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Long working distance portable smartphone microscopy for metallic mesh defect detection

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Abstract: Metallic mesh is a transparent electromagnetic shielding film with a fine metal line structure. However, it can develop defects in the production preparation or in actual use that affect the optoelectronic performance. The development of in situ non-destructive testing (NDT) devices for metallic mesh requires long working distances, reflective optical path design, and miniaturization. To address the limitations of existing smartphone microscopes, which feature short working distances and inadequate transmission imaging for industrial in situ inspection, we propose a novel long-working-distance reflective smartphone microscopy (LD-RSM) system. LD-RSM comprises a $4f$ optical imaging system with external optical components and a smartphone. This system uses a beam splitter to achieve reflective imaging with the illumination system and imaging system on the same side of the sample. It achieves an optical resolution of 4.92 μm and a working distance of up to 22.23 mm. Additionally, we introduce dual-prior weighted robust principal component analysis (DW-RPCA) for defect detection. This approach leverages spectral filter fusion and the Hough transform to model different defect types, which enhances the accuracy and efficiency of defect identification. Coupled with a double-threshold segmentation approach, the DW-RPCA method achieves a pixel-level defect detection accuracy (f-value) of 0.856 and 0.848 in square and circular metallic mesh databases, respectively. Our work exhibits strong potential for growth in the field of in situ on-line inspection of industrial products.

Key words: Smartphone microscope; Defect detection; Reflective portable imaging; Metallic mesh; Low-rank decomposition

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1 Introduction

Recently, the rapid development of optoelectronic devices, including communication and medical devices and detectors, has enhanced human life significantly (Li et al., 2023). However, these devices emit large amounts of electromagnetic radiation, leading to electromagnetic interference (EMI). A well-designed metallic mesh can provide effective EMI shielding while maintaining transparency (Liang et al., 2023; Zhang et al., 2021). Metallic mesh is formed of periodic structures of thin metal films, and achieves high-frequency visible light transmission and low-frequency microwave cutoff by carefully selecting structural unit periods and line widths (Lu et al., 2024).

At present, there are many methods for the preparation of metallic mesh, such as photolithography coating (Qiu et al., 2022), the cracked template

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method (Zhu et al., 2021), nanoimprint lithography (Baracu et al., 2021), and direct writing (Li et al., 2022). However, these mature technologies can still result in defects such as broken lines, metal deposition, and photoresist residue due to lithography process parameters and operator errors. In practical applications, metallic mesh can develop significant defects from scratches, impacts, and chemical erosion, which affect the performance of optoelectronic equipment. Defect detection in transparent electromagnetic shielding films during production is often limited to manual visual inspection, with a lack of adequate detection devices suitable for practical applications. Developing a miniaturized, cost-effective, portable device for microscopic defect detection could substantially improve the durability and performance of transparent electromagnetic shielding films.

Although the use of smartphone technologies in engineering detection remains relatively limited, significant progress has been made in developing portable diagnostic tools. These smartphone-based devices offer notable advantages, including high performance, low cost, miniaturization, and portability (Wang et al., 2023; Bui et al., 2023). Recent studies have documented various applications for these microscopes, demonstrating their broad utility (Huang et al., 2024; Zheng et al., 2023; Ahmed et al., 2023). Smartphone microscopes are capable of identifying white blood cells (Janev et al., 2023), imaging fresh tissue (Zhu et al., 2020), and measuring environmental lead (Pb) content (Lai et al., 2022). Most of these devices are designed as transmitted light microscopy systems, which are commonly used in biological and medical imaging. In this configuration, samples are positioned between the illumination and imaging systems, allowing light to pass through the sample.

The capacity to observe opaque objects is one of the significant extensions provided by the development of reflected light microscopy on smartphone-based platforms (Kim and Lee, 2023). However, the short working distance of most existing smartphone microscopes (typically $\leq$5 mm) (Rabha et al., 2022a; Kheireddine et al., 2019; Lee et al., 2021) poses a significant challenge for nondestructive detection during displacement scanning. To overcome this limitation, we introduce a reflective smartphone microscope with an extended working distance (LD-RSM) of 22.23 mm, which is engineered explicitly for the detection of defects in large-scale micro- and nanostructures. This advancement opens up new possibilities for industrial inspection applications using smartphone-based microscopy.

On the software side, detecting defects in structures like metallic mesh represents a significant challenge due to the intricate textures and diverse nature of potential defects. Traditionally, these precision devices undergo manual visual inspections during production—a labor-intensive process that underscores the need for a robust and systematic inspection framework. Defect detection in periodic texture structures, such as fabrics, remains a focal research area within defect detection. Researchers have developed several fabric defect detection algorithms using approaches such as the spectral method (Sakhare et al., 2015), statistical method (Alper Selver et al., 2014), modeling method (Zhou et al., 2017) and deep learning method (Jing et al., 2022; Zhou et al., 2023). However, each method has its limitations.

Spectral methods often struggle with accuracy when detecting minor defects due to filter sensitivity. Statistical methods, on the other hand, tend to overlook global information and are computationally intensive. Although promising, deep learning algorithms require extensive datasets that are frequently unavailable in industrial settings, leading to compromised accuracy. Recently, defect detection algorithms based on low-rank decomposition models have garnered significant attention as a potential avenue for future research (Li et al., 2024). These algorithms decompose images into low-rank (background), sparse (defect), and noise components (Candès et al., 2011). Ji et al. proposed a weighted low-rank and Laplace regularization approach to enhance defect-background separation, although its effectiveness is limited due to the use of Gabor features (Ji et al., 2020). Liu et al. (Liu and Li, 2022) advanced the field by introducing structural constraints in robust principal component analysis (RPCA), incorporating noise terms and defect priors, and leveraging spatial connections and 8D texture features for better defect detection. Bao et al. (Bao et al., 2022) developed a method called PTVLR, which uses the structural similarity index (SSIM) as prior information. However, these approaches often fall short in accuracy, are time-consuming when extracting defect information from metallic mesh, and result in suboptimal detection efficiency. In this paper, we introduce

