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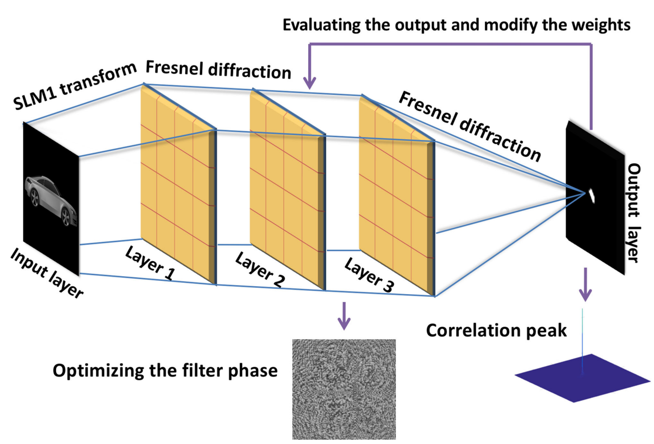

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Research on 2F Optical Correlator Based on Neural Network Filter for Recognizing Large-Angle Rotation Distortion Target

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Abstract: It is difficult for optical correlator to recognize the target with large rotation distortion by using existing filters. To solve this problem, a new neural network model is constructed based on the physical recognition process of planar integrated 2F optical correlator. The new optical filter is optimized by training the neural network. The planar integrated 2F optical correlator can output sharp correlation peaks by using the new filter to recognize targets with arbitrary rotation distortion. Compared with the traditional OTSDF filter, the average increase of correlation peak index is up to 1402.4%, while the recognition performance of distortion invariant is also better than the new NNCRF filter. The simulation and experimental results show that the optical filter designed in this paper can effectively solve the problem of weak recognition ability of optical correlator for rotating distortion targets, especially for large angle rotating distortion targets.

Index Terms: Optical recognition, neural network, optical filter, rotation distortion recognition.

1. Introduction

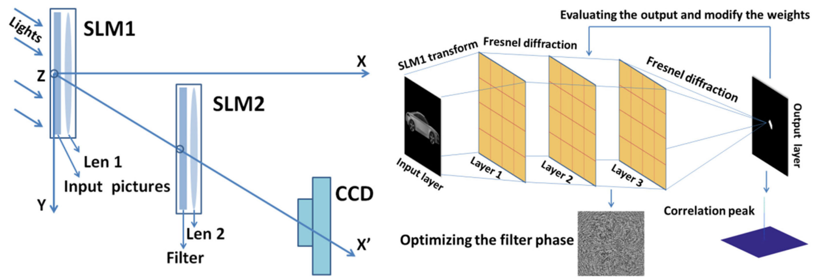
Compared with traditional computer pattern recognition, optical correlation recognition has advantages in ultra-high speed operation, high bandwidth, anti-electromagnetic interference and strong stability, so it has broad application prospects. At present, optical correlation recognition has been applied to complex background moving target recognition, face recognition and other fields, playing its unique advantages [1]–[4]. The matched filter in the optical correlator is the key device to determine the recognition performance of the system. At present, the design algorithm of the optical filter is mainly generated by the mathematical transformation of the distortion target set spectrum. The main design algorithms include Synthetic discriminant functions (SDF) [5], [6], Minimum-variance synthetic discriminant functions (MVSDF) [7], Minimum average correlation energy (MACE) [8], Maximum average correlation height (MACH) [9], etc. The Optimized trade-off SDF (OTSDF) [10] filter can output a sharp correlation peak for the recognition of distortion targets by optimizing the former-mentioned various filters. It has strong anti-noise ability and is the most widely used filter at present. However, when the target is greatly rotationally distorted, the indexes of the correlation peaks decline a lot, which is bad for the discrimination of the target. At present, the filter algorithms, specific for the target recognition of rotational distortion are diverse. One is a circular harmonic transform filter [11], which realizes the recognition of the rotating target by the circular harmonic transformation function, without preparing the training target set, but the disadvantage is that the correlation peak of the output is wider and difficult to discriminate. Another is also a modified SDF filter [12], whose correlation peak of the rotational distortion target recognition output is not sharp enough, side lobes are large, and the problem of difficulty in discriminating occurs when the target rotation angle is too large. Amit Aran with her partners designed a log-polar transform-based WaveMACH filter to recognize the output bright spot in the optical path for the target of rotational distortion [13], but the method requires the correlation operation between the distortion target and the filter in the computer. Then, the calculated result is loaded onto the spatial light modulator, and then recognized on the optical path. Compared with the all-optical recognition, this method obviously decreases the recognition speed, and because of the use of complex filter, the output light field energy is attenuated, and the height of the correlation peak is not high enough, and the side lobes are large, which is bad for the discrimination of the correlation peak. There are also methods of using volume holographic storage filters and linear, nonlinear multi-filter cascades to recognize the target of rotational distortion. These methods have difficulty in recognizing because of complicated optical paths and the high optical path stability requirement, while the correlation peaks are not sharp enough [14], [15]. The latest optical filter design algorithm is the Neural network correlation recognition filter (NNCRF) generated by a neural network optimization method. It enables the optical correlator to easily recognize the distortion target, and each index is greatly improved, but in terms of rotational distortion, it can only recognize the left and right rotations distortion of 50 degrees according to the existing reports. [16] In conclusion, optical correlators applying existing filters still have difficulty in recognizing large rotational angle distortion targets

