A hybrid method to recognize 3D object

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Abstract: A hybrid method using the support vector machine (SVM) correlation filter and the phase-shift interferometry (PSI) holography is proposed to recognize 3D object, which can improve the correct decision rate and resist the distortion of object rotation and noise. The different images of two types of both in-plane and out-of-plane rotated object recorded by digital holography are reconstructed. The reconstructed images of two types are selected to synthesize the SVM correlation filter, respectively. To compare the correct decision rates of the SVM correlation filter with other three ones, it is found that the experimental result is better in rotation resistance and noise tolerance.

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1. Introduction

Recently, the digital holography has been applied in the 3D object recognition. A digital hologram can be used to record the 3D information which maintains the phase and amplitude information of an object, and conquer the complexity of traditional method that adopts sequentially several 2D images to synthesize the 3D information [1,2]. The digital holographic process can reconstruct and recognize the 3D object more simply and flexibly, which simplifies the recognition process and has application potential [3]. In order to improve the correct decision rate of the 3D object recognition, the digital holography is proposed to combine with the Support Vector Machine (SVM) correlation filter [4] as shown in Fig. 1.
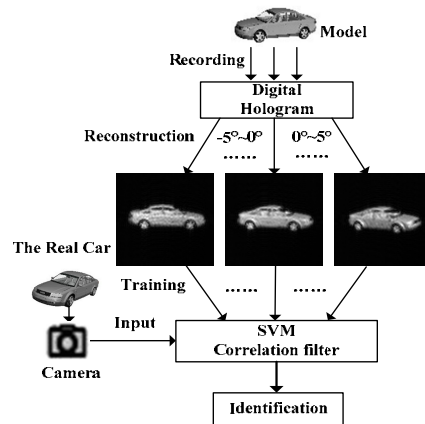

Fig. 1. The 3D object recognition scheme is that the series cars during (−5°~ + 5°) are generated using digital holography and training with the SVM.

The theory of SVM was developed on the basis of the Statistics Learning Theory (SLT) [5]. The SVM has its unique strengths in solving the problems of small sample, nonlinear and high-dimension pattern recognition. However, the traditional composite correlation filter still shows its parallel computation ability and shift invariance property in recognition except for its low tolerance in distortion and noise depending on the design criteria. Therefore, when the SVM network is combined with the correlation filter, the SVM correlation filter absorbs their two advantages, which exhibits shift invariance and fast parallel computation as well as excellent generalization ability and high decision rate under noisy and rotation. Therefore, an experiment scheme of two-class classification is proposed to verify the performance to resist rotation and noise. And comparing with the same experiments of other three correlation filters (i.e., Synthetic Discriminant Function (SDF) [6–8], Maximum Average Correlation Height (MACH) [6–8], and Hybrid Optical Neural Network (HONN) filters [9]), the SVM correlation filter has better performance to resist rotation and noise [10].

2. Phase-shifting interference digital holography

According to the phase-shift interferometry digital holography [1], by aligning successively the different slow and fast axes of the phase retarders with the direction of polarization, the different phase values (i.e., $0, -\pi/2, -\pi$, and $-3\pi/2$) can be produced. Supposing the phase of the parallel beam after the second retarder plate equals to zero when the fast axis of two plates is aligned with the direction of polarization of the incident light. The intensity pattern for each phase is recorded by the CCD. The object beam on the CCD surface, as shown in Fig. 2,
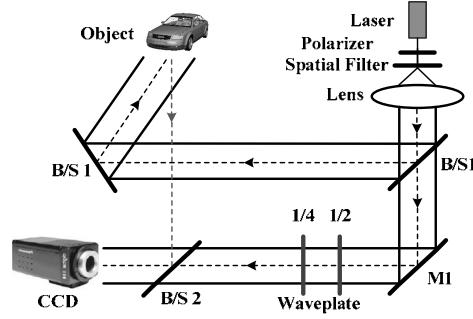
Fig. 2. Experimental scheme of 3D object recognition with a single exposure on-axis scheme.