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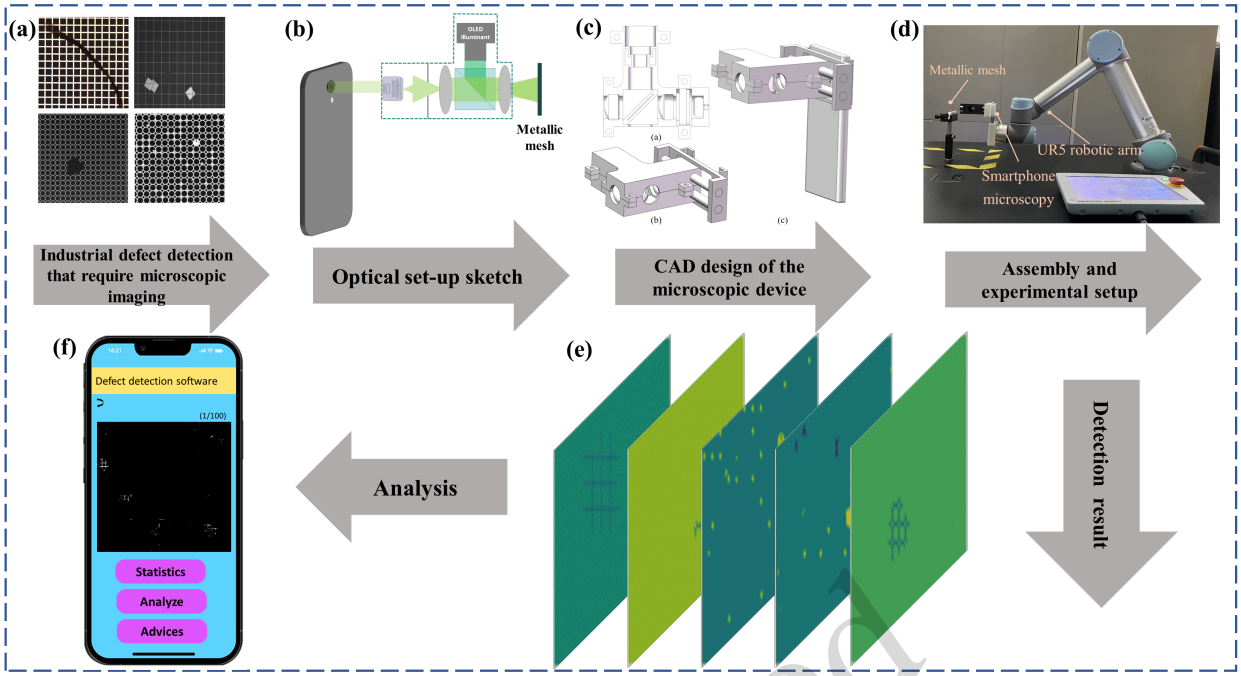

Fig. 1 Schematic of the rapid prototyping of the LD-RSM system. (a) Microscopic imaging aids the in situ defect detection needs of metallic mesh. (b) Optical setup (LD-RSM) sketch. (c) Three-dimensional design of the microscopic device (LD-RSM) by Computer-Aided Design (CAD). (d) Assembly and experimental setup including robotic arm, LD-RSM, and metallic mesh samples. (e) Defect detection results of LD-RSM-acquired images using DW-RPCA. (f) Defect detection software displays the detection results and allows for defect statistics, analysis, and advice.

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an enhanced low-rank decomposition model, dual-prior weighted robust principal component analysis (DW-RPCA), which is based on spectral filter fusion and the Hough transform. This model extracts prior defect information in metallic mesh and guides accurate low-rank decomposition. Furthermore, we employ a robotic arm for image scanning across the field of view, enabling comprehensive detection of defects in metallic mesh. When integrated with our miniaturized portable smartphone microscope (LD-RSM), this system markedly enhances the detection of defects in large-scale micro- and nanostructures, offering significant contributions to the field of industrial inspection. This work exemplifies a notable advancement in the synergy of hardware development and algorithmic innovation, improves inspection capabilities for metallic mesh defects, and paves the way for broader applications in industrial quality control.

2 Methodology

2.1 Smartphone microscope for industrial defect detection

Fig. 1 illustrates the prototyping of the long-working distance reflective smartphone microscopy system (LD-RSM) for industrial defect detection. This system is engineered to meet the demands of real-time, in situ defect detection, and incorporates a reflective optical path and extended working distance. The simplicity of its optical design not only ensures ease of production and deployment, but also contributes to its robust performance. The LD-RSM integrates critical components, including imaging optics, illumination optoelectronics, and a mechanical structure for attachment to a robotic arm flange, all housed in a durable, 3D-printed casing. The optical design of the present imaging system is depicted in Fig. 2a and is discussed in detail in Section 2.2. A monochromatic high-power coaxial point light source at a wavelength of 550 nm serves as the LD-RSM's illumination, effectively minimizing the impact of the

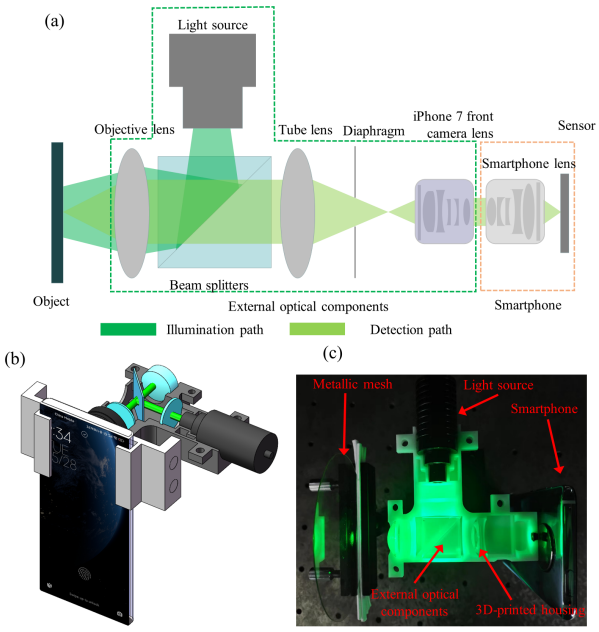

Fig. 2 Design and fabrication of the LD-RSM system. (a) Schematic of a 4*f* optical configuration. (b) 3D rendering of the LD-RSM system and (c) prototype of the developed microscopic system.

chromatic aberration on imaging quality. Components are securely mounted within a housing that is fabricated by a fused-deposition modeling (FDM) 3D printer (model Raise N2). An optical clamping device secures industrial samples, ensuring stability during inspections. A three-dimensional (3D) rendering of the LD-RSM system is presented in Fig. 2b, and the prototype of the developed microscopic system is showcased in Fig. 2c.

