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Adaptive synthetic discriminant function filters for pattern recognition

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Abstract. New adaptive correlation filters based on a conventional synthetic discriminant function (SDF) for reliable recognition of an object in cluttered background are proposed. The information about an object to be recognized, false objects, and a background to be rejected is utilized in an iterative training procedure to design a correlation filter with a given value of discrimination capability. Computer simulation results obtained with the proposed adaptive filter in test scenes are discussed and compared with those of various correlation filters in terms of discrimination capability, tolerance to input additive noise that is always present in image sensors, and to small geometric image distortions. [DOI: 10.1117/1.2205232]

Subject terms: pattern recognition; correlation; adaptive filter; composite correlation filter.

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1 Introduction

Since the introduction of the matched spatial filter[1] (MSF), many different types of filters for pattern recognition based on correlation have been proposed.[2–14] The traditional way to design correlation filters is to make filters that optimize different criteria. Several performance measures for correlation filters have been proposed and summarized.[5] Some of the measures can be essentially improved using an adaptive approach to the filter design. According to this concept, we are interested in a filter with good performance characteristics for a given observed scene, i.e., with a fixed set of patterns or a fixed background to be rejected, rather than in a filter with average performance parameters over an ensemble of images.

One of the most important performance criteria in pattern recognition is the discrimination capability (DC), or how well a filter detects and discriminates different classes of objects. A theoretical analysis of correlation methods was made by Yaroslavsky.[7] He suggested a correlation filter with a minimum probability of anomalous localization errors (false alarms) and called it the optimal filter (OF). An important feature of the OF is its scene-adaptivity in applications to pattern recognition or target detection because its frequency response takes into account the power spectrum of wrong objects in the observed scene or the background to be rejected. The disadvantage of the OF in optical implementation is its extremely low light efficiency. A filter with maximum light efficiency is the phase-only filter (POF) introduced by Homer and Gianino.[2] The drawback of the POF is its poor discrimination capability for a low-contrast target embedded on a complicated background scene.[7] An approximation of the OF by means of POFs with a quantization was made.[8] There, the approximate filters with high light efficiency and discrimination capability close to that of the OF were suggested. When the object to be recognized is in the presence of disjoint background noise, the design of the optimal filter was also obtained.[9] Another fruitful method to synthesis of adaptive filters by zero-masking of correlation filter spectrum components with improved capability to discriminate between similar objects was proposed.[11,12]

An attractive approach to distortion-invariant pattern recognition is based on a synthetic discriminant function (SDF) filter.[3] Basically SDF filters use a set of training images to synthesize a template that yields a prespecified central correlation outputs in the response to training images. The main shortcoming of the SDF filters is appearance of sidelobes owing to the lack of control over the whole correlation plane in the SDF approach. As a result, the SDF filters often possess a low discrimination capability. A partial solution of this problem was suggested by Mahalanobis et al.[4] They proposed to control over the whole correlation plane by producing sharp correlation peaks for easy detection of the target as well as by minimizing the average correlation energy to suppress the presence of extraneous correlation peaks. However, these filters are not tolerant to input noise. They perform control over false alarms in an indirect way, and, finally, they are more sensitive to interclass variations than other composite filters.[13]

In this paper, a new algorithm to design an adaptive SDF filter with a given discrimination capability is proposed. The designed correlation filter is adaptive to the input test scene, which is constructed with the target, false objects, and background to be rejected. The filter is able to suppress sidelobes of the given background as well as false objects. In other words, the suggested filter performs a direct control over the whole correlation plane. The performance of the adaptive filter in test scenes is compared with those of various correlation filters in terms of discrimination capability and robustness to input additive noise.

Section 2, reviews the SDF filters. The design algorithm

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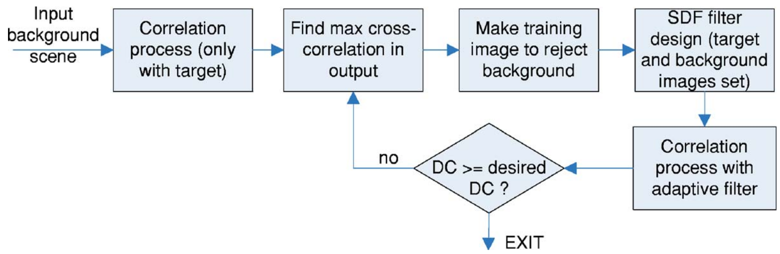


Fig. 1 Block diagram of the iterative algorithm to design the adaptive SDF filter.

of adaptive SDF filters is given in Sec. 3. Computer simulation results are presented and discussed in Sec. 4. Section 5 summarizes our conclusions.