An optical filter is a phase-type device consisting of multiple phase points. The key to the design is to solve the optimal combination of phase points. Based on the NNCRF research, this paper designs and optimizes a new optical filter for the planar integrated 2F optical correlator by improving the neural network parameters and evaluation mechanism, so that the planar integrated 2F optical correlator can recognize the distortion target of any rotation angle. The method of designing the filter is simple and efficient, and the correlation peak of the recognition output is sharp, with small side lobes and easy discrimination. So the recognition efficiency of the optical correlator for the large-angle rotation distortion target can be greatly improved, and therefore, this method is of great significance for the practical application of optical recognition.

2. Construction of Optical Recognition Neural Network

The planar integrated 2F optical system [17] has fewer components, higher stability, more compact structure and higher space utilization than the classic 4F optical system [18], and the system can be integrated into various applications. A new optical filter is optimized for planar integrated 2F optical correlators to recognize rotational distortion targets and it is named NNRRF (Neural Network Rotation Recognition Filter).

The equivalent optical path diagram of the planar integrated 2F optical correlators is as shown in Fig. 1(a), where X, Y, and Z represent the X-axis, Y-axis, and Z-axis of the Cartesian coordinate system respectively. *Input pictures* represents the target to be recognized. The digital microlens *Len1* is superimposed on the input pictures and then loaded on the spatial light modulator *SLM1*. Filter represents a matched filter, which is superimposed with the digital microlens *Len2* and then loaded into the spatial light modulator *SLM2*. *Lights* represents input light. *CCD* is used to receive the recognition result. The planar integrated 2F optical correlator performs optical correlation operation on the input target as well as the matched filter, and the correlator obtains a pulse function on the output surface. CCD detects a concentrated spot which is the correlation peak. Thus, the authenticity of the input target will be known by determining whether the CCD receives the bright spot. If the target to be recognized matches the filter, the CCD will receive the concentrated bright spot.



(a) (b)

Fig. 1. (a) 2F system equivalent optical path diagram and (b) 2F optical system neural network model.

In this paper, the neural network structure model shown in Fig. 1(b) is constructed according to the recognition process of planar integrated 2F optical correlator. Each layer of neurons in the model represents the result of optical transformation of each step of the correlator. The mapping between every two neurons strictly follows the optical transformation process of the 2F optical correlator, and the filter phase is set to the weighting factors that can be optimized between Layer 2 and Layer 3 in the network. Wherein the *Input layer* is the layer from which the image to be recognized is input, the mapping between *Input layer* and *Layer 1* is the transformation of the incident light which is passing through the spatial light modulator SLM1. *Layer 1* represents the light field distribution of the incident light after passing through the SLM1; The mapping between *Layer 1* and *Layer 2* is Fresnel diffraction transformation. And *Layer 2* represents the result of Fresnel diffraction transformation, that is, the light field distribution of the front surface of SLM2. The mapping relationship between *Layer 2* and *Layer 3* is the transformation of SLM2, that is, the transformation between the matched filter and the second digital microlens. The transformation relationship is as shown in equation (1):

$$Layer3 = A(y, z)e_1^{-i\theta(y,z)} \bullet \left(e_2^{-i\delta(y,z)} \bullet e_3^{-i\varphi(y,z)}\right) \tag{1}$$

