Smart Structures and Systems, *Vol. 24, No. 5 (2019) 659-668*
DOI: https://doi.org/10.12989/sss.2019.24.5.659

Assessment of speckle image through particle size and image sharpness

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(Received June 4, 2019, Revised August 5, 2019, Accepted August 14, 2019)

Abstract. In digital image correlation, speckle image is closely related to the measurement accuracy. A practical global evaluation criterion for speckle image is presented. Firstly, based on the essential factors of the texture image, both the average particle size and image sharpness are used for the assessment of speckle image. The former is calculated by a simplified auto-covariance function and Gaussian fitting, and the latter by focusing function. Secondly, the computation of the average particle size and image sharpness is verified by numerical simulation. The influence of these two evaluation parameters on mean deviation and standard deviation is discussed. Then, a physical model from speckle projection to image acquisition is established. The two evaluation parameters can be mapped to the physical devices, which demonstrate that the proposed evaluation method is reasonable. Finally, the engineering application of the evaluation method is pointed out.

Keywords: digital image correlation; speckle image; particle size; image sharpness; autocovariance; focusing evaluation function

1. Introduction

As a non-contact measurement method, machine vision and image processing have been widely used in structural health monitoring. For example, in the field of civil engineering, Ye *et al.* (2013, 2016a) developed a vision-based system used for structural dynamic displacement measurement. The verification experiments were performed to measure the mid-span vertical displacement of the long-span bridges during loading tests.

Digital image correlation (DIC) is also one of the vision measurement methods based on speckle images, which is usually used for measuring material's mechanical properties in experimental mechanics. It has been widely applied in mechanics, civil engineering, aerospace, biomedicine, and other disciplines. Aggelis *et al*. (2016) applied acoustic emission and DIC during four-point bending tests of large beams to follow the damage accumulation. Dai *et al*. (2017) investigated the bond behavior and buckling behavior of CFRP-steel composite members. Kumar *et al*. (2019) used digital single-lens reflex (DSLR) camera to do tension and fatigue tests on steel specimens. As a numerical method based on speckle images, the quality of speckle patterns has an important influence on the measurement accuracy (Hu *et al*. 2018). Therefore, problems such as what is a good speckle pattern, how to make a good speckle pattern, and how to adjust the calculation parameters to control the measurement accuracy according to the quality of the speckle pattern have attracted a large number of scholars.

Lecompte *et al*. (2006) thought the speckle pattern is composed of size and density of the particles and calculated the speckle size distribution by image morphology. Nevertheless, both in natural speckle pattern such as microscopic crystalline grain and rock fracture surface and artificial speckle by spraying paint, most particles are not in discrete state and have no distinct boundaries. Lin (2007) used full width at half maximum (FWHM) as average diameter of the speckle and calculated by the auto-correlation function. Subsequently, some methods based on the grayscale of image were presented, including subset entropy (Sun *et al*. 2007), sum of square of subset intensity gradients (SSSIG) (Pan *et al*. 2008), mean intensity gradient (MIG) (Pan *et al*. 2010), mean subset fluctuation (Tao *et al*. 2011) and Shannon entropy (Liu *et al*. 2015). These methods do operation directly on image grayscale and are often mentioned because of the convenience of calculation. However, Wang *et al*. (2009) derived interpolation function, noise, sub-pixel displacement and image subset grayscale are all the factors that affect the measurement accuracy. Dong *et al*. (2015) thought it is not simply considered that the larger the grayscale gradient, the higher the quality of speckle pattern. In the last few years, it has been believed that the quality of speckle images should be evaluated from multiple perspectives. Crammond *et al*. (2013) identified that pattern's physical properties have a large influence on the measurement precision, and devised a morphological methodology using edge detection to evaluate the physical properties of different speckle patterns. Yu *et al*. (2014) considered the smooth transition of image gray gradient and introduced the mean intensity of the second derivative based on MIG. Reu (2014 and 2015) described four properties of a speckle including size, contrast, speckle edge sharpness, and speckle density and distribution. Dong *et al*. (2017) comprehensively summarized the classification,

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http://www.techno-press.com/journals/sss&subpage=7
ISSN: 1738-1584 (Print), 1738-1991 (Online)

preparation and evaluation methods of speckle patterns, and concluded that the quality of speckle patterns should not be evaluated with a single parameter. Su *et al*. (2016) analyzed the influence of interpolation function and speckle patterns on measurement accuracy in detail, stated that the measurement accuracy includes mean deviation and standard deviation, and then used the root mean square error (RMSE) to describe the overall accuracy. However, these two kinds of deviations may be in different orders of magnitude.

In this paper, the average particle size and image sharpness are used to evaluate the quality of speckle images. Different from the above research, the former is calculated by a simplified auto-covariance function and the latter by focusing function. Appropriate particle size reflects the smoothness of speckle brightness and facilitates accurate sub-pixel interpolation; large image sharpness ensures prominent features and is conducive to the stable convergence of the iteration. The two parameters can be ultimately mapped on a physical model.

2. Principle and methodology

The calculation of digital image correlation includes correlation function, interpolation function, shape function and iterative method (Pan *et al.* 2009). The gray value and gray gradient at sub-pixel need to be continuously updated during the iteration process. This indicates that the calculation precision is directly related to the gray value prediction ability of the interpolation function at sub-pixel. Therefore, a good speckle pattern should help to provide accurate grayscale at sub-pixel. Moreover, in order to avoid the iteration falling into local minimum, there should be a great difference on the grayscale at different locations of the subset.