2 Synthetic Discriminant Functions

It is well known that the performance of conventional correlation filters degrades rapidly with image distortions. In this case, a set of training images (patterns) that are sufficiently descriptive and representative of the expected distortions can be used to improve pattern recognition. The designed SDF filter is a linear combination of MSFs for different patterns.[3,6] The coefficients of the linear combination are chosen to satisfy a set of constraints on the filter output requiring a prespecified value for each pattern used in the filter synthesis.

2.1 *Intraclass Recognition Problem*

Let $\{t_i(x,y), i=1,2,\ldots,N\}$ be a set of (linearly independent) training images each with d pixels. The SDF filter function $h(x,y)$ in the space domain can be expressed as a linear combination of the set of the reference images, i.e.,

$$h(x,y) = \sum_{i=1}^{N} a_i t_i(x,y), \tag{1}$$

where $\{a_i,\ i=1,2,\ldots,N\}$ are weighting coefficients, and they are chosen to satisfy the following conditions:

$$t_i \circ h = u_i. \tag{2}$$

Here the symbol $\circ$ represents the correlation, and $\{u_i,\ i=1,2,\ldots,N\}$ are prespecified values in the correlation output at the origin for each training image.

Let $\mathbf{R}$ denote a matrix with N columns and d rows (number of pixels in each training image), where its i'th column is given by the vector version of $t_i(x,y)$. Let $\mathbf{a}$ and $\mathbf{u}$ represent column vectors of $\{a_i\}$ and $\{u_i\}$, respectively. We can rewrite Eqs. (1) and (2) in matrix-vector notation as follows:

$$\mathbf{h} = \mathbf{R}\mathbf{a}, \tag{3}$$

$$\mathbf{u} = \mathbf{R}^{+}\mathbf{h}, \tag{4}$$

where superscript + means conjugate transpose. By substituting Eq. (3) into Eq. (4) we obtain

$$\mathbf{u} = (\mathbf{R}^{+}\mathbf{R})\mathbf{a}. \tag{5}$$

The (i,j)'th element of the matrix $\mathbf{S}=\mathbf{R}^{+}\mathbf{R}$ is the value at the origin of cross-correlation between the training images $t_i(x,y)$ and $t_j(x,y)$. If the matrix $\mathbf{S}$ is nonsingular, the solution of the equation system is given by

$$\mathbf{a} = (\mathbf{R}^{+}\mathbf{R})^{-1}\mathbf{u}, \tag{6}$$

and the filter vector is

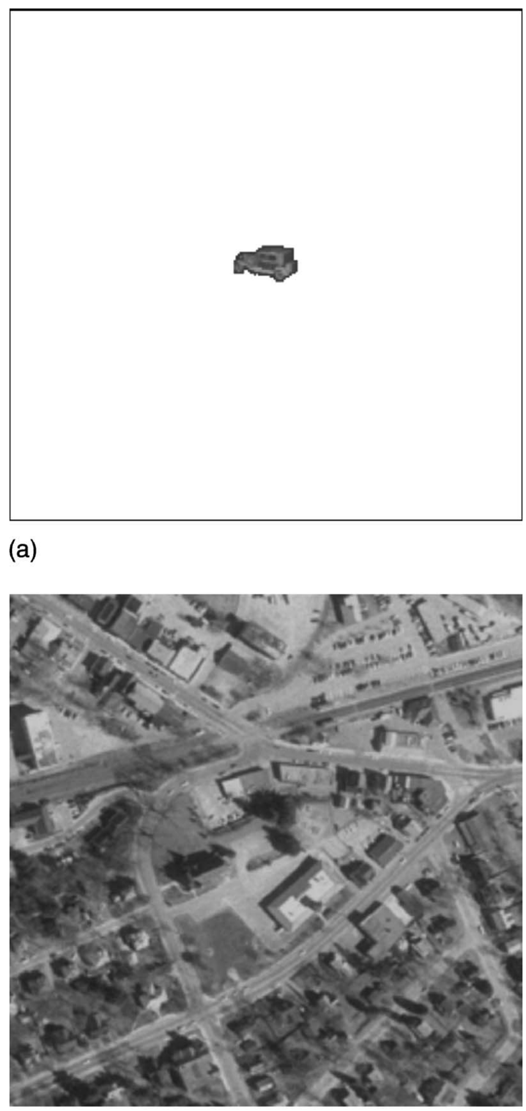


Fig. 2 (a) Target and (b) real background used in experiments.