Where *Layer3* represents the light field distribution on the rear surface of SLM2; $A(y, z)e_1^{-i\theta(y,z)}$ represents the light field distribution reaching the front surface of SLM2, where $A(y, z)$ represents the amplitude matrix of the light field, and $\theta(y, z)$ represents the phase matrix of the light field; $e_2^{-i\delta(y,z)}$ represents the transmittance of the matched filter where $\delta(\mathrm{y}, \mathrm{z})$ is set as a phase matrix that can be optimized; $e_3^{-i\varphi(y,z)}$ represents the transmittance of second digital microlens where $\varphi(y, z)$ represents the phase matrix of the digital microlens; y and z represent the positions of each data point in the matrix corresponding to the coordinate system in Fig. 1(a). The light on the back surface of the SLM2 is also subjected to Fresnel diffraction to the output surface (ie, the Output layer). If the filter can match the input image, a sharp correlation peak can be obtained [19], and the peak indicates in the experiment that the CCD can receive a concentrated bright spot.

The output evaluation function of the neural network will affect the optimization efficiency of the optical filter. The performance of the filter is mainly based on the output correlation peak indicators of recognizing the target, such as correlation peak intensity (CPI), peak-to-correlation energy (PCE) [10], and signal to noise ratio (SNR) [20]. In our early methods [15], these indicators are used as the evaluation factors directly when training the neural network to optimize the filter, it may cause series of problems, such as the position shift of correlation peak, and sometime it even leads to output the correlation peak for the pseudo target. We had to select the optimal filter results through multiple optimization and programming screening. Therefore, the early methods are relatively time-consuming, and the optimization efficiency is relatively low. For this problem, this paper establishes an ideal output label for each training image, and uses the true and pseudo targets as the neural network training images at the same time. Therefore, the output label corresponding to the true target is the ideal correlation peak. By contrast, the output label corresponding to the pseudo

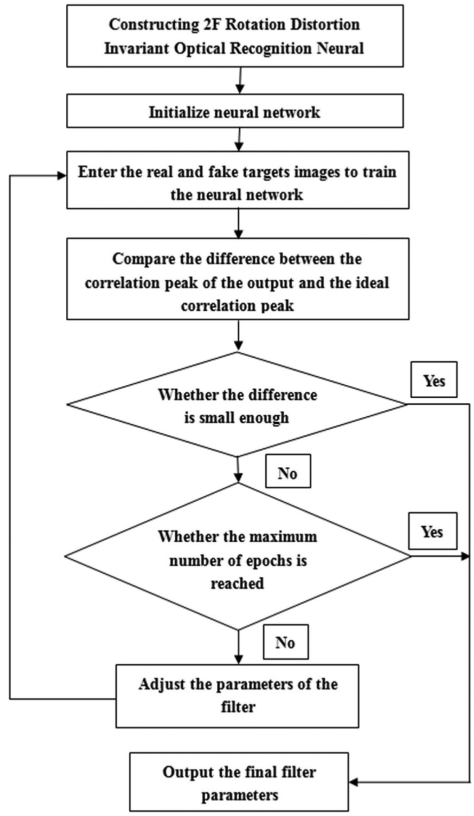


Fig. 2. Flowchart of neural network optimization optical filter.

target has no correlation peak output. And thus the optimization method of "supervised learning" is established. We set the specific form of the evaluation function of the neural network as:

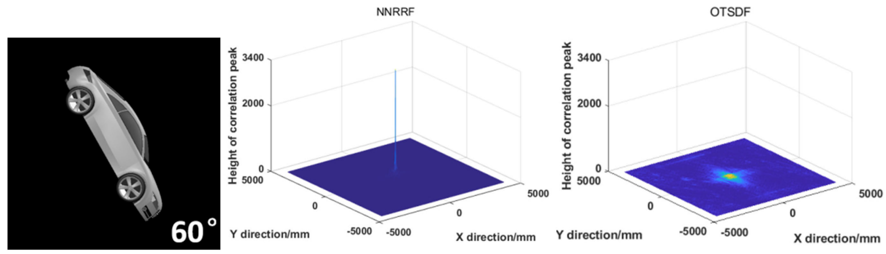
$$Loss = \left|Label - Output\right| \tag{2}$$