In this paper, both the average particle size and image sharpness are used as two key factors to describe speckle patterns. The particle size affects the smoothness of the gray distribution of the image, and then determines the interpolation accuracy. If the particle size is too small, the intense gray fluctuation would weaken the grayscale prediction ability of interpolation function at sub-pixel. However, if the particle size is too large, the difference of gray level in the subset will not be obvious. The less information content of the subset may cause the iteration to converge to local minimum. So the image sharpness should be considered at the same time.

2.1 A simplified auto-covariance function and Gaussian fitting to calculate the average particle size

Typical speckle pattern is composed of a large number of small particles. After imaging by camera, the edges of particles are no longer sharp, but show smooth gray transition. The point spread function of the imaging system can be described by Gaussian distribution. Therefore, the speckle pattern have the characteristics of Gauss spot after imaging.

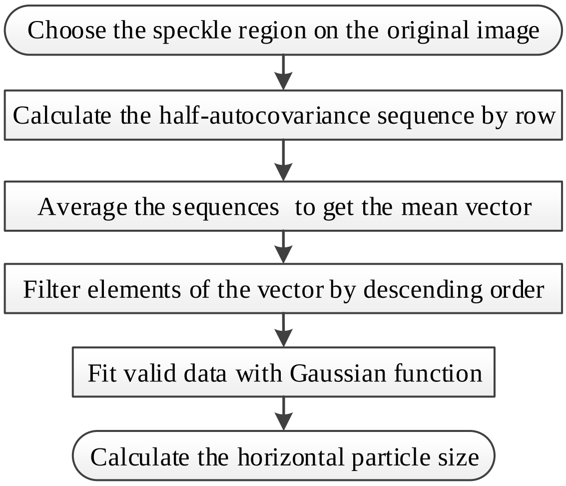


Fig. 1 Calculation process of the average particle size

For the image with randomly and densely distributed speckle particles, a method by simplified auto-covariance function and Gaussian fitting is presented to calculate the average diameter of particles in the horizontal and vertical direction. Taking the horizontal size of the particles as an example, the calculation flow is shown in Fig. 1. After choosing the speckle region on the image, the specific steps are as follows:

1) For grayscale data $\vec{g}=\left[g_1,g_2,\cdots,g_n\right]$ of each row, Set $\vec{x}=\left[x_1,x_2,\cdots,x_n\right]$, sample centralization $x_i=g_i-\frac{1}{n}\sum_{i=1}^{n}g_i$; Set $\vec{z}=\left[z_1,z_2,\cdots,z_n\right]$, $z_i=\sum_{j=1}^{n+1-i}x_j x_{j+i-1}$; half-autocovariance sequence $\vec{v}=\left[v_1,v_2,\cdots,v_n\right]$ can be obtained by $\vec{v}=\vec{z}/z_1$.

2) Average the sequences of all rows to get a mean vector $\vec{w}$. Check the elements of $\vec{w}$ in order. If the current element is positive and less than the previous one, put it into the vector $\vec{y}$ orderly. Otherwise, stop examination.

3) Assume that the final length of $\vec{y}$ is m+1. Set $\vec{t}=\left[0,1,\cdots,m\right]$. Fit $\vec{y}$ and $\vec{t}$ to get a and b with Gaussian function $y=a\exp\left(-t^2/b\right)$. If the fitting deviation (RMSE) is larger than 0.05, remove the final element of $\vec{y}$ and fit the function again.

4) The value of t at $y=e^{-2}$ is taken as the average particle size D: $a\exp\left(-D^2/b\right)=e^{-2}$, $D=\sqrt{b\left(2+\ln a\right)}$.

2.2 Focusing functions to calculate image sharpness

Imagine that a camera is facing a plane with speckle patterns. When changing the focal length of lens continuously, the speckle image gradually ranges from blurred to clear. Therefore, speckle image is the combination of speckle pattern and imaging process. Naturally, the assessment of speckle images should be regarded as the evaluation of both “speckle” and “image”. The former has been evaluated by particle size. We use