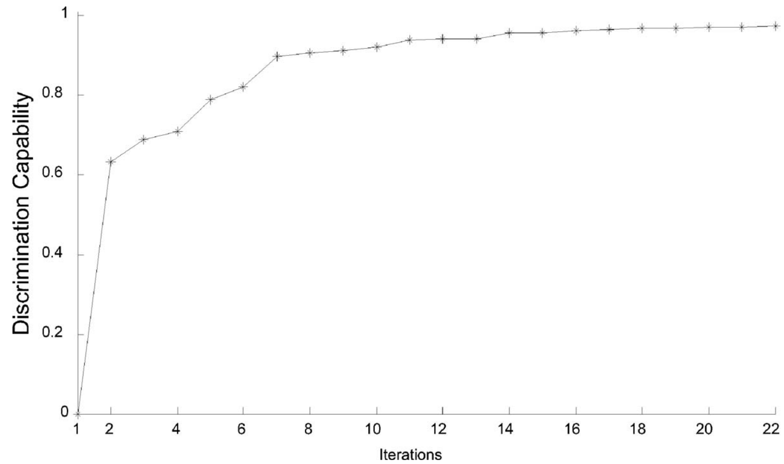


Fig. 3 Performance of the adaptive SDF filter in the filter design process with real background.

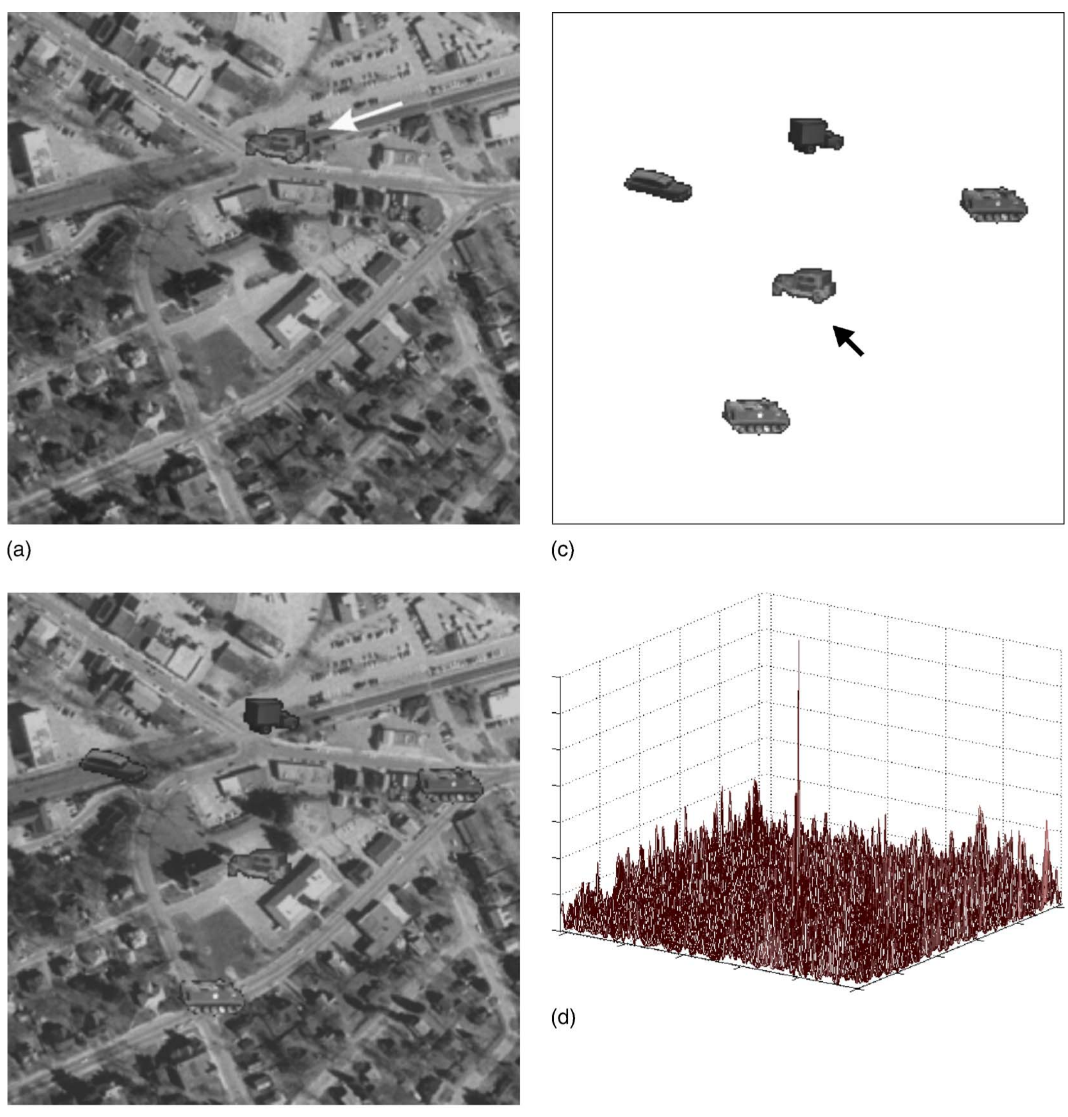
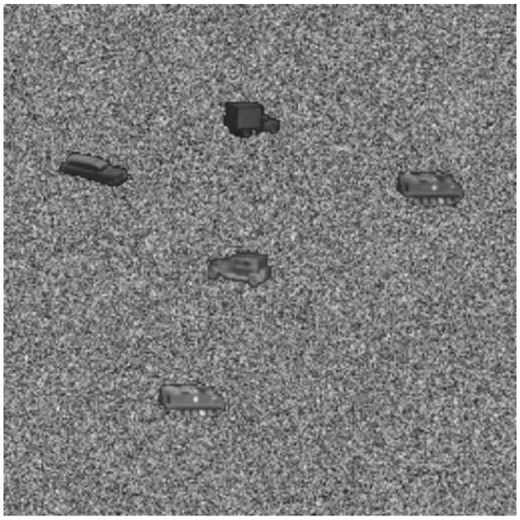
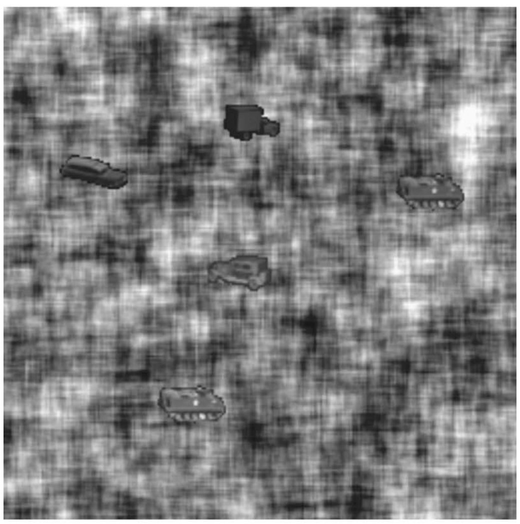