2.2 Imaging system design

There are two conventional approaches to configuring a microscopic setup on a smartphone: the 3*f* and 4*f* imaging systems (Rabha et al., 2022b). In the 3*f* configuration, an external lens is mounted directly to the outside of the camera module of the smartphone to form a finite conjugate system. The external lens functions as the objective lens, and the smartphone's built-in set of lenses functions as the imaging system's tube lens. The sample is positioned at the focal plane of the objective lens. After the sample passes through the objective and tube lenses, the optical field is captured on the smartphone sensor. Given the short focal length of the smartphone lens (typically only a few millimeters), the external lens must have a similar short focal length to achieve greater magnification for microscopic imaging. However, due to its small magnification capability and the constraints imposed by the pixel pitch of the smartphone sensor, the setup often struggles with limited resolution and field of view, making it less suitable for practical industrial inspection.

To develop a high-quality, cost-effective optical system, we opted for the 4*f* imaging configuration for LD-RSM. This setup includes two long focal length lenses, a large-diameter lens as the objective, and a tube lens, along with a beam splitter, diaphragm, and light source, making it ideal for in situ imaging measurements of metallic mesh. The imaging principle is illustrated in Fig. 2a. Both the illumination and imaging optical paths are aligned on the same side of the sample to enable imaging measurements during equipment servicing without disassembly. Light from the source first passes through a beam splitter, which directs the reflected light onto the sample via the objective lens. The sample is placed at the focal plane of the objective lens. The reflected light carrying sample information then passes through the objective lens and the tube lens, forming an image on the focal plane of the tube lens. This image is then transferred to the smartphone camera module through a relay lens and captured on the camera sensor.

The imaging system employs a Redmi K30 Ultra smartphone (Xiaomi Inc., Beijing, China) equipped with a Sony IMX582 CMOS sensor (64-megapixel with a pixel size of 0.8 μm). The built-in lens of the smartphone features a focal length of 5.43 mm. Because the imaging focal length of the smartphone camera module is only 5.43 mm, the focal length of the relay lens cannot be too long considering the magnification of the system. The relay lens used here is derived from the iPhone 7 front camera module, which offers an imaging focal length of 2.87 mm and a numerical aperture (NA) of 0.23. Compared with the widely used ball lens and achromatic objective lens, a better imaging effect can be obtained by using the smartphone lens set.

The LD-RSM system requires placing the sample at the focal plane of the objective lens, where the focal length of the objective lens is crucial for determining the working distance. In this paper, the objective lens is an achromatic double-glued lens from Edmund, with a focal length of 30 mm, a diameter of 25 mm, and an NA of 0.38. A long working distance

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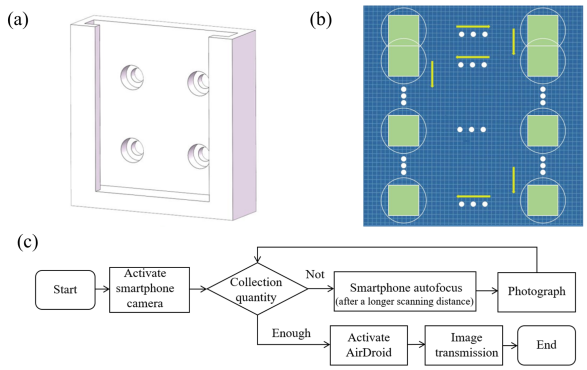

Fig. 3 Image acquisition and transmission strategies. (a) Fixed mechanics for the UR5 arm and LD-RSM, (b) UR5 robotic arm scanning program, (c) LD-RSM script for automatic image acquisition and transmission.

of 22.23 mm is realized. The tube lens is integral for converged imaging, achieves adequate magnification, and maintains a compact form factor for the external device. We use an Edmund plano-convex lens with a focal length of 40 mm and a diameter of 25 mm. LD-RSM uses light from the transmitted portion of the beamsplitter to image the sample, and the reflected portion is used for sample illumination. The Edmund beamsplitter has a size of 35 mm × 35 mm and a reflectance-to-transmittance ratio of 50/50.

2.3 Imaging acquisition and transmission

In this study, we employed the UR5 robotic arm to execute a programmed scanning sequence aimed at capturing images of metallic mesh within a defined area. The tool flange of the UR5 arm, equipped with four M6 threaded holes, facilitates the attachment of the LD-RSM device. We designed a mechanical structure, as illustrated in Fig. 3a, based on the parameters of the UR5 arm's tool flange, using SolidWorks software (Onwubolu, 2017). This structure effectively connects the LD-RSM to the UR5 arm and provides stable support for the scanning operation. The scanning protocol, depicted in Fig. 3b, was developed using the PolyScope programming environment. The UR5 robotic arm, carrying the LD-RSM, autonomously scans the designated area of the metallic mesh in an S-pattern, systematically capturing images. To mitigate the risk of missed defect detection due to potential motion errors of the arm, we incorporated a degree of image redundancy in which the UR5 arm advances in 500 μm increments with each node.

The control flow of the script program is shown in Fig 3c. The automatic image acquisition and transmission of LD-RSM begins with the activation of the smartphone camera, then the number of images to be captured is determined, and the smartphone auto-focus (after a longer scanning distance) and photograph operations are performed cyclically. It should be noted that the parallelism between the sample and the LD-RSM imaging surface is high. It is found that the smartphone only needs initial focusing during the short-distance scanning process. After scanning a long distance, LD-RSM completes re-focusing, that is, through the smartphone's auto-focusing function. Therefore, to ensure the imaging quality, we stayed at each frame for 2 s, to provide enough time for the auto-focusing process. Next, when the required number of images is met, the AirDroid software (Huang et al., 2015) is used to transmit the images.

2.4 Low-rank decomposition defect detection based on spectral filter fusion and the Hough transform

The defects that affect the photoelectric performance of metallic mesh fall into two categories: broken line and block defects. Based on the characteristics of these two types of defects, we propose DW-RPCA for metallic mesh defect detection. The proposed overall DW-RPCA detection process is shown in Fig. 4, which is mainly composed of three parts: prior information extraction, RPCA, and threshold segmentation.