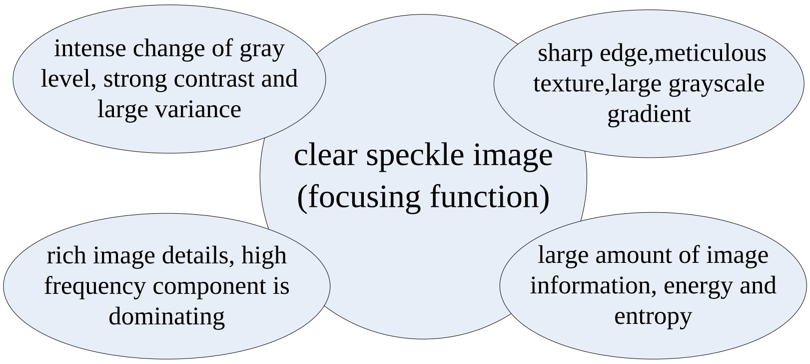


Fig. 2 Image sharpness evaluation

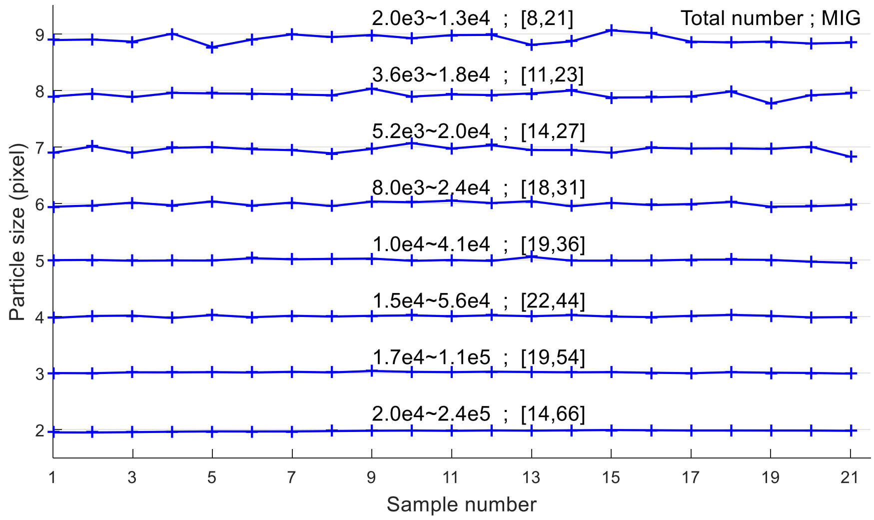


Fig. 3 Calculation results of average particle size under different particle densities

focusing functions to evaluate the latter.

As shown in Fig. 2, the commonly used evaluation functions of image sharpness are divided into four categories. 1) Grayscale fluctuation: grayscale jump intensely (large grayscale variance); 2) Grayscale gradient: texture is obvious (high gradient level); 3) Image entropy: information content is large (large entropy value); 4) Frequency spectrum: the high frequency component of image is prominent (large amplitude).

All of them are consistent. A high quality speckle image has great diversity of grayscale and large information content. The distinct image shows clear texture and high contrast, which can be described by the grayscale gradient. In addition, the frequency is an indicator of the grayscale fluctuation in the image. The frequency spectrum can be obtained by the two-dimensional Fourier transform of the image. If there are a large number of bright pixels in the image of the frequency spectrum, the edges of the original image are obvious and the details are rich. The calculation formulas for image clarity are shown in Table 1 in the section 3.2.

3. Numerical simulation and discussion

Zhou *et al*. (2001) had designed a speckle pattern in which each speckle provides brightness for adjacent areas. The grayscale of each pixel is derived from the sum of the luminance projected by the surrounding speckles. Since this model is beneficial to produce speckle image whose deformation is controllable, it is used to generate speckle images and their deformed images for verification in this paper. The formulas for the initial and deformed images are:

$$\begin{cases} I_0(x,y)=\sum_{k=1}^{s} A_k \exp\left(-\dfrac{(x-x_k)^2+(y-y_k)^2}{(D/2)^2}\right) \\ I_1(x,y)=\sum_{k=1}^{s} A_k \exp\left(-\dfrac{(x-x_k-u)^2+(y-y_k)^2}{(D/2)^2}\right) \end{cases} \tag{1}$$

where D is the particle diameter, s is the total number of speckle particles, (x_k, y_k) and A_k is the position and intensity of the *k-th* particle. u stands for translation in the horizontal direction. The resolution of all images is 800 × 800 pixels^2.

Table 1 Formulas for calculating the image sharpness

Evaluation function	Expression
Mean subset fluctuation	$SubF = \frac{1}{W \times H}\sum_{x=2}^{W-1}\sum_{y=2}^{H-1}\left(\sum_{i=-1}^{1}\sum_{j=-1}^{1}\left\vert f(x+i,y+j)-f_{\mu}(x,y)\right\vert\right),\ f_{\mu}(x,y)=\frac{1}{9}\sum_{i=-1}^{1}\sum_{j=-1}^{1} f(x+i,y+j)$
Subset entropy	$SubE = \frac{1}{W \times H}\sum_{x=2}^{W-1}\sum_{y=2}^{H-1}\left(\sum_{i=-1}^{1}\sum_{j=-1}^{1}\left\vert f(x+i,y+j)-f(x,y)\right\vert\right)$
Shannon entropy	$ShaE = -\sum_{j=0}^{255} p(a_j)\log(p(a_j))$
Mean intensity gradient	$MIG = \frac{1}{W \times H}\sum_{x=1}^{W}\sum_{y=1}^{H}\sqrt{f_x(x,y)^2 + f_y(x,y)^2}$
Sum of difference	$SMD = \frac{1}{W \times H}\sum_{x=1}^{W}\sum_{y=1}^{H}\left(\left\vert f_x(x,y)\right\vert+\left\vert f_y(x,y)\right\vert\right)$
Fourier amplitude	$LFT = \sum_{u=1}^{W}\sum_{v=1}^{H}\ln\left\vert F(u,v)\right\vert, F(u,v)=\frac{1}{W \times H}\sum_{x=1}^{W}\sum_{y=1}^{H} f(x,y)\exp(-j2\pi(\frac{ux}{W}+\frac{vy}{H}))$

3.1 Verify the calculation method of average particle size

According to the above formula, the particle size D is set to 2~9 pixels to generate a series of speckle images. For each D, the validity of the calculation method for particle size is tested. Firstly, record the number of particles when MIG of the generated speckle image is maximum. Secondly, 21 speckle images are generated from a small particle number to the above number in the form of arithmetic progression. Then, noise with standard deviation of 4 is added to each speckle image. Finally, Calculate the average particle size of these speckle images by the proposed method. The calculation results are shown in Fig. 3. The legend shows the number of particles and the corresponding MIG.