Fig. 4 Pattern recognition in test scenes with real background: (a) test scene containing only the target marked by the arrow; (b) test scene containing the target and four nontargets; (c) positions of the target and nontargets in the scene, the target is marked by the arrow; (d) correlation intensity distribution for the test scene (b) obtained with the A-SDF filter.



(a)



(b)

Fig. 5 Pattern recognition in test scenes with stochastic background: (a) test scene containing the target and four nontargets embedded into white noise background with a standard deviation of 40 and a mean value of 128; (b) test scene contains the target and four nontargets embedded into colored noise background with a standard deviation of 40, a mean value of 128, and a correlation coefficient of 0.9. The positions of the target and nontargets are similar to those of in Fig. 4(c).

$$\mathbf{h} = \mathbf{R}(\mathbf{R}^{+}\mathbf{R})^{-1}\mathbf{u}. \tag{7}$$

The SDF filter with equal output correlation peaks can be used for intraclass distortion-invariant pattern recognition, i.e., detection of distorted patterns belonging to the true class of objects. This can be done by setting all elements of $\mathbf{u}$ to unity, i.e.,

$$\mathbf{u} = [11 \ldots 1]^{\mathrm{T}}. \tag{8}$$

2.2 *Multiclass Recognition Problem*

Assume that there are distorted versions of the reference and various classes of objects to be rejected. For simplicity, we consider two-class recognition problem. Thus, we design a filter to recognize training images from one class (called the true class) and to reject training images from another class (called the false class).

Suppose that there are M training images from the false class $\{p_i(x,y), i=1,2,\ldots,M\}$. According to the SDF approach, the composite image $h(x,y)$ is a linear combination of all training images $\{t_1(x,y),\ldots,t_N(x,y), p_l(x,y),\ldots,p_M(x,y)\}$. Both intraclass recognition and interclass discrimination (i.e., discrimination of the true class objects against the class objects) problems can be solved by means of SDF filters. We can set the filter output $\{u_i=1, i=1,2,\ldots,N\}$ for the true class objects and $\{u_i=0, i=N+1, N+2,\ldots,N+M\}$ for the false class objects, i.e.,

$$\mathbf{u} = [11 \ldots 100 \ldots 0]^{T}. \tag{9}$$

Using the filter given in Eq. (7) for pattern recognition, we expect that the central correlation peak will be close to unity for the true class objects and it will be close to zero for the false class objects. Obviously, the preceding approach can be easily extended to any number of classes to be discriminated. Note that this simple procedure is the lack of control over the full correlation output because we are able to control only the correlation output at the location of cross-correlation peaks. Thus, other sidelobes (false peaks) may appear everywhere on the correlation plane.