In the prior information extraction phase, spectral and Hough priors are designed for defects of square metallic mesh and circular metallic mesh. These priors guide the low-rank decomposition process. As shown in Fig. 4, we use the Fourier transform to get the spectrogram whose frequency gradually increases from the center to the periphery. In this study, three square low-pass filters f_1, f_2, and f_3 were designed, and the side lengths of the square low-pass filters were 10, 20, and 40, respectively. These filters were applied to the spectrogram obtained previously. The Fourier inverse transform was then performed on the filtered spectrogram to obtain F_1, F_2, and F_3.

We utilize a linear combination to fuse the images obtained after filtering with three different filter

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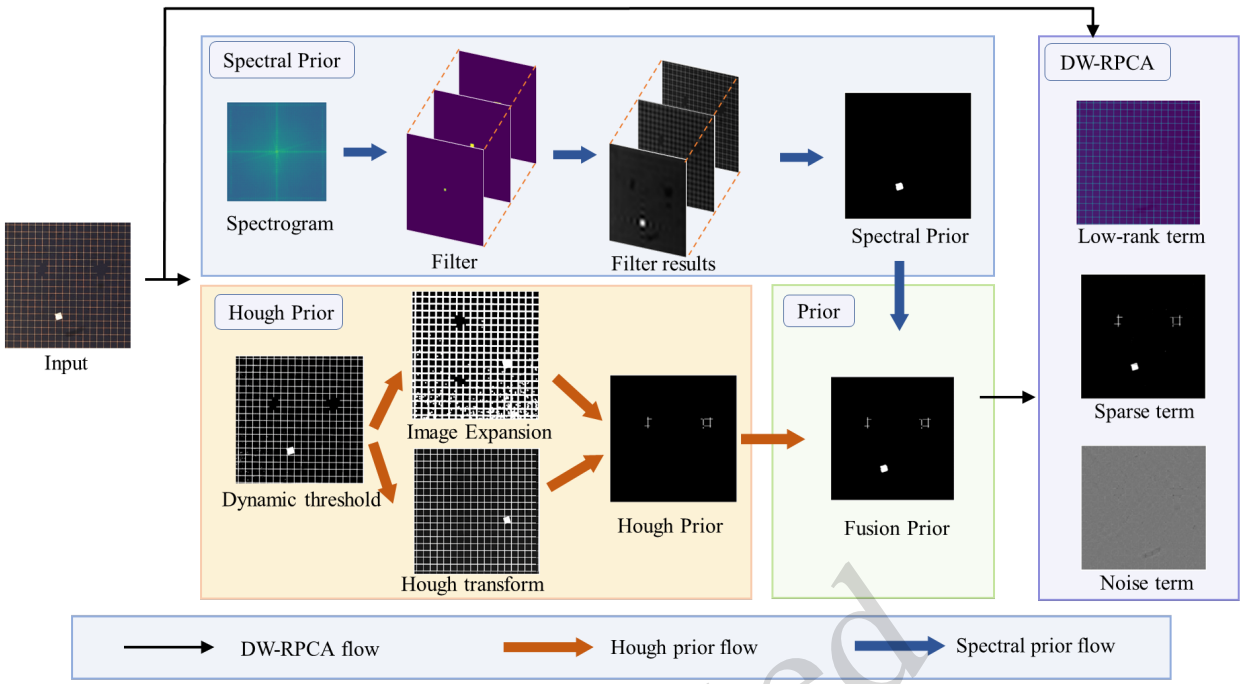

Fig. 4 The overall DW-RPCA detection process.

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sizes, respectively:

$$P_{\text{spectral}} = k_1 \times F_3 + k_2 \times (F_1 + F_2) - k_3 \times (F_2 - F_1) \quad (1)$$

where k_1, k_2, and k_3 are 0.8, 0.2, and 0.3. Then, the spectral prior about block defects is obtained by binarizing the resulting fusion map $P_{spectral}$.

RPCA and optimized RPCA-based models have difficulty in identifying a large range of multi-period broken line defects because these defects no longer satisfy the sparsity property. The Hough transform converts an image into a parameter space, which in turn maps the line or circle to be recognized to a point on the parameter space, thus transforming the problem of detecting shapes into a problem of peak point statistics. Therefore, for broken line defects, DW-RPCA introduces the Hough prior, as shown in Fig. 4, where the input image is first binarized using the dynamic thresholding algorithm, and the binarized image is then subjected to both image expansion and Hough transform detection. It should be noted that the Hough transform recognizes and converts the same line segment or circle into a complete line or circle in the image space. The result of the image expansion operation acts as a mask that prevents the complete line after the broken line completion from being slightly shifted and incorrectly recognized as the defect. Eventually, the two are differentiated to obtain the final Hough prior result P_{hough}.

In DW-RPCA, Hough prior P_{hough} and spectral prior $P_{spectral}$ are feature fused to obtain the fusion prior P, which is used to guide the decomposition process in the sparse part, and then ensures the accurate extraction of defects. The model is as follows:

$$\begin{aligned} &\min_{A,E} \|A\|_* + \lambda \|W \odot E\|_1 + \frac{\beta}{2}\|N\|_F^2, \\ &\text{s.t. } I = A + E + N, \end{aligned} \quad (2)$$

where I, A, E, $N \in R^{d\times d}$ are the input image, background matrix, defect matrix, and noise matrix, respectively. $W \in R^{d\times d} = \exp(-P)$ is the weight matrix. $\|A\|_* = \mathrm{Tr}((A^TA)^{1/2})$ denotes the nuclear norm of the low-rank matrix A. $\|E\|_1$ represents the 1-norm of the sparse matrix E. $\|N\|_F^2$ is the Frobenius norm of the noise term N. $\odot$ is the Hadamard product, and the parameters λ and β are weights of different terms.