$H(x,y) = A_H(x,y)\exp(\phi_H(x,y))$ can be derived as follows [11]:

$$H(x,y) = \frac{1}{4U_R^*}\left\{I_H(x,y;0) - I_H(x,y;\pi) + i\left[I_H(x,y;\pi/2) - I_H(x,y;3\pi/2)\right]\right\} \quad (1)$$

where the $I_H(x,y;a)$ denotes the intensity corresponding to four different phase values and the $H(x,y)$ represents the recorded hologram of the 3D object with its amplitude $A_H(x,y)$ and its phase $\phi_H(x,y)$. The reconstruction of the input 3D object can also be obtained with Fresnel propagation integral or convolution method [12]. The experimental results figures are shown in Fig. 3 and Fig. 4.
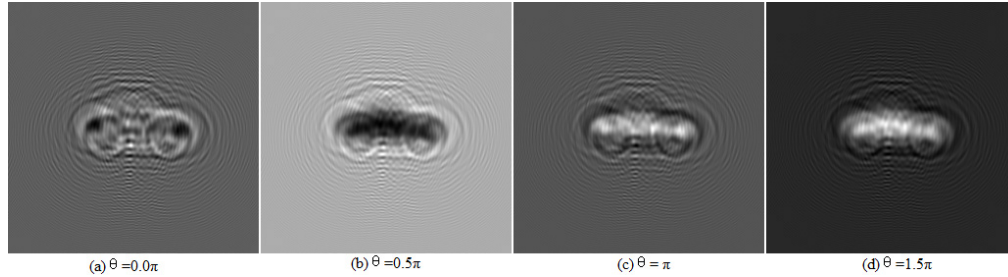

(a) $\theta = 0.0\pi$ (b) $\theta = 0.5\pi$ (c) $\theta = \pi$ (d) $\theta = 1.5\pi$

Fig. 3. Digital holograms using phase-shift interferometry.

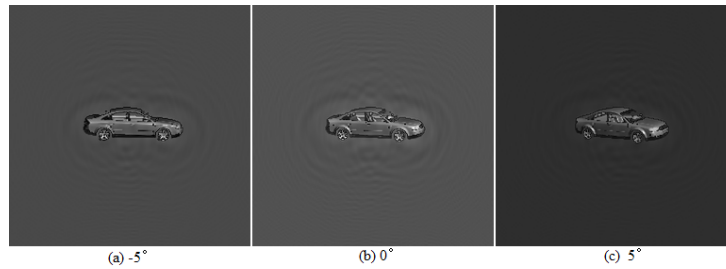

(a) -5°   (b) 0°   (c) 5°

Fig. 4. Reconstructed images using different view angles.

3. Synthetic discriminant function (SDF)

In order to resist the distortion of 3D object recognition, several approaches have been studied in pattern recognition. The SDF can be considered as a basic way [6–8]. The SDF filter is made with the linear combination of the reference images $s_i(x,y)(i=1,2,...N)$ as follows [6]:

$$h(x,y) = a_1 s_1(x,y) + a_2 s_2(x,y) + ... + a_n s_n(x,y) = \sum_{i=1}^{n} a_n s_n(x,y) \qquad (2)$$

The undetermined coefficients $a_i (i=1,2,...N)$ can be calculated [6–8] under the assumption that the origin values of the cross correlation between the impulse response $h(x,y)$ and all N-input training images are the same. The SDF correlation filter has low noise tolerance. If it is input with any noise, the correct decision rate could be severely influenced [6].

On the basis of SDF, the numerous correlation filters have been improved and used in pattern recognition, including maximum average correlation height (MACH) filter, maximum average correlation energy (MACE) filter [6], etc. The theory of machine learning has been adopted in those filters. The hybrid optical neural network (HONN) filter [9] and the linear kernel-base SVM correlation filter [13] have proved that the combination of the SVM and the fast parallel ability of correlation filter improve the correlation filter design. In following sections, the SVM correlation filter is described and its performance is verified in 3D object recognition with holography.