The deviation in Fig. 3 is mainly derived from the conversion of *double* to *uint8* when generating the speckle image. It can be seen that the simplified auto-covariance function can correctly calculate the average particle size under different particle densities. The calculation results are still correct when inverting the value of the speckle images. It is also shown that with the increase of particle size, the maximum MIG decreases, which indicates that the size and the sharpness of particles are contrary to a certain extent.

3.2 The equivalence of the calculation method of image sharpness

In this paper, we believe that subset entropy (Sun *et al.* 2007), mean intensity gradient (Pan *et al.* 2010), mean subset fluctuation (Tao *et al.* 2011) and Shannon entropy (Liu *et al.* 2015) are the evaluations of the image sharpness essentially. In Table 1, two typical focusing functions for image sharpness evaluation are added. These six functions are used to calculate the image sharpness of the 21 speckle images generated in the section 3.1 (D=2). For the two local evaluation parameters *SubF* and *SubE*, the whole image is regarded as a subset. When calculating gray gradient in horizontal and vertical directions (f_x and f_y), central difference and backward difference are used in *MIG* and *SMD*, respectively. $W \times H$ is the size of the speckle region here refers to image size.

The results of each calculation method are normalized independently. Then draw curves in Fig. 4. It can be seen from the curves that these evaluation functions are equivalent. All of the four methods in the above literatures evaluated the sharpness of speckle image. Therefore, image sharpness can be calculated by focusing evaluation function, such as frequency domain evaluation function *LFT* and Sum of difference function *SMD*. *SMD* is recommended, for it works well with small computation.

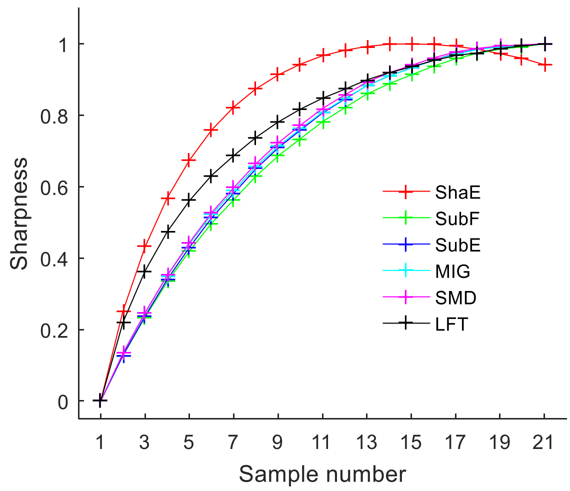
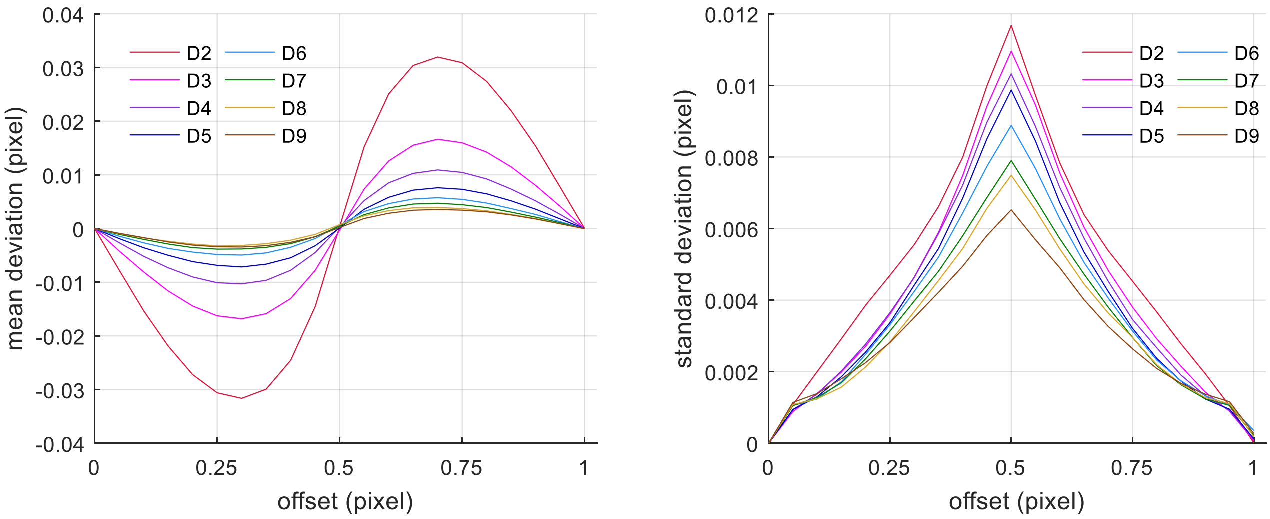


Fig. 4 Sharpness evaluation functions under different particle densities



(a) Mean deviation (b) Standard deviation

Fig. 5 The deviations under different particle diameters (MIG=21)

3.3 The influence of evaluation factors on the accuracy

Generate 21 speckle images by translating 0.05 pixels gradually in the horizontal direction. Analyse the influence of each factor on the measurement accuracy based on single variable principle. Statistics on the calculated displacement includes mean deviation e_j and standard deviation σ_j are as follows

$$\begin{cases} e_j = \bar{u}_j - u_j \\ \sigma_j = \sqrt{\dfrac{1}{N-1}\sum_{i=1}^{N}(x_{ji}-\bar{u}_j)^2} \end{cases} \tag{2}$$

where $\bar{u}_j = \dfrac{1}{N}\sum_{i=1}^{N} x_{ji}$, x_{ji} is the calculated displacement of the *i-th* node on the *j-th* speckle image, u_j is the theoretical displacement of the *j-th* speckle image, N is the total number of nodes.