The Lagrangian function of the model is con-

Table 1 ADMM flow chart for solving the DW-RPCA model

Input: Metallic mesh image I, defect prior W, parameter λ, β, ρ.
Initialize: $A_0 = E_0 = N_0 = Y_0 = 0$, $maxstep = 10$, $k = 0$, $\mu_0 = 1/\|I\|_2$, $\varepsilon = 1e-4$, $W = \exp(-P)$.
while not converged or $k < maxstep$ **do**
1. Update E by
$E_{k+1} = \arg\min_E \frac{\lambda}{\mu_k}\|W \odot E\|_1 + \frac{1}{2}\|E + A_k + N_k - \mu_k - I\|_F^2$
2. Update N by
$N_{k+1} = \arg\min_N L(A_k, E_{k+1}, N, Y_k, \mu_k) = \frac{\mu_k(I - A_k - E_{k+1}) + Y_k}{\beta + \mu_k}$
3. Update A by
$A_{k+1} = \arg\min_A L(A, E_{k+1}, N_{k+1}, Y_k, \mu_k) = \arg\min_A \frac{1}{\mu_k}\|A\|_* + \frac{1}{2}\|A + E_{k+1} + N_{k+1} - Y_k/\mu_k - I\|_F^2$
where A can be solved by singular value decomposition (SVD) computations.
4. Update Y by
$Y_{k+1} = Y_k + \mu_k(I - A_{k+1} - E_{k+1} - N_{k+1})$
5. Update u by
$u_{k+1} = \rho u_k$
6. Check the convergence conditions $\|I - A_{k+1} - E_{k+1} - A_{k+1}\|_F^2 / \|I\|_F^2 < \varepsilon$
6. Update $k = k + 1$
end while
Output: Background matrix A, defect matrix E, noise matrix N.

structed as follows:

$$\begin{aligned}&\min_{A,E,N,Y,\mu} L(A,E,N,Y,\mu)\\&= \|A\|_* + \lambda\|W \odot E\|_1 + \frac{\beta}{2}\|N\|_F^2 +\\&\langle Y, I - A - E - N\rangle + \frac{\mu}{2}\|I - A - E - N\|_F^2.\end{aligned} \tag{3}$$

Using the alternating direction method of multipliers (ADMM) (Qiu et al., 2016) to solve the above equation, the specific solution procedure after introducing the prior information and adding the weight matrix is as follows:

$$\begin{aligned}E_{k+1} &= \arg\min L(A_k, E, N_k, Y_k, \mu_k)\\&= \arg\min_E \frac{\lambda}{\mu_k}\|W \odot E\|_1 + \frac{1}{2}\|E - X_E\|_F^2,\end{aligned} \tag{4}$$

where $X_E = I - A_k - N_k + Y_k/\mu_k$. The L1-norm optimization problem with weight matrices can be transformed into an operation between individual elements:

$$\begin{aligned}&E_{k+1}(i,j) = S_{\varepsilon(i,j)}(X(i,j))\\&= \mathrm{sgn}(X(i,j)) \times \max[\mathrm{abs}(X(i,j)) - \varepsilon(i,j), 0],\end{aligned} \tag{5}$$

where $\varepsilon(i,j) = \lambda W(i,j)/\mu_k$, S_ε denotes the soft-threshold operator, a solving procedure that replaces the dot-multiplication of matrices with operations between single elements. The overall flow of the DW-RPCA is shown in Table 1.

After the DW-RPCA, defects need to be extracted by threshold segmentation. The gray value of broken line defects in the sparse part is typically less than zero, whereas block defects exhibit gray values greater than zero. Furthermore, the absolute gray value for broken line defects is relatively small, in contrast to the significantly larger absolute gray value of block defects. Based on these characteristics, defects are extracted using a double-threshold segmentation approach:

$$E(x,y) = \begin{cases}255, & \text{if } E(x,y) \le t_1,\\255, & \text{if } E(x,y) > t_2,\\0, & \text{else.}\end{cases} \tag{6}$$

where t_1 and t_2 are thresholds, and t_1 and t_2 are determined to be -5 and 50, respectively, by parameter scanning.

2.5 Sample preparation

The line widths of the metallic mesh are on the micron scale and are therefore processed using UV lithography, metal sputtering, and stripping processes (Wang et al., 2019). Initially, the mask design is prepared using L-Edit software, followed by mask fabrication using electron beam direct writing equipment. Subsequently, the process involves substrate pre-treatment, spin-coating of photoresist, pre-baking, UV exposure, post-baking, developing, rinsing, and drying. After the above process, the metallic mesh pattern on the mask plate is successfully transferred to the substrate photoresist (Lu et al., 2023). For the stripping process, the neg-

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ative photoresist AR-N 4400-05 from ALLRESIST is employed. This photoresist offers high sensitivity and ease of removal, as well as high resolution of the contours of the photoresist pattern after development. Next, the metal layer is deposited on the adhesive film samples using a Technocor JCPF-2000A ultra-high vacuum dual target magnetron sputtering machine, achieving a final thickness of approximately 100 nm. The metallic mesh is finalized using a stripping process, which involves immersion in an acetone solution combined with low-power ultrasonication and brush scrubbing. The samples are then thoroughly washed and dried to complete the fabrication process.

3 Results and discussion

3.1 Imaging system characterization

To obtain the best results from the LD-RSM system, an optimal distance of 22.23 mm was maintained between the sample and the external lens assembly edge. The optical magnification of LD-RSM is M1 (the ratio of the tube lens FL (focal length) = 40 mm to the objective lens FL = 30 mm) times M2 (the ratio of the phone's internal lens FL = 5.43 mm to the relay lens FL = 2.87 mm) = Mo = 2.52×. The phone has a screen size of 6.67 inches (diagonally) with an aspect ratio of 20:9, and its imaging sensor size is 1/1.7 inches (diagonally). Thus, the displayed image will have a digital magnification of Md = 18.0× on the phone's screen.

The resolution of LD-RSM has been characterized by imaging the 1951 USAF target. This is shown in Fig. 5a. Experimentally, under green light illumination, we measured a resolution of 4.92 μm, because it can resolve element 5 in group 6.

Due to the roughness of the sample surface, along with scattering and reflection within the optical system, the LD-RSM has significant stray light interference compared to transmission microimaging systems. The presence of stray light in the LD-RSM system primarily arises from three sources. First, the uneven illumination from the LED source contributes to non-uniform light distribution. Second, scattering is induced by irregularities in the surface structure of the metallic mesh. Meanwhile, stray light is also caused by reflections from multiple optical elements and the inner wall of the housing.