Where *Output* is the actual output of the network; *Label* is the ideal output corresponding to the input target. The input target samples consist of pseudo-target and real target with rotation distortion. If the input is a pseudo-target, the corresponding *Label* is the output without any correlation peak. If the input is a true target, the corresponding *Label* is the ideal correlation peak; and *Loss* is the loss function value of the network. When the neural network is trained in the input sample sets, the back propagation algorithm [21] returns the loss function value of the network output between Layer 2 and Layer 3. According to the loss function value, the gradient descent method optimizes the network weight parameter, that is, the phases of the filter. The phases of the filters are optimized, so that the Loss value is continuously reduced and the correlation peak of the actual output light field is close to the ideal shape.

In this paper, TensorFlow [22] is used to program the neural network framework. Through repeated iterative training of the training target set, the filter finally obtains the optimal weight parameter, so that the correlation peak of the output of the rotation distortion target is close to the ideal shape. The flow chart of the neural network is shown in Fig. 2:

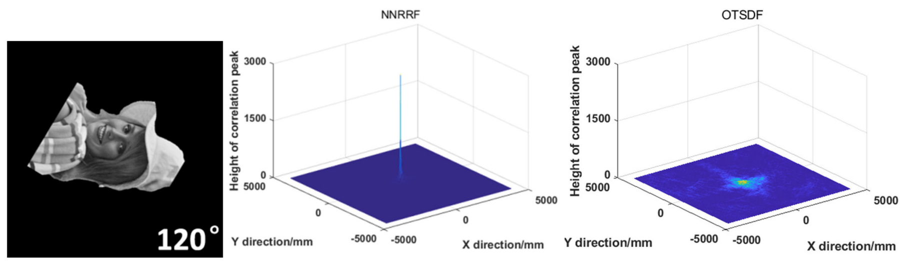
3. Simulation Comparison Experiment Results of NNRRF Filter

In this paper, three different targets of Car, Tank and Portrait are selected as the images to be recognized. Starting from 0 degrees, one image is rotated to 360 degrees with interval of 30 degrees, i.e., each training image set with 12 images of different rotation angles is generated.



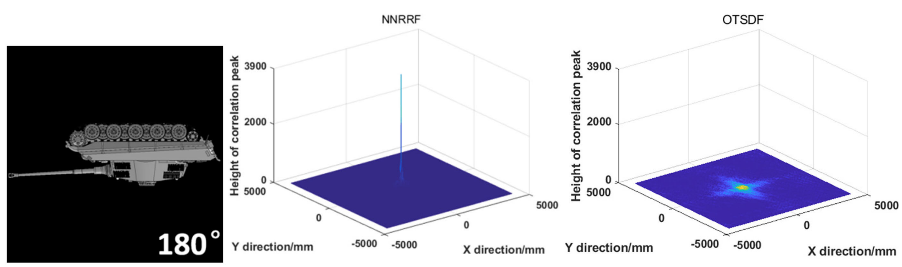
(a) (b) (c)

Fig. 3. (a) The Car target picture to be recognized (b) correlation peak output by NNRRF (c) correlation peak output by OTSDF.



(a) (b) (c)

Fig. 4. (a) The Portrait target picture to be recognized (b) correlation peak output by NNRRF (c) correlation peak output by OTSDF.

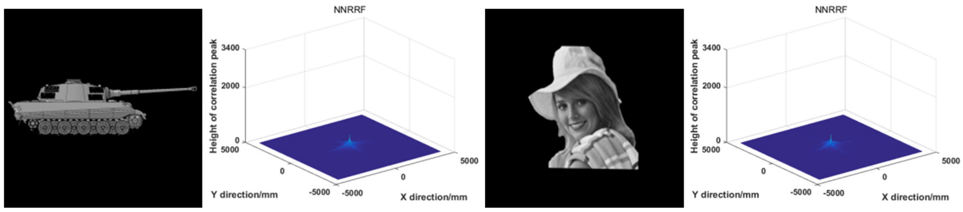


(a) (b) (c)

Fig. 5. (a) The Tank target picture to be recognized (b) correlation peak output by NNRRF (c) correlation peak output by OTSDF.