In this paper, sum of squared differences (SSD) with linear intensity coefficients is used as correlation function (Pan *et al.* 2009); bilinear interpolation and first order shape function are chosen. The subset size is 27×27 pixels, and the step length is 15 pixels. The total number of compute nodes is 2256. The termination condition of iteration is that the change of each coefficient is less than 0.01. Items are as follows, whose results are shown in Fig. 5 and Fig. 6.

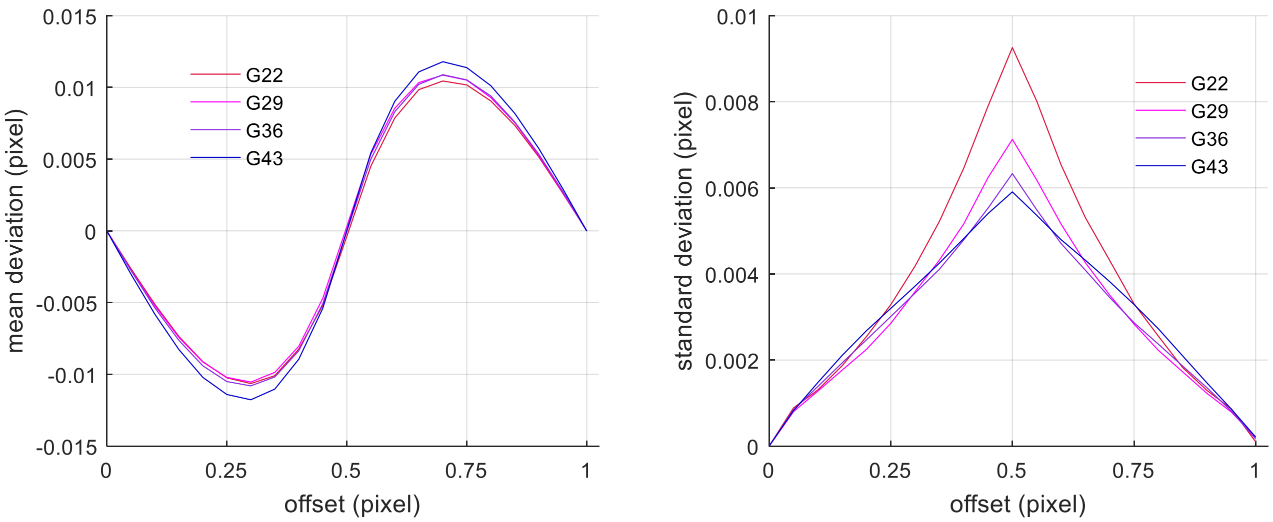
1) Mean intensity gradient is same (MIG=21) while the particle size different (D=2, 3..., 9)

2) The particle size is same (D=4) while mean intensity gradient different (MIG=22, 29, 36, 43)

From Figs. 5 and 6, it can be seen that the average particle size mainly affects the mean deviation. When MIG is same, the smaller the particle size, the larger the mean deviation. The image sharpness mainly affects the standard deviation. When the particle size is same, the clearer the image, the smaller the standard deviation.

The average particle size affects the smoothness of gray distribution. Large average particle size makes the fluctuation of the grayscale slow, so interpolation is more accurate at sub-pixel. Large image sharpness means large gray change, which can ensure the iteration with global convergence. However, it is negative correlation between particle size and image sharpness. With the increasing of particle size, the maximum image sharpness decrease. For the accuracy of measurement, when the image sharpness is large, the intense fluctuation of the grayscale distribution reduces the interpolation accuracy. Then a higher-order interpolation function is needed. In a comprehensive consideration, first the average particle size should be in 3~6 pixels, and then the larger the image sharpness, the higher the quality of the speckle image. If MIG is used to evaluate the image sharpness, Fig. 3 provides the best sharpness corresponding to each particle size for reference. For other focusing functions, the best sharpness can be easily obtained by numerical simulation. Because the interpolation function works separately in the horizontal and vertical directions during correlation matching, the particle size in the horizontal direction affects the accuracy of displacement calculation in the corresponding direction.

From view of this paper, Gaussian filtering can smooth the image, so that the average particle size of the speckle image after Gaussian filtering is increased, which is conducive to accurate interpolation. However, Gaussian filtering causes the image details lost slightly and the image sharpness smaller. Therefore, Gaussian filtering before correlation calculation will reduce the mean deviation, while increase the standard deviation. When the speckle image has noise and average particle size is small, the appropriate filter parameters according to the proposed evaluation method can improve the overall measurement accuracy.



(a) Mean deviation (b) Standard deviation

Fig. 6 The deviations under different MIG (*D*=4)

4. Physical model

As shown in Fig. 7, a physical model from speckle projection to image acquisition is established to further explain the proposed view. Set D = 2 and s = 2.4e5 to generate a speckle image. Convert the image to binary one, and then engrave it on the glass.