4. Support vector machine (SVM) correlation filter

It is the SVM filter [4,5,13–16] with a two-class classification that its $(\vec{x}_i, y_i)(i=1,...,n, x_i \in R^d, y_i \in (-1,+1))$ is a linearly separable sample set, with the input feature vector $\vec{x}_i$ and its expected class identifier y_i. Commonly, the linear classification function of the d dimensional space is denoted by $g(x) = \vec{w} \cdot \vec{x} + b$, where the $\vec{w}$ is the weighing vector and the b is the bias. The optimal classification function can be obtained:

$$f(x) = \text{sgn}\left\{(\vec{w}^* \cdot \vec{x} - b^*)\right\} = \text{sgn}\left\{\sum_{i=1}^{n} a_i^* y_i (\vec{x}_i \cdot \vec{x}) - b^*\right\} \qquad (3)$$

The coefficients a_i^* and b^* can be derived according to the SVM algorithm. And the bias b^* can be regarded as the thread value of the classifier. Assume $f'(x) = \sum_{i=1}^{n} a_i^* y_i (\vec{x}_i \cdot \vec{x})$, and the optimal classification function can be divided into two parts: 1) Determinative component $f'(x)$. 2) The thread value b^*. The $f'(x)$ can be formally changed into the Eq. (4) as follows:

$$f'(x) = \sum_{i=1}^{n} a_i^* y_i (\vec{x}_i \cdot \vec{x}) = \vec{x} \cdot \sum_{i=1}^{n} a_i^* y_i \vec{x}_i = \vec{x} \cdot \sum_{i=1}^{n} A_i^* \vec{x}_i = \vec{x} \cdot h'(x) \qquad (4)$$

where the $h'(x) = \sum_{i=1}^{n} A_i^* \vec{x}_i$ is formally similar to Eq. (2) (i.e., the synthetic filter). Therefore, the SVM correlation filter $h'(x)$ can be formed according to Eq. (4), which possesses most advantages of the SVM algorithm. The implementation of the SVM correlation filter includes two steps:

1. Training all samples into the SVM network to obtain the optimal classification function.

2. Synthesizing the SVM correlation filter using the obtained support vectors and the coefficients of the optimal classification function.

5. Experimental analysis

In order to realize above scheme, a computer is adopted to simulate these experiments. Its results are shown in Figs. 5(a)-5(b) for the 2D images of the target and the non-target class object of the real car (test samples), respectively. Then we collect the 820 samples for the experiments, i.e., the 360 in-plane rotated samples for two classes with rotation interval of 1° and the 50 out-of-plane rotated samples for two classes with rotation interval of 0.2°. Figures 5(c)-5(d) show the synthetic SVM correlation filter synthesized from in-plane rotated samples and out-of-plane rotated samples, respectively.
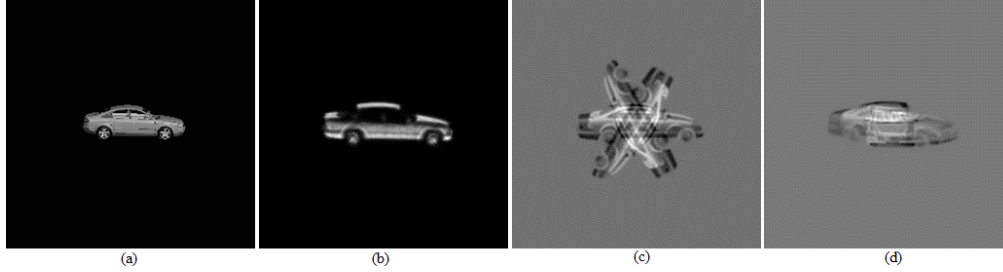

Fig. 5. (a) Collected image of the target objects(256 × 256 pixels), (b) collected image of the non-target objects(256 × 256 pixels), (c) SVM correlation filter synthesized by the in-plane rotated samples of the reconstructed image, and (d) SVM correlation filter synthesized by the out-of-plane rotated samples of the reconstructed image.