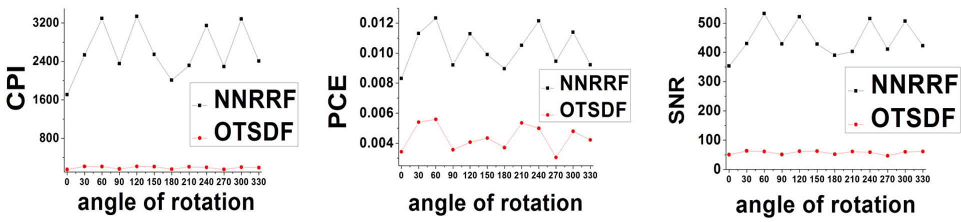
And 12 different pseudo-target images are added in each set of images. The training image set of each target contains 24 images. Each image contains a total of 1080 $\times$ 1080 pixels and each pixel has a size of 8 μm $\times$ 8 μm. Every training image has a corresponding ideal output label. Then by using these three sets of training images to train the neural network constructed in the previous paper, the loss function of the network output is continuously reduced. Finally, three kinds of NNRRF filters that can recognize the corresponding targets are obtained. For comparison, we use the above-mentioned distortion target sets to generate three target-corresponding OTSDF filters according to the design algorithm of the OTSDF filter. Eventually, we use a planar integrated 2f optical correlator, keeping the other components of the correlator the same. Then we apply the NNRRF filter and the OTSDF filter to the correlator respectively to recognize the distortion targets with different rotation angles, and compare the correlation peak shapes of the output as well as the specific correlation peak indexes.

Fig. 3, 4, and 5 show the correlation peak shape of the Car, Tank, and Portrait output from the planar integrated 2F optical correlator using the corresponding NNRRF filter and OTSDT filter



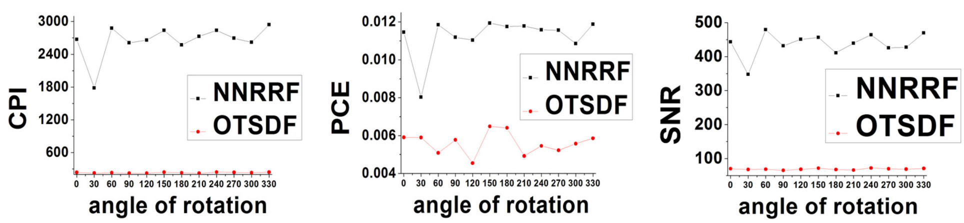
(a) (b)

Fig. 6. The correlation peak height picture of recognizing (a) the Tank and (b) the Portrait with the NNRRF Car filter.



(a) (b) (c)

Fig. 7. The output correlation peak of NNRRF filter and OTSDF filter recognizing Car target contrasting (a) CPI (b) PCE (c) SNR.



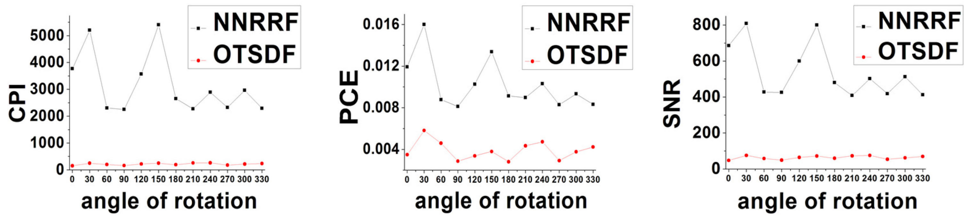
(a) (b) (c)

Fig. 8. The output correlation peak of NNRRF filter and OTSDF filter recognizing Portrait target contrasting (a) CPI (b) PCE (c) SNR.

respectively. In the comparison, the correlation peak of NNRRF filters is significantly higher and sharper than the OTSDF's. Fig. 6 shows the correlation output applying the Car's NNRRF filter to recognize the Tank and the Portrait. However, it is found that there is no correlation peak output. The simulation results show that the NNRRF filter designed in this paper can not only distinguish the authenticity of the target, but also recognize the targets with large rotation angle distortion.

The planar integrated 2F optical correlator uses NNRRF filter and OTSDF filter to recognize different rotational distortion targets respectively, and we compare the correlation peak evaluation indexes of the recognition output.