3 Design of the Adaptive SDF Filter

Now we state the pattern recognition problem to be solved. We wish to design a correlation filter that ensures a high correlation peak corresponding to the target while suppressing possible false peaks. In other words, to achieve good recognition of the target it is necessary to reduce correlation function levels at all false peaks except at the origin of the correlation plane, where the constraint on the peak value must be met. For a given object to be recognized, false objects, and a background to be rejected, it can be done with the help of an iterative algorithm. At each iteration, the algorithm suppresses the highest sidelobe peak and therefore monotonically increases the value of discrimination capability until a prespecified value will be reached. The discrimination capability is formally defined[7] as ability of a filter to distinguish a target among other different objects. If a target is embedded into a background that contains false objects, then the DC can be expressed as follows:

$$\mathrm{DC} = 1 - \frac{|C^{B}(0,0)|^2}{|C^{T}(0,0)|^2}, \tag{10}$$

where C^B is the maximum in the correlation plane over the background area to be rejected, and C^T is the maximum in the correlation plane over the area of target position. The area of target position is determined in the close vicinity of the actual target location. The background area is complementary to the area of target position. The further accurate estimation of the target location with correlation filters can be carried out.[10] In our computer simulations, the area of target position is chosen as a circle with the origin at the actual target location and with the area of about 8% of the target area. Negative values of the DC indicate that a tested filter fails to recognize the target.

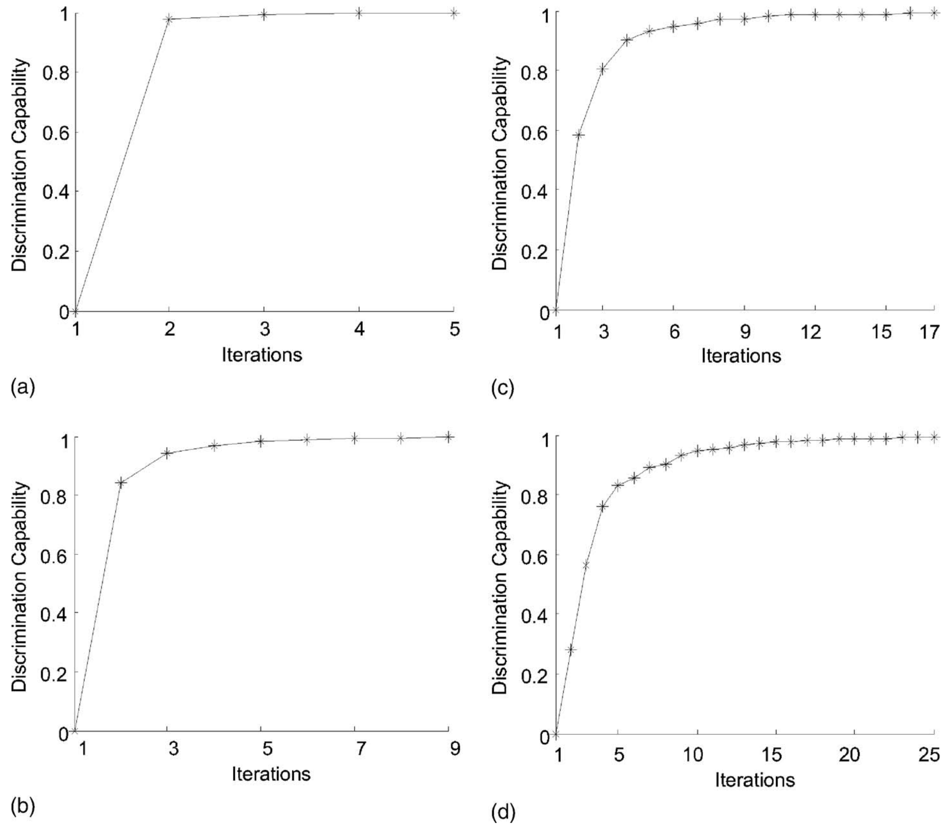


Fig. 6 Performance of the adaptive SDF filter in the filter design process when the nonoverlapping background is white noise with different standard deviations of (a) $\sigma=10$, (b) $\sigma=20$, (c) $\sigma=30$, and (d) $\sigma=40$.