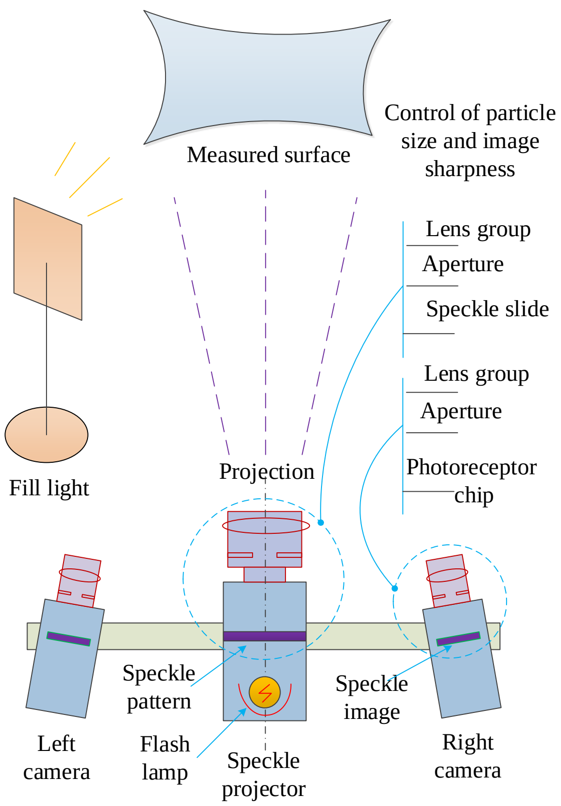


Fig. 7 Physical model for producing of speckle image

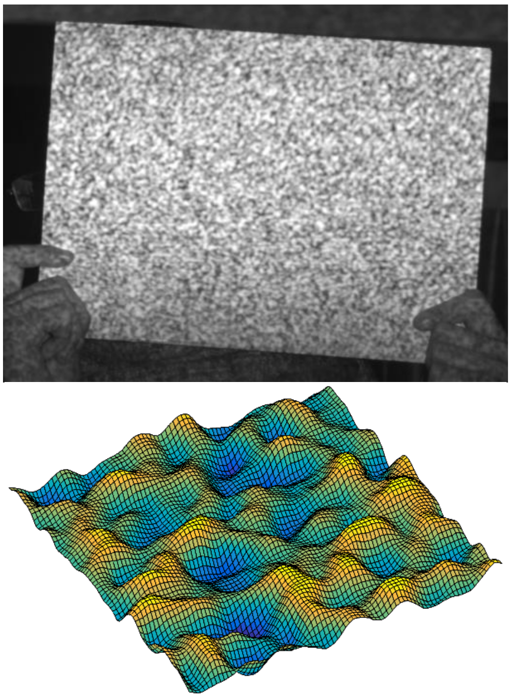
The focal length of the camera lens controls the clarity of imaging, while the focal length of the projector lens controls the size and sharpness of the particles. In practical application, in order to get high quality speckle image, firstly adjust the focal length of the camera lens to make the image clearest, and then adjust the focal length of the speckle projector lens to make the particle size and sharpness appropriate.

5. Application

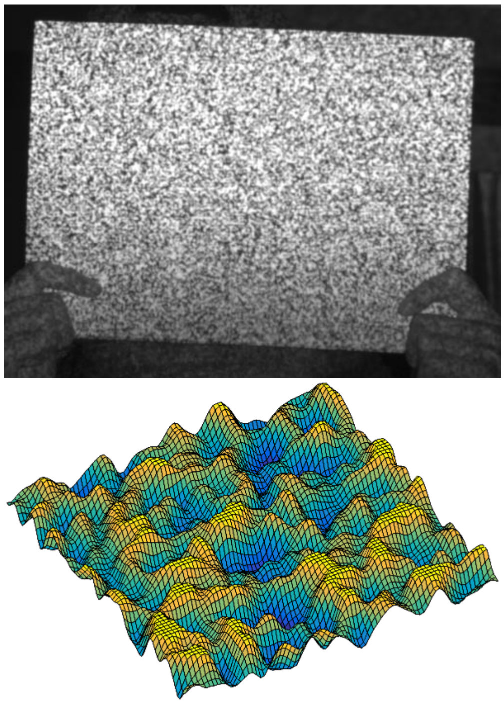
5.1 Evaluation and adjustment of projective speckle image

As shown in Fig. 7, the speckle pattern is projected on the measured surface. The surface profile of the measured object can be obtained by the 3D digital image correlation. The physical model has been applied in body scanning. It is able to resist the interference from the body's subconscious tremble because of its rapid measurement. As the contour of the measured surface is complex, it is necessary to get high quality speckle image for stereo matching. In Fig. 8, the left column is the images obtained after adjusting the focal length of the projector lens, and accordingly the right column is a gray distribution of 80×80 pixels on the white paper. Data below the picture are the average particle size in the horizontal and vertical direction and image sharpness on the feature region. Based on the calculation results, the speckle quality in Fig. 8(d) is the best.

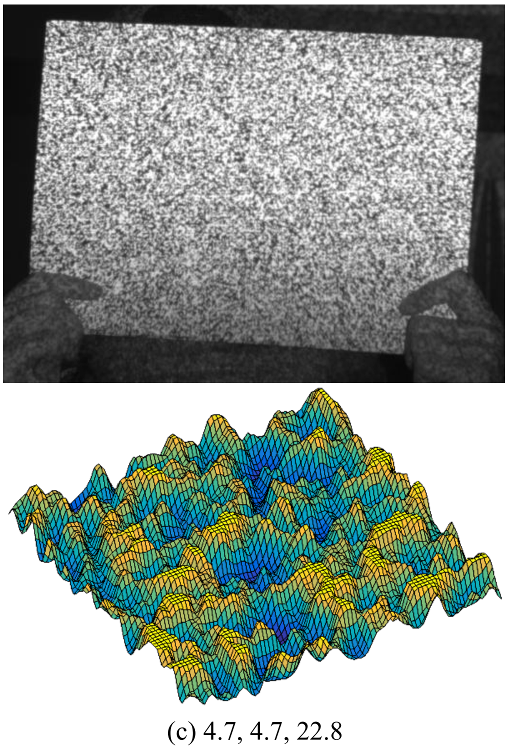
To verify the quality of speckle images, there are 20×20 nodes on the binocular speckle images under each projection situation are matched. Left image point $m_i^l = (u_i^l, v_i^l, 1)^T$ and right image point $m_i^r = (u_i^r, v_i^r, 1)^T$ are a pair of corresponding image points. The matching errors can be compared according to epipolar geometry. In each case of projection: Estimate the fundamental matrix F by random-sample consensus (RANSAC) from corresponding image points. Then matching error can be defined as