In experiments, because the correlation filter is shift invariance, only the in-plane and the out-of-plane rotation distortion are considered. The resistance to rotation and noise distortion of the SVM correlation filter are tested with numerical simulation, and compared with other three filters (i.e., SDF, MACH, and HONN filters).

The ability of four filters is shown in Fig. 6. We find the SVM correlation filter exhibits the best ability to resist the in-plane rotation. Especially the number of training samples is small as shown in Fig. 6(a). The capability of the SDF filter is the second position and can differentiate the two classes with a larger N. However, the correct decision rates of other two filters are quite low. In addition, the SVM filter still has best decision rate when the target is exposed to noise as shown in Fig. 6(b).To test the ability to resist the out-of-plane rotation, several experiments have been conducted. The performance of the four filters to recognize different distortion range was tested first. Using sampling interval of the 20° angles, Fig. 6(c) indicates the experiment results without any noise. The MACH filter shows the best performance, followed by the SVM filter. The HONN and SDF filters are in the third and the fourth place, respectively.

However when the target is exposed in noise, the MACH filter could not retain its advantage any more as shown in Fig. 6(d), because it is highly sensitive to noise and shows the poorest performance. In contrast, the SVM and HONN filters tolerate the noise well. It can be concluded that the SVM filter exhibits best performance to resist the out-of plane rotation in a distortion range that is less than 180°angles. The HONN filter may show best performance in a large distortion range, but one thing should be considered is that the performance of the HONN filter depends on the initial conditions of the training process, it is unstable.

Figures 6(e)-6(f) represent the relations between the filter performance to resist the out-of-plane rotation and training sample numbers when the distortion range is fixed. It can be concluded that the SVM filter performance is better when the number is small because the object information will be interfered. Therefore it is recommended that the training sample number should be relative small. The noise tolerance ability is also tested under this condition, and the conclusion is the same as previous tests.