We are interested in a correlation filter that identifies the target with a high discrimination capability in cluttered and noisy input scenes. Actually in this case, conventional correlation filters may yield a poor performance. With the help of adaptive SDF filters, a given value of the DC can be achieved. The algorithm of the filter design requires knowledge of the background image. Thus, we are looking for the target with unknown location in the known input scene background. The background can be described either stochastically, for instance, it can be considered as a realization of a stochastic process, or deterministically, which can be a picture. The background can also contain false objects with unknown locations. The first step is to carry out correlation between the background (deterministic picture or realization of stochastic process) and a basic SDF filter, which is initially trained only with the target. Next, the maximum of the filter output is set as the origin, and around the origin we form a new object to be rejected from the background. This object has the region of support equals to that of the target. The created object is added to the false class of objects. Now, the two-class recognition problem described in Sec. 2 is utilized to design a new SDF filter; that is, the true class contains only the target and the false class consists of the false class objects. The described iterative procedure is repeated till a given value of the DC is obtained. Finally, note that if other objects to be rejected are known, they can be directly included into the false class and used for the design of adaptive SDF filter (A-SDF). A block-diagram of the procedure is shown in Fig. 1. Thus, the proposed algorithm consists of the following steps:

1. Design a basic A-SDF filter as a conventional SDF filter trained only with the target.
2. Carry out correlation between the background and the A-SDF filter.
3. Calculate the DC using Eq. (10).
4. If the value of the DC is greater or equal to the desired value, then the filter design procedure is finished, else go to the next step.
5. Create a new object to be rejected from the background. The origin of the object is at the highest sidelobe position in the correlation plane. The object is included into the false class of objects.
6. Design a new A-SDF filter utilizing the two-class recognition problem described in Sec. 2. The true class contains only the target and the false class consists of the false class objects. Go to step 2.

At each iteration the algorithm chooses among all sidelobes such a peak to be suppressed in next step to ensure a monotonically increasing behavior of the DC function versus the iteration index during the filter design. As a result of the procedure, the adaptive composite filter is synthesized. The performance of the filter in the recognition process is expected to be close to that of in the synthesis process. Extensive computer simulations showed that for compli-

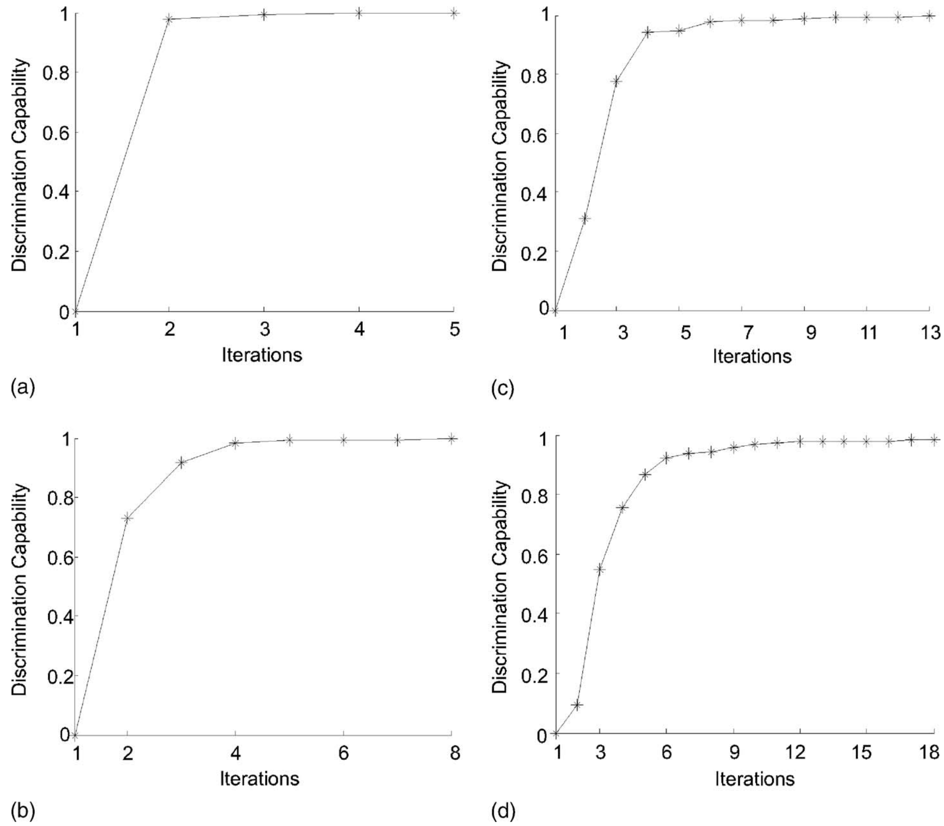


Fig. 7 Performance of the adaptive SDF filter in the filter design process when the nonoverlapping background is colored noise with the correlation coefficient of 0.9 and different standard deviations of (a) σ=10, (b) σ=20, (c) σ=30, and (d) σ=40.