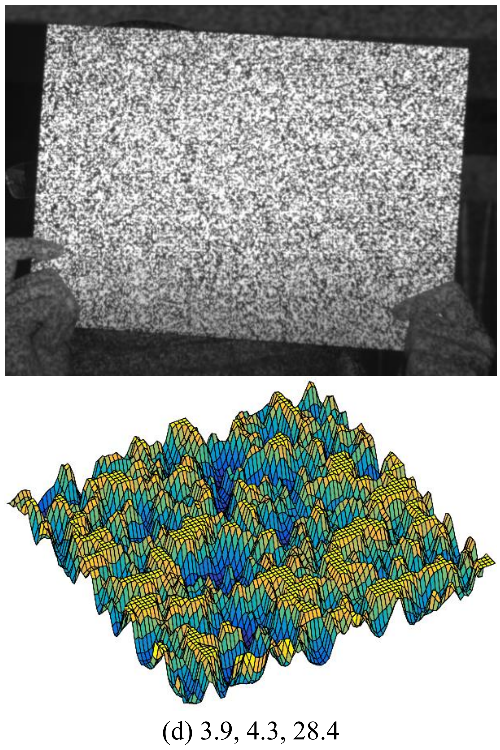
(a) 7.4, 7.2, 10.3



(b) 5.3, 5.7, 17.5



(c) 4.7, 4.7, 22.8



(d) 3.9, 4.3, 28.4

Fig. 8 Speckle images with different size and sharpness and its local gray distribution: Data below the picture are the average particle size in horizontal and vertical direction and image sharpness on the feature region

$\sum m_i^{lT}\mathbf{F}m_i^r$. After comparison, the deviation in (d) is the smallest. It confirms that the matching accuracy in (d) is the highest. Thus, the quality of speckle image in (d) is the best.

5.2 Evaluation and improvement of integrated speckle image

Both artificial and natural speckle patterns are integrated speckle patterns. They are mainly used to obtain the deformation field on the measured surface under force. According to the proposed method, the evaluations of

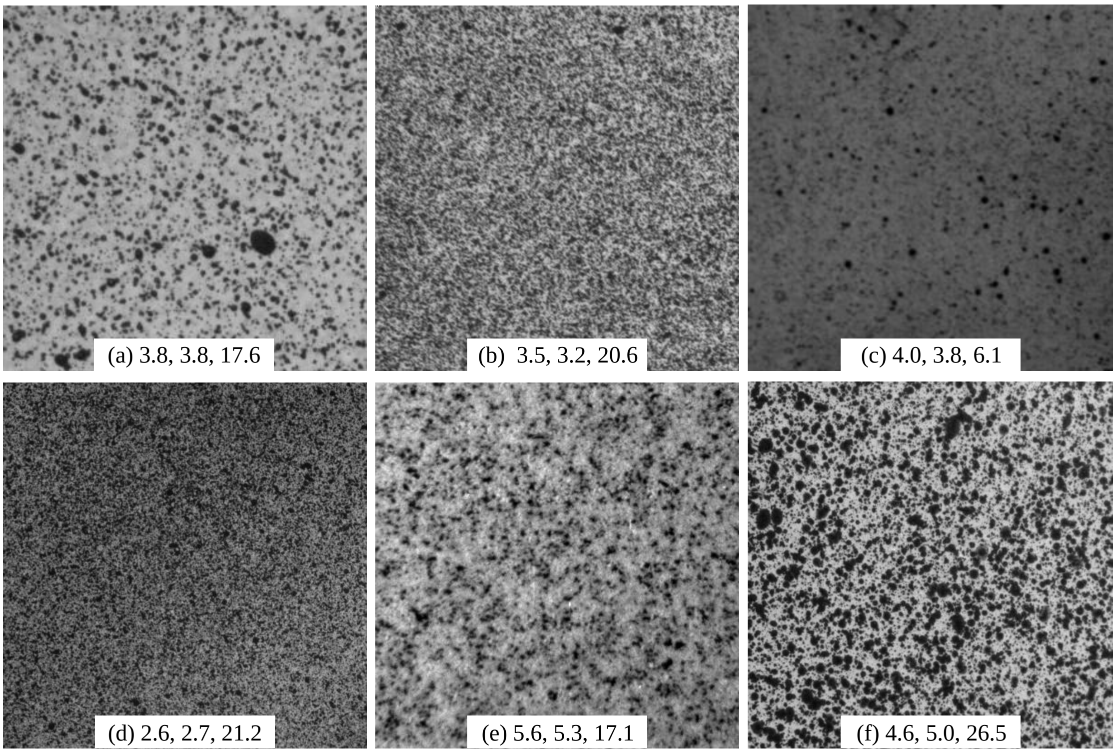
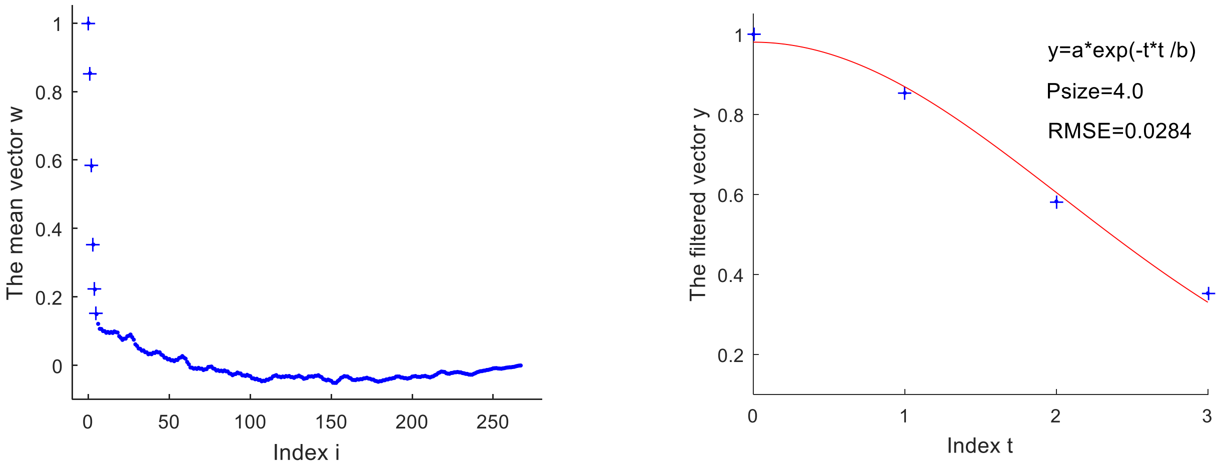


