\mathrm{d}x\mathrm{d}y\right)^{1/2}}\ . \tag{S5}$$

Similar to the NIPC method, where 0<ZNCC<1, I_0 can be set to any state (such as frame i–1) to improve the dynamic range.

C: Image moments/first-order moment

Currently, the image moments obtained using physical concepts have been widely used in the field of computer vision. The acquired speckle image can be regarded as a grayscale matrix I (x, y), where the mean value expressions of speckle field intensity with position information in the x and y directions are as follows:

$$\mu_x = \frac{\sum_{x,y} xI(x,y)}{\sum_{x,y} I(x,y)},\ \text{and}\ \mu_y = \frac{\sum_{x,y} yI(x,y)}{\sum_{x,y} I(x,y)}\ . \tag{S6}$$

The expression of the p-order moment is as follows[S6]:

$$\mu_p = \frac{\sum_{x,y}[(x-\mu_x)^2+(y-\mu_y)^2]^{p/2}I(x,y)}{\sum_{x,y} I(x,y)}\ . \tag{S7}$$

The representation value in the form of a p-order moment satisfies the integrity of various information extractions during processing. The first-order moment algorithm, p=1, is used here.

D: Gray-level co-occurrence matrix

Haralick[S7] et al. proposed one method to describe texture features using a gray-level cooccurrence matrix (GLCM) to show the spatial distribution of the image and the overall complexity of the image. The matrix is established based on the spatial relationship of the gray level pairs of the speckle pattern and is defined as the joint probability distribution of two pixels with the same gray value in the image, as shown in Eq. (S8):

$$GLCM_\theta(i,j) = \sum_{m=1}^{M}\sum_{n=1}^{N}\begin{cases}1,\ \text{if}\ I(m,n)=i\ \text{and}\ I\ (m+d\cos\theta, n+d\cos\theta)=j\\ 0,\ \text{else}\end{cases}\ , \tag{S8}$$

where the value of the matrix coordinates (i, j) represents the number of times a pixel with intensity i is adjacent to a pixel with intensity j. Some commonly used feature parameters can be extracted from the GLCM method for the subsequent calculations.

Here, the contrast of the GLCM method is used as the speckle statistical eigenvalue, which can be used to describe the sharpness of the image texture. In an image, a clearer texture correlates to a greater gray difference between the adjacent pairs of pixels and a greater contrast, which is shown in Eq. (S9)[S8]:

$$\mathrm{CON} = \sum_{i=0}^{M}\sum_{i=0}^{N}\mathrm{GLCM}(i,j)|i-j|^2\ . \tag{S9}$$

E: Mutual information

Mutual information (MI) is a common evaluation index of image registration results. Unlike other algorithms for processing pixels, the core idea of the MI method is entropy, which represents the information contained in the image. The information entropy $H(X)$ can be quantified as follows[S9]:

$$H\,(X) = -\sum_i p\,(x_i)\log p\,(x_i)\ \ , \tag{S10}$$

where p (x_i) is the probability distribution function. Image information entropy is a form of feature statistics that reflects the average amount of information in an image. If there are images A and B, their mutual information values are calculated by the following:

$$I(A,B) = H(A) + H(B) - H(A,B) \ , \tag{S11}$$

where $H(A, B)$ is the joint entropy of A and B, which is calculated using the joint histogram of A and B[S10] and can be understood as the information contained by A and B together (intersection in mathematics). Suppose that the joint distribution functions of A and B are $p\ (x,\ y)$ and the edge distribution functions are $p\ (x)$ and $p\ (y)$, respectively, then, the mutual information $I\ (X,\ Y)$ can be rewritten as follows:

$$I(X,Y) = \sum\nolimits_{x\in X}\sum\nolimits_{y\in Y} p(x,y)\log\frac{p(x,y)}{p\,(x)\,p\,(y)} \ . \tag{S12}$$

When images A and B are two consecutive speckle images, MI can be used for image registration to compare speckle variability.

F: Sum of squared differences

An improved method based on the differential image processing method is proposed, namely, the sum of squared differences (SSD). The difference mentioned in the original differential image processing method is squared and summed to obtain the SSD method. By difference here, we mean relative difference, which is the treatment of two adjacent frames, that is, $k=i-1$.

$$I_{\rm SSD}\,(i) = \frac{1}{M\cdot N}\sum\nolimits_{x}^{M}\sum\nolimits_{y}^{N}[I_k(\,x,y) - I_i(x,y\,)]^2 \ . \tag{S13}$$

Similar to the differential image processing method, the SSD method is simple to implement and has low algorithmic complexity. However, the SSD method typically presents low robustness to non-Gaussian noise[S11].

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