cated input scenes with real and stochastic cluttered backgrounds the number of iterations needed to achieve the value of DC higher than 0.9 is about 10. Note that other iterative optimization algorithms frequently used for composite filter design such as simulated annealing and genetic algorithms require significantly higher computational complexity.[13]

4 Computer Simulations

In this section, computer simulation results obtained with adaptive SDF filters are presented. The results are compared with those of the MSF, the SDF, the POF, and the OF filters. The target is the car shown in Fig. 2(a). The size of all images used in our experiments is 256×256 pixels. The signal range is 0 to 255. The mean value and the standard deviation over the target area are 91 and 27, respectively. The size of the target is about 32×18 pixels. In the first experiment, we use a real spatially inhomogeneous background, as shown in Fig. 2(b). The mean value and the standard deviation of the background are 116 and 40, respectively.

Figure 3 shows the performance of the adaptive filter in the filter design process in terms of the DC versus the iteration index. After the first iteration the value of the DC is negative (DC=−0.24). Since negative values of the DC mean that a filter fails to recognize the target, in all plots negative values are substituted by zeros. After 22 iterations, the obtained A-SDF filter yields DC=0.975. This means that a high level of control over the correlation plane for an input scene constructed from the background and the target can be achieved. Next, we test the recognition performance with the adaptive filter when the target is placed into the background at arbitrary coordinates. The input scene is shown in Fig. 4(a). We compare the performance of the A-SDF with those of the POF and the OF. The transfer function of the conventional POF is given by[2]

$$H_{\mathrm{POF}}(u,v)=\frac{T^*(u,v)}{|T(u,v)|}=\begin{cases}\exp\left(-i\Phi_t(u,v)\right) & \text{if } |T(u,v)|\neq 0\\ 0 & \text{otherwise}\end{cases}, \tag{11}$$

where $T(u,v)$ and $\Phi_t(u,v)$ are the Fourier transform and the phase distribution of the target. The asterisk denotes

Table 1 Performance of correlation filters in terms of DC for input scenes in Fig. 4.

Scene	MSF	POF	OF	A-SDF
a	−0.24	−0.63	0.83	0.98
b	−0.53	−0.39	0.54	0.94

Table 2 Performance of correlation filters in terms of DC for input scenes in Fig. 5.

Scene	MSF	POF	OF	A-SDF
a	−0.12	−0.18	0.3	0.91
b	−0.92	−0.87	0.35	0.93

complex conjugate. The transfer function the OF can be approximated in the Fourier domain as[7]

$$H_{\mathrm{OF}}(u,v)=\frac{T^{*}(u,v)}{|T(u,v)|^{2}+|B(u,v)|^{2}}, \tag{12}$$

where $B(u,v)$ is the Fourier transform of the input scene. The remarkable feature of the approximated OF is its scene-adaptivity because its frequency response takes into account an estimation of the power spectrum of the background to be rejected. The performance of the MSF, the POF, and the OF in terms of the DC is given in line 1 of Table 1. The proposed filter referred to as A-SDF gives the best performance. We used statistical trials of our experiment for different positions of the target. With 95% confidence the DC is equal to 0.9752 ± 0.0003. Note that the MSF and the POF fail to recognize the target.

Next, we place four false targets into the background, as shown in Fig. 4(b). Figure 4(c) shows locations of the target and false objects in the input scene. The performance of correlation filters in terms of the DC is given in line 2 of Table 1. In this case, the proposed adaptive filter also yields the best performance in terms of the DC. To guarantee statistically correct results, 30 statistical trials of the experiment for different positions of the target and nontargets were performed, and with 95% confidence, the DC is equal to 0.9434 ± 0.0072. Figure 4(d) demonstrates the intensity distribution obtained with the A-SDF filter for the last test scene. The MSF and the POF are not able to recognize the target.