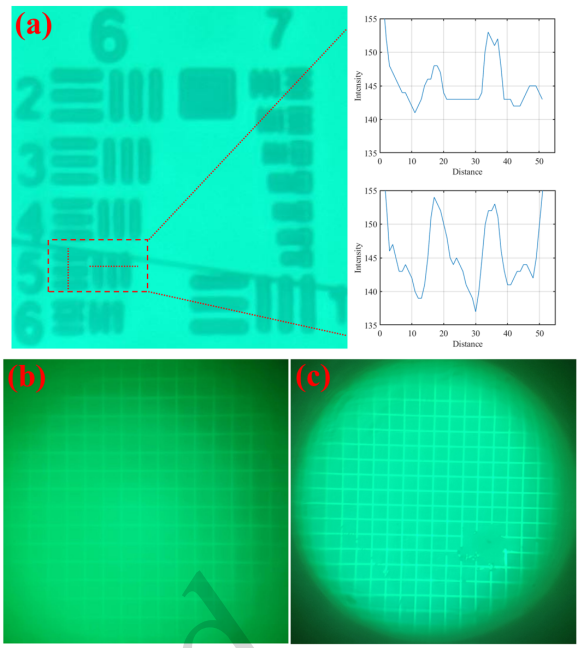

Fig. 5 Characterization of the LD-RSM system. (a) Image of a USAF-1951 resolution test target acquired by the LD-RSM. (b) Imaging result before improvement. (c) Imaging result after the measures to suppress stray light.

The diaphragm is situated in the focal plane to the left (near the tube lens). Note that the relay lens, adapted from an iPhone 7 front lens with a short 2.87 mm focal length, complicates precise diaphragm placement. Despite slight positional inaccuracies, this arrangement successfully reduces stray light and enhances imaging quality. To avoid degradation of image clarity from light reflecting off the shell and re-entering the imaging path, an opening is strategically placed in the transmitted path after the splitter. Figs. 5b and 5c compare the imaging results before and after the measures to suppress stray light. The imaging results show that the above improvement measures greatly reduced the impact of stray light on the system's imaging quality, and the imaging clarity was significantly improved.

3.2 Quantitative analysis of DW-RPCA by metallic mesh defect detection

(A) Metallic mesh databases: As the core device of transparent conductive film and transparent electromagnetic shielding, the photoelectric performance of metallic mesh is limited by two types of defects: broken lines and block defects. Broken line defects are caused by wear and scratches during pro-

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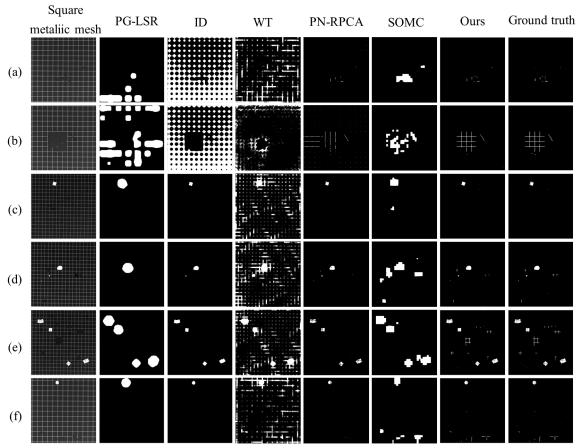

Fig. 6 Visual comparisons with four representative methods on the square metallic mesh dataset.

cessing and application. The cause of block defects is the presence of metal residues due to improper operation or temperature during the photolithography process. To verify the performance of DW-RPCA, this study prepared the metallic mesh of square and circular structures. The square metallic mesh database and the circular metallic mesh database are two sets of 60 images containing broken lines, blocks, and mixed defects used by the laser confocal microscope OLYMPUS OLS5000. Labelme software (Russell et al., 2008) is used to label the ground truth. It should be pointed out that the resolution is configured to 256×256 pixels for standardization with existing defect databases.

(B) Evaluation Metrics and parameter analysis: To quantitatively assess the state-of-the-art of the model, true positive (TP), true negative (TN), false positive (FP), and false negative (FN) are introduced for the detection performance of the defect detection algorithms. From these values, we derive the following as evaluation metrics, which are critical for performance assessment:

$$\begin{aligned} \mathrm{TPR} &= \frac{\mathrm{TP}}{\mathrm{FN}+\mathrm{TP}}, \quad \mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP}+\mathrm{TN}}, \\ \mathrm{PPV} &= \frac{\mathrm{TP}}{\mathrm{FP}+\mathrm{TP}}, \quad \mathrm{NPV} = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FN}}, \end{aligned} \tag{7}$$

$$f = \frac{\left(\gamma^2+1\right) \times TPR \times PPV}{TPR + \gamma^2 \times PPV}, \tag{8}$$

where the value of f combines the true rate and the positive predictive value, and we set $\gamma = 1$.

Table 2 Quantitative comparisons of square metallic mesh datasets (the best results are in bold text)

Defect	TPR	FPR	PPV	NPV	f	Method
Broken	0.3909	0.1565	0.0086	0.9966	0.0168	PG-LSR
	0.1821	0.4680	0.0009	0.9939	0.0019	ID
	0.3413	0.2579	0.0046	0.9956	0.0091	WT
	0.5097	0.0011	0.7423	0.9974	0.6009	PN-RPCA
	0.6905	0.0298	0.0730	0.9980	0.1274	SOMC
	0.8158	**0.0003**	**0.8860**	**0.9995**	**0.8480**	Ours
Block	0.9227	0.0237	0.1372	**0.9997**	0.2356	PG-LSR
	0.8667	0.0445	0.8148	0.9994	0.8023	ID
	0.9456	0.2592	0.0172	**0.9997**	0.0334	WT
	0.7768	**0.0001**	**0.9892**	0.9989	0.8651	PN-RPCA
	0.9713	0.0252	0.1429	0.9995	0.2464	SOMC
	0.8772	0.0004	0.8769	0.9995	**0.8753**	Ours
Mixed	0.5720	0.0365	0.1142	0.9972	0.1886	PG-LSR
	0.5388	0.0918	0.7114	0.9963	0.5783	ID
	0.5750	0.2441	0.0218	0.9950	0.0412	WT
	0.3667	**0.0001**	**0.9841**	0.9943	0.5174	PN-RPCA
	0.8605	0.0441	0.1423	0.9986	0.2414	SOMC
	0.8157	0.0006	0.8815	**0.9989**	**0.8460**	Ours

In the DW-RPCA model, there are two weighting parameters λ and β. Using the gridded parameter scanning method, $\lambda = 0.11$, $\beta = 0.003$ are determined in the square metallic mesh image set. We set $\lambda = 0.06$, $\beta = 0.004$ in the circular metallic mesh.