All aspects above demonstrate the SVM filter is more appropriate for 3D object recognition. The average synthesizing time (second) for each training sample under the same condition is also compared as Table 1. The average synthesizing time of the SVM correlation filter is least.
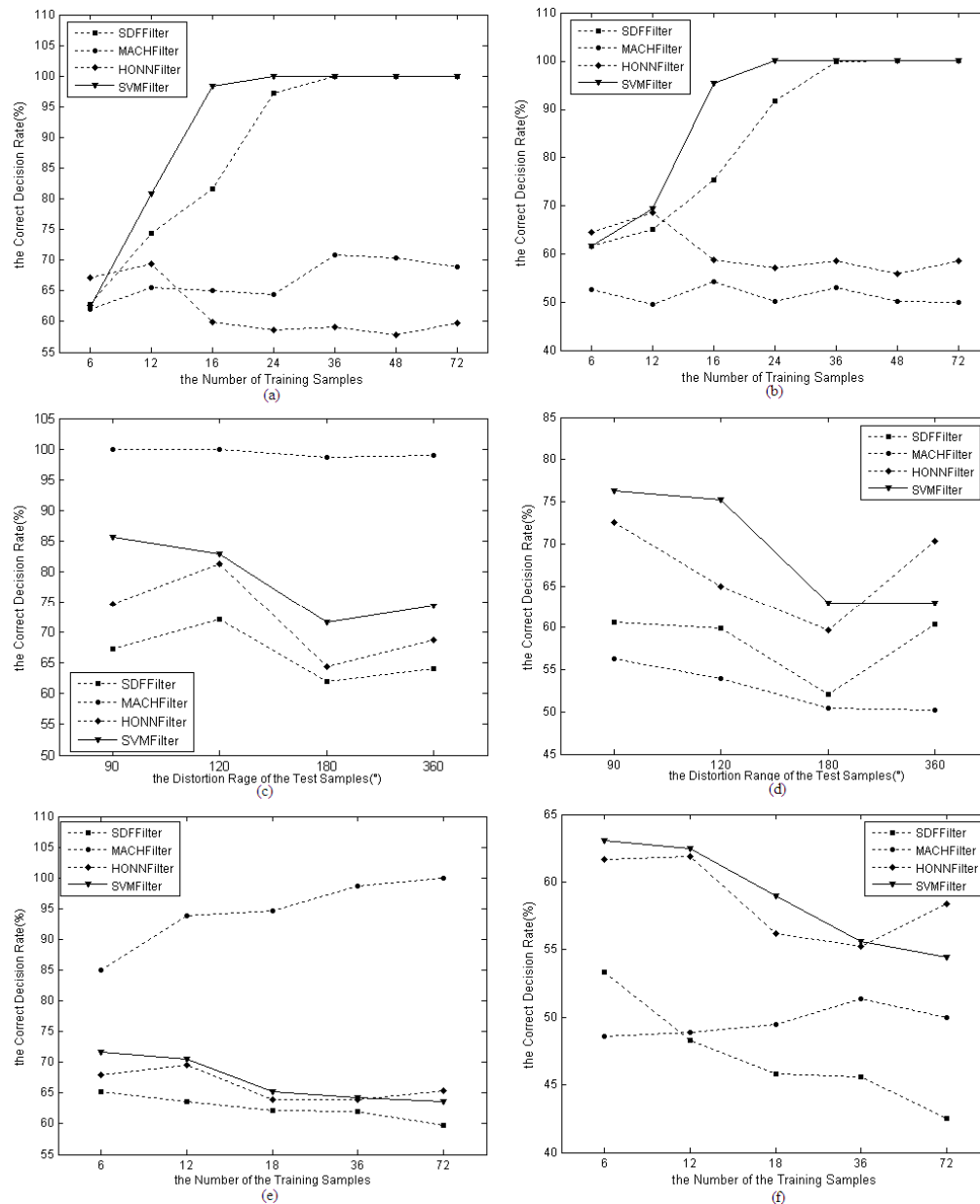

Fig. 6. (a) Comparison of resistance to in-plane rotation of four correlation filters, (b) comparison of resistance to in-plane rotation of four correlation filters under certain noise distortion, (c) comparison of resistance to out-of-plane rotation of four correlation filters, (d) comparison of resistance to out-of-plane rotation of four correlation filters under certain noise distortion, (e) under certain out-of-plane rotation angle and without noise distortion, the correction decision rate obtained with the number of training samples for four correlation filters, and (f) with both certain out-of-plane rotation angle and noise distortion, the correction decision rate obtained with the number of training samples for four correlation filters.

Table 1. Comparison of average synthesizing time (second).

Filter	SDF	MACH	HONN	SVM
Average Training Time	0.0079	0.0258	1.6980	0.0072

6. Conclusion

A 3D object recognition scheme is proposed. The scheme which is recording 3D information by digital holography can effectively reduce the complexity of collecting the samples. The different images of two types of both in-plane rotated object and out-of-plane rotated object recorded by digital holography are simulated, and some of the images are selected to synthesize the SVM correlation filter. The correct decision rate of the SVM correlation filter for target objects is tested. Under the same experimental condition, other three filters are also tested for its performance. The experimental results show that the SVM correlation filter has excellent generalization and fast parallel computation ability, which exhibits the best performance in in-plane rotation resistance and noise tolerance. Though its ability to resist out-of-plane rotation seems a little worse than the MACH filter in noise-free environment, the better noise tolerance performance makes the SVM correlation filter more practical and robust in the 3D object recognition with digital holographic fields.

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