Fig. 9 Evaluations of speckle patterns from different experiments



(a) Mean vector w (b) Fit valid data by Gaussian function

Fig. 10 The calculation of particle size in Fig. 9(c) by half-autocovariance and Gaussian fitting

speckle patterns from different experiments are shown in Fig. 9. The meaning of the data are consistent with Fig. 8. The good speckle image are f, e, b and a, while the bad are c and d.

For the limitation of space, only the computational process of horizontal particle size in Fig. 9(c) is shown in Fig. 10. In Fig. 10 (a), the first six data of mean vector $\overline{w}$ are marked as '+' for clarity. After filtering, there are 4 valid data left. It can be seen from Fig. 10(b) that the deviations of fitting with Gaussian function is small, which proves that the computation method is practical for speckle images with random particles.

The proposed method can guide the design of the template for thermal transfer (Mazzoleni *et al.* 2015, Chen *et al.* 2015, Ashrafi *et al.* 2016). According to the size of the measured surface and the camera resolution, the delimiter of the solid circular is increase the density of the particles gradually to generate speckle patterns. The speckle patterns is the best when the sharpness is the largest.

The method can also optimize the experimental conditions. It was demonstrated that illumination had a critical effect on the measurement results of the vision-based system (Ye *et al*. 2016b). Spray white and black paint on the white paper to make speckle pattern. Hold the distance unchanged between the industrial camera and speckle pattern. Take speckle images in fixed focus under illumination with different brightness. Calculate the particle size of the collected images. The calculation results indicate that light intensity on the measured surface does not change the average particle size of the speckle image, but has a great influence on the image sharpness. Therefore, in actual measurement, sufficient, even and invariable illumination should be provided to improve the image sharpness, which can reduce the standard deviation. If average particle size is small after imaging, by changing the resolution of camera and adjusting the focal length of the lens and shooting distance, particle size can be increased and the mean deviation reduced.

6. Conclusions

In this paper, based on texture features and imaging process, a comprehensive method for evaluating the quality of speckle patterns is proposed, verified by numerical simulation and then applied in engineering practice. The main conclusions are as follows:

1) The quality of speckle patterns should be evaluated by both average particle size and image sharpness. The two evaluation parameters are calculated by a simplified auto-covariance function and focusing evaluation function, respectively.

2) The average particle size affects the grayscale prediction ability of the interpolation function at sub-pixel. In a certain range, the larger the particle size, the more smooth the gray distribution of the speckle image. Thus, the interpolation result is more accurate and the mean deviation is smaller. The image sharpness determines information content of the subset. The clearer the texture, the more stable the correlation matching and the smaller the standard deviation.

3) There is a negative correlation between the average particle size and the image sharpness. Large particle size makes the gray change of the image slow and the grayscale gradient small, and then the image sharpness is weak. Therefore, the mean deviation and the standard deviation are the two aspects of the accuracy evaluation and are negatively correlated.

4) High quality speckle image can be defined like this: On the premise of average particle size with 3~6 pixels, the greater the image sharpness, the higher quality of speckle image. The former ensures the smooth gray distribution, which is conducive to accurate interpolation. The latter ensures that the subset contains sufficient information to make iteration stable.

5) The evaluation method is mainly used to guide the preparation of speckle patterns and adjustment of the experimental conditions in contour and deformation measurement. In contour measurement, to adjust each component of speckle projection device can optimize the speckle patterns. In deformation measurement, to select the proper focal length of the lens and camera resolution and provide adequate lighting can improve the accuracy of measurement. To design the template for thermal transfer, maximize the image sharpness after setting the proper particle size.

Finally yet importantly, from the perspective of texture image, gray-level co-occurrence matrix (GLCM) is expected to be used in the further study.

Acknowledgments

The research described in this paper is supported by National Natural Science Foundation of China (Grant No. 51675404 and 51421004).

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