(C) Comparative models: To validate the performance of DW-RPCA, we conducted comparisons with traditional defect detection algorithms, including PG-LSR (Cao et al., 2017), ID (Ng et al., 2014), WT (Imamoglu et al., 2013), PN-RPCA (Cao et al., 2016), and SOMC (Li et al., 2019).

PG-LSR (Cao et al., 2017) calculates an irregularity map by prior knowledge-guided least squares regression after extracting feature vectors for each block of the fabric image. Defective regions are obtained through automatic thresholding. The ID (Ng et al., 2014) method models a defective fabric image as a superposition of cartoon and texture structures. It employs the total variation and a seminorm in negative Sobolev space to regularize those two components. This image decomposition process is optimized by maximizing the correlation between a defect-free reference fabric image and the texture structure of the testing image. WT (Imamoglu et al., 2013) creates feature maps by inverse wavelet transformation on multi-level decompositions. Each feature map captures band-pass local information at different frequency bandwidths. The final saliency map is generated by combining local and global saliency maps. PN-RPCA (Cao et al., 2016) incorporates a noise term and defect prior based on RPCA. The defect prior guides matrix recovery, enabling accu-

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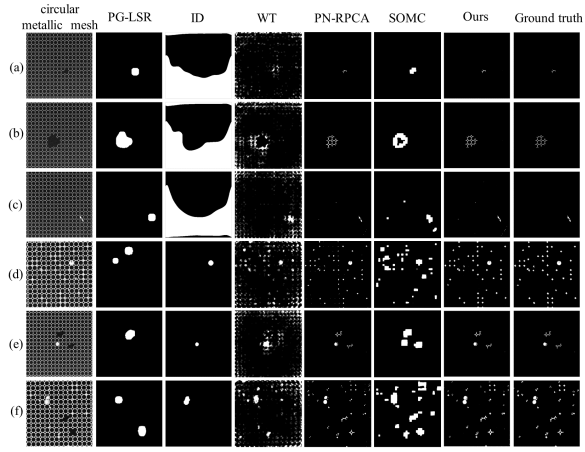

Fig. 7 Visual comparisons with four baseline methods on the circular metallic mesh database.

rate identification of sparse terms as fabric defects. SOMC (Li et al., 2019) first generates a second-order multi-channel feature descriptor inspired by the P-type ganglion cell coding in the primate retina. Using a joint low-rank decomposition framework, the fabric image is decomposed into background and salient defect components.

(D) Experiments on the Metallic Mesh Database of DW-RPCA: Validation is conducted using the square metallic mesh defect image dataset, with representative results shown in Fig. 6. Quantitative comparisons of the measurement metrics of different methods are listed in Table 2. PG-LSR and WT struggle to detect broken line defects. PG-LSR integrates local priors with the global feature space structure, making it sensitive to block defects. Although it has a low false detection rate, it fails to identify more minor defects. WT has high FPR and low PPV due to its ability to detect block defects but with significant noise. Similarly, ID fails to detect broken line defects and may misidentify other elements. PN-RPCA can basically detect broken wires and block defects, but it fails to detect mixed type defects, resulting in significant missed detections. Although FPR is low, TPR is poor. SOMC has a high TPR but a low F-number. This is because SOMC can detect defects, but the significant blocks are large, and it also misses mixed defects. In contrast, DW-RPCA demonstrates a clear advantage in detecting defects in square metallic mesh data.

Fig. 7 presents the comparison of defect detection methods for the circular metallic mesh database. PG-LSR can generally locate significant defects, however, defect characterization makes it difficult to classify defects. ID fails to detect broken line defects and small-sized block defects. WT can detect obvious defects, but it generates significant FPs due to noise. The inability of the 8D texture method in PN-RPCA to extract prior information about small-area block defects results in poor performance in detecting these defects. SOMC can detect most defects but struggles to distinguish between defect types. DW-RPCA can accurately localize and characterize defects, closely matching the ground truth. Quantitative comparisons of the measurement metrics of different methods are listed in Table 3. It can be seen that PN-RPCA has advantages in FPR and PPV, but TPR and f-value are not as good as DW-RPCA because the former has more missed detections. SOMC has a higher TPR but a lower PPV, whereas DW-RPCA offers comprehensive advantages across metrics.

Table 3 Quantitative comparisons of circular metallic mesh datasets (the best results are in bold text)

Defect	TPR	FPR	PPV	NPV	f	Method
	0.6159	0.0246	0.0539	0.9996	0.0983	PG-LSR
	0.1821	0.4680	0.0009	0.9939	0.0019	ID
Broken	0.2466	0.1985	0.0049	0.9980	0.0096	WT
	0.4469	**0.0001**	**0.9382**	0.9975	0.6035	PN-RPCA
	0.9008	0.0219	0.1508	0.9993	0.2537	SOMC
	0.9564	0.0004	0.8089	**0.9998**	**0.8716**	Ours
	0.3350	0.0333	0.1110	0.9908	0.1360	PG-LSR
	0.8667	0.0445	0.8148	**0.9994**	0.8023	ID
Block	**0.9629**	0.2131	0.0512	0.9993	0.0948	WT
	0.6079	0.0066	**0.8365**	0.9946	0.6566	PN-RPCA
	0.7352	0.0414	0.1496	0.9958	0.2446	SOMC
	0.8479	**0.0019**	0.8095	0.9977	**0.8288**	Ours
	0.3015	0.0225	0.1294	0.9878	0.1618	PG-LSR
	0.5388	0.0918	0.7114	0.9963	0.5783	ID
Mixed	0.6424	0.2013	0.0815	0.9890	0.1409	WT
	0.3821	0.0069	**0.8526**	0.9832	0.5027	PN-RPCA
	0.7014	0.0586	0.2194	0.9897	0.3277	SOMC
	0.8514	**0.0025**	0.8489	**0.9974**	**0.8496**	Ours

The TPR-FPR scatter plot and f-value histogram are shown in Fig. 8. In the scatter plot, the upper-left corner is most desirable, indicating a higher TPR and a lower FPR, signifying superior defect detection performance by the algorithm. Higher values correlate with better performance in the f-value histogram.