As shown in Figs. 7, 8 and 9, the abscissa is the rotation angle of the input target, and the ordinate is the corresponding correlation peak indexes such as CPI, PCE, and SNR. The higher these evaluation indexes, the higher and sharper the correlation peaks of the output are, and the easier they are to be discriminated in the experiment. It can be clearly seen from the figures that the evaluation indexes of the NNRRF correlation peaks are greatly improved compared with those of OTSDF filter. The correlation peak index of the output of the NNRRF filter is increased by at least 103.2% on average, and the maximum increase is up to 1402.1%. The increased values of the



(a) (b) (c)

Fig. 9. The output correlation peak of NNRRF filter and OTSDF filter recognizing Tank target contrasting (a) CPI (b) PCE (c) SNR.

TABLE 1
The Average Increasing Value of the Correlation Peak Indexes That Using the NNRRF Relative to the OTSDF to Recognize the Rotational Distortion Target Sets

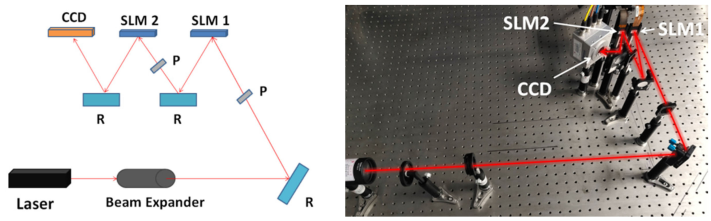
Average improvement of indexes	Car	Portrait	Tank
CPI average increase	1285.4%	1042.5%	1402.1%
PCE average increase	140.4%	103.2%	169.1%
SNR average increase	679.4%	533.8%	766.3%

three target recognition results are shown in Table 1. It can be seen from the comparison that peak evaluation indexes are relatively high when NNRRF recognizing the target of rotational distortion, especially those of large-angle rotation distortion. This improvement indicates that the filter has better recognition ability for the target of rotational distortion.

The NNCRF filter which was previously reported [15] can only recognize the left and right rotation distortion of 50 degrees of the Portrait. The target beyond the range of the rotational distortion cannot be recognized. However, the NNRRF designed in this paper can achieve 360° rotation distortion recognition, with complete rotational distortion recognition capability; previously reported NNCRF filter within the identifiable angle, compared to the OTSDF filter, CPI increased by 155.2%, PCE increased by 95.6%, and SNR increased by 91.4% [15]. In contrast, the NNRRF filter designed in this paper increases the CPI of the same target by 887.3% more than the NNCRF filter, the PCE by 7.6%, and the SNR by 442.4%. It can be seen that the NNRRF filter has better ability to recognize the target with large-angle rotation distortion than NNCRF.

OTSDF filter is an optical filter calculated directly by analytic method. This filter is the best compromise of many filter algorithms. It combines many performance advantages and becomes a common optical filter in the early stage. But through our research, we find that the performance of OTSDF filter itself is not good enough, when OTSDF filter is used to recognize distorted target in optical correlator, the evaluation indexes of output correlation peak decreases sharply with the increase of target distortion. This phenomenon makes it very difficult to distinguish the true and pseudo targets in the experiment. Therefore, we think that the filter designed by this analytical method may have some limitations, and these filters are not the optimal results. Although the NNCRF filter adopts the optimizing thinking, it only uses the three correlation peak indexes of CPI, PCE and SNR as the evaluation function. It not only does not consider the difference of the recognition between true and pseudo targets, but also does not strengthen the effect of the evaluation function in the supervised learning [23]. These drawbacks result in insufficient inference of the filter for large-angle rotation distortion targets.

Different from the above two kinds of filters, in this paper, when the NNRRF is trained with the target of rotational distortion, different idealized labels of different true and pseudo targets are



(a) (b)

Fig. 10. (a) Planar integrated 2F structure light path diagram and (b) physical light path diagram.

introduced in the evaluation function. When inputting training targets with different distortions, the neural network dynamically adjusts the parameters of each pixel on the filter according to the difference between the label and the actual output result. Then the network optimally combines the phases of the entire filter. When each true target passes through the input and operation, the macroscopic performance on the output surface is the sharper correlation peak and the higher signal-to-noise ratio. The high correlation peak will not be obtained on the output surface when the pseudo target is input. By doing so, the neural network is guided to supervise learning, and the training efficiency can be significantly improved. So the final obtained filter not only has better distinguishing ability for pseudo targets, but also has excellent recognition ability for true targets with large-angle rotation distortion. In the meanwhile, the correlation peak of the output is closer to the ideal form, and its indexes are better. Furthermore, the performance of the optical correlation recognition system applied in this paper can also be fully utilized.

4. Experimental Verification of Planar Integrated 2F Optical Correlator With NNRRF

In this paper, based on the planar integrated 2F optical correlator structure, the verification system of the correlator is built on the experimental platform, and the recognition ability of the NNRRF filter is verified by experiments. The experimental optical path diagram is shown in Fig. 10. In Fig. 10(a), a He-Ne laser with a wavelength of 632.8 nm is applied as source. After Beam Expander, a parallel light source is provided to the system. According to the structural parameters, the incident angle of the light beam is obliquely incident at an angle of 6°. P is a polarizer, R is a mirror, SLM1 and SLM2 are pure phase reflection spatial light modulators. There are 1080×1080 pixels on each SLM, and each pixel size is $8\mu\text{m} \times 8\mu\text{m}$. Fig. 10(b) shows the experimental setup of the physical light path diagram, the SLM1 is loaded with the composite image of the input target and the digital microlens 1, the SLM2 is loaded with the composite image of the NNRRF filter and the digital microlens 2, and the CCD is used to receive the correlation peak signal.

In this paper, the image sets of different rotation angles of Cars, Portraits and Tanks. The corresponding NNRRF filters are loaded onto the planar integrated optical correlator, and the peaks of the final output are received on the CCD. Fig. 11(a) shows the correlation peak bright spots of the Car with different rotation angles, Fig. 11(b) shows the correlation peak bright spots of the Portrait with different rotation angles, and Fig. 11(c) shows the correlation peak bright spots of the Tank with different rotation angles. Each mark on the lower right corner of the smaller pictures is the rotation distortion angle of the target.

As can be seen from Fig. 11, when the corresponding NNRRF filter is used to recognize the image sets with various rotational distortions, bright spots which are easy to discriminate can be observed on the CCD while the noise is small. If the above three filters are used to recognize the pseudo target, no bright spot can be observed on the CCD. It can be inferred that the spot received by the CCD is the correlation peak of the recognition output, and the output spot of true target with large-angle rotation distortion can be seen very bright and easy to discriminate.

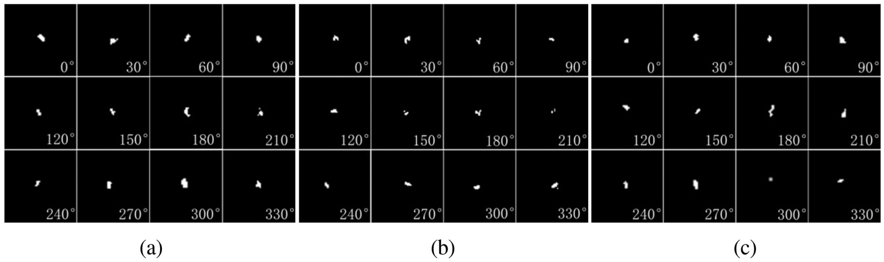


Fig. 11. (a) Output correlation peak of Car target (b) Output correlation peak of Portrait target (c) Output correlation peak of Tank target.

The experimental results verify the excellent recognition ability of NNRRF for targets with any rotational angle distortion.

5. Conclusion

In this paper, based on the physical recognition process of planar integrated 2F optical system, a new neural network model is constructed. The neural network learning ability is used to optimize the NNRRF filter that can recognize the target of rotational distortion. Compared with the OTSDF filter, the planar integrated 2F optical correlator applying NNRRF can be used to recognize the target with rotational distortion, especially for targets with large angle-rotation distortion, furthermore, the correlator can output sharp correlation peaks with smaller side lobes and noise. The average peak of the correlation peak indexes can be increased with the maximum of 1402.1% and the minimum of 103.2%. The distortion invariant recognition performance of NNRRF is also better than the new NNCRF filter. In the experimental verification, when the planar integrated 2F optical correlator applying the NNRRF filter recognize the true targets of various rotational distortions, the CCD can receive bright spots. But when the targets are pseudo, there is no spot observed on CCD. Both the simulation results and the experimental results prove that the NNRRF optical filter designed in this paper have excellent recognition ability for various rotating distortion targets, especially large-angle rotation distortion targets, and the NNRRF filter is of great significance for the wide application of optical correlators.

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