The scatter distributions for PG-LSR, WT, ID, and SOMC are notably scattered and far from the vertical axis, which indicates marked underperformance compared to DW-RPCA. The scatter distributions of PN-RPCA, although closer to the vertical

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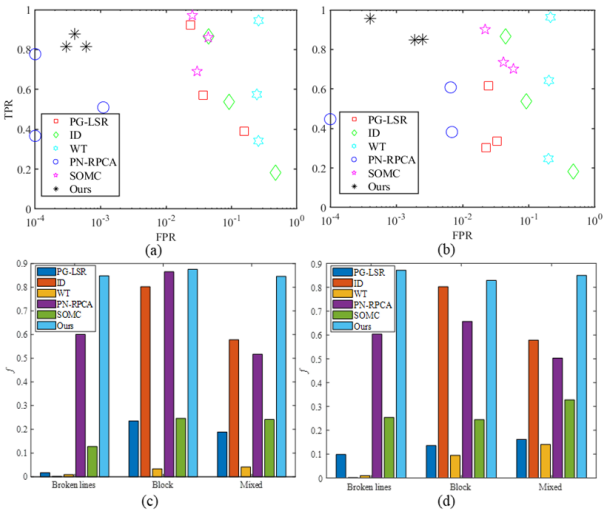

Fig. 8 TPR-FPR scatter plot of (a) square metallic mesh and (b) circular metallic mesh; f-value histogram of (c) square metallic mesh and (d) circular metallic mesh.

axis, suggest higher FPRs and worse TPRs compared to DW-RPCA. In the f-value histogram for the square and circular metallic meshes, PG-LSR, ID, WT, and SOMC perform poorly, PN-RPCA achieves good results, and DW-RPCA achieves an optimal f-value for all three types of defective image sets.

3.3 Experimental results of LD-RSM

Square metallic mesh and circular metallic mesh images were acquired by the proposed LD-RSM system to validate the performance of DW-RPCA. Note that ground truth is generally not available due to the large number and complexity of the actual collection scenarios. Fig. 9 shows the acquired image of the square metallic mesh and the circular metallic mesh with the comparison of multiple defect detection results. Columns 2–6 show the PG-LSR, ID, WT, PN-RPCA, SOMC, and DW-RPCA assays used for comparison and prior information, as in columns 7 and 8, respectively. It can be found that PG-LSR has a certain detection effect. However, PG-LSR has a more severe misdetection phenomenon and is ineffective for the detection of defects with a small area. ID detects defects with a large-area misdetection, and this study determined that the problem is caused by uneven light intensity and image noise. WT also fails to detect. PN-RPCA can generally detect defects. However, its performance on authentic images is not as good as before due to

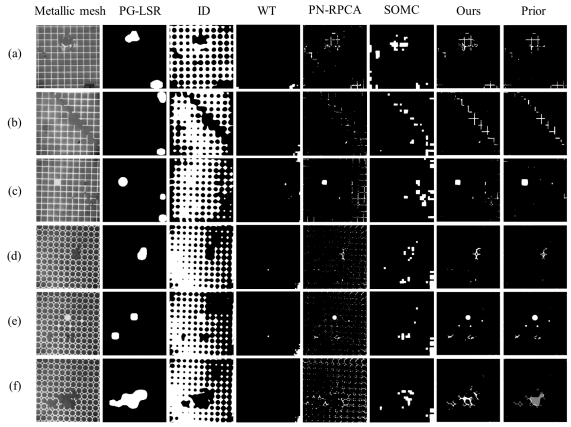

Fig. 9 The acquired image of square metallic mesh and circular metallic mesh with the comparison of multiple defect detection results.

its insufficient anti-interference ability. SOMC can detect defects, but there are some FPs. DW-RPCA is robust to uneven illumination, noise, and other problems and can realize fast and accurate detection for three types of defects of different sizes and shapes, effectively improving the misdetection and leakage issues.

DW-RPCA is utilized to detect defects in the acquired image of a specific region (2 mm × 2 mm) by LD-RSM. The detection result of large metallic mesh defects is shown in Fig. 10. The defect detection results are accurate. This indicates that the refined metallic mesh defect detection system constructed in this study can realize the ultra-field-of-view range of specific areas of the metallic mesh by scanning the image using the UR5 robotic arm and LD-RSM, and then using DW-RPCA for fast and accurate detection.

4 Conclusion

In this paper, a reflective portable imaging system (LD-RSM) is proposed to realize imaging of metallic mesh in the in situ state. The optical path structure coupled with an external optical lens set and a smartphone camera module is adopted to increase the working distance (22.23 mm) of the imaging system. The introduction of an aperture diaphragm and other stray light filtering designs effectively reduces the impact of stray light on the imaging system's quality. Experimental results show that the resolution of the reflective portable imaging system is 4.92 μm, and the magnification

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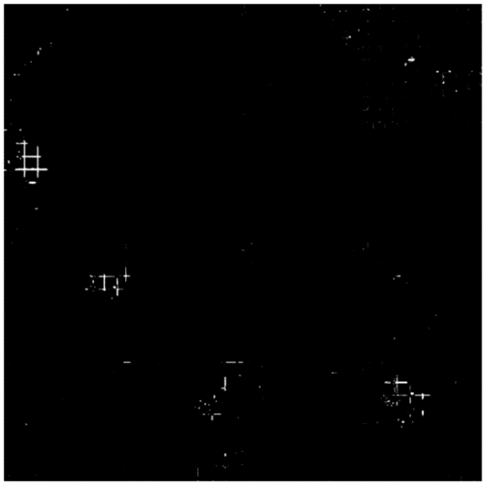

Fig. 10 Detection results of large metallic mesh (2 mm × 2 mm) defects.

meets the imaging quality requirements of metallic mesh. A low-rank decomposition defect detection algorithm based on the fusion of spectral filtering and the Hough transform (DW-RPCA) is also proposed to detect defects in square and circular metallic mesh. DW-RPCA has the best detection results compared to other methods, achieving an f-value of 0.856 for square metallic mesh and 0.848 for circular metallic mesh. Finally, the performance of LD-RSM and DW-RPCA are demonstrated in combination with a UR5 robotic arm to realize the ultra-field-of-view inspection of large-scale micro- and nanostructures. This provides a low-cost and efficient solution for industrial in situ inspection.

Contributors

Zhengang LU supervised and conceptualized the research, contributed to methodology, validation, and paper writing. Hongsheng QIN handled investigation, visualization, formal analysis, and data curation. Jing LI worked on software development, data curation, and provided resources and validation. Ming SUN wrote and reviewed the paper. Jiubin TAN provided supervision and helped review the paper.

Conflict of interest

All the authors declare that they have no conflict of interest.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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