Next we analyze the performance of correlation filters for a nonoverlapping target and spatially homogeneous background noise. Two models of background noise with the Gaussian distribution are considered; that is, white and colored realizations of stationary processes. The mean value is always $\mu_B=128$ and the standard deviations are $\sigma=10$, 20, 30, and 40. For colored noise, the correlation coefficient is taken $\rho=0.9$. Examples of test scenes with the standard deviation of background noise of 40 are shown in

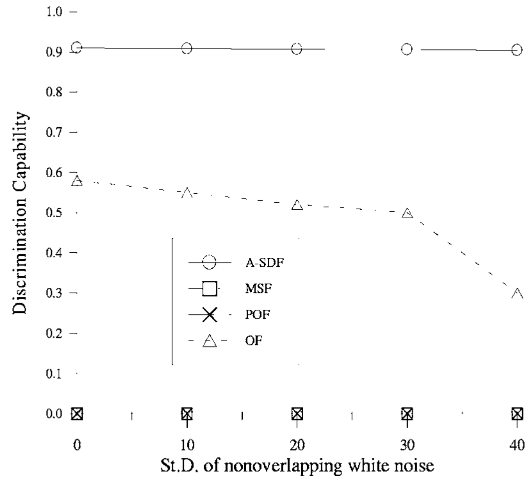


Fig. 8 Performance of correlation filters with the input scene shown in Fig. 5(a) in terms of the DC versus the standard deviation of white background noise.

Fig. 5. Computer simulations were conducted in a similar manner that those with real background. First we tested correlation filters with the target arbitrarily embedded into the input scene. Next we additionally insert four nontargets into the scene [see Fig. 5]. Figures 6 and 7 show the performance of the adaptive filter in the filter design process in terms of the DC versus the iteration index for a set of standard deviation values. The both white and colored background noise models are considered. One can observe that the performance of the adaptive filter for these two models is similar. Moreover, a specified high value of the DC in both cases can be achieved in a few iterations. It has been shown[9,10] that for disjoint (nonoverlapping) model of an object to be detected and background noise a new target signal must be formed as the sum of the object signal and the weighted inverse support function of the object; that is, in the Fourier domain the spectrum of the new target is given by $\hat{T}(u,v)=T(u,v)+\mu_B W(u,v)$. Here μ_B is the mean value of the background, $W(u,v)$ is the Fourier transform of the inverse support function defined as zero within the target area and unity elsewhere.[10] The transfer function the OF in Eq. (12) utilizes the spectrum of the new target. The performance of various correlation filters with respect to the DC for the test scene in Fig. 5(a) versus the standard deviation of white background noise is shown in Fig. 8. Clearly that the proposed algorithm is able to adapt well the designing filter to background noise variations, whereas the

Table 3 Performance of correlation filters in terms of DC for the input scene in Fig. 4(a) for recognition of rotated object.

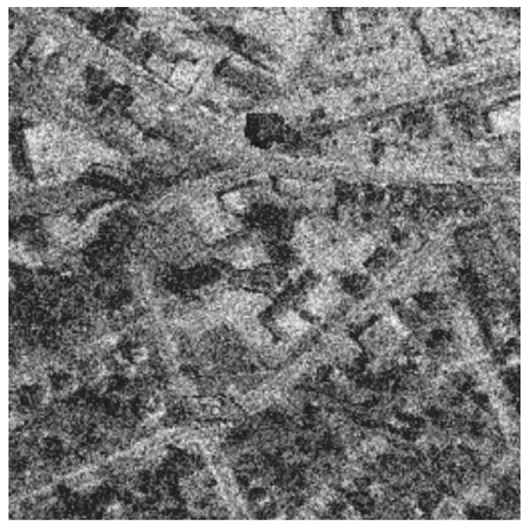
	Degrees of Rotation													
	0	1	2	3	4	5	6	7	8	9	10	11	12	13
OF	0.83	0.68	0.32	0.26	0	0	0	0	0	0	0	0	0	0
A-SDF	0.95	0.94	0.93	0.91	0.9	0.91	0.93	0.94	0.95	0.94	0.91	0.88	0.83	0.81

Table 4 Performance of correlation filters in terms of DC for the input scene in Fig. 4(a) for recognition of scaled object.

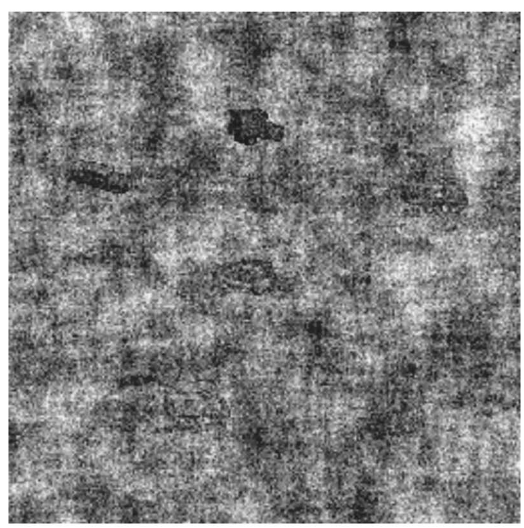
	Scale factors										
	0.8	0.84	0.88	0.92	0.96	1.0	1.04	1.08	1.12	1.16	1.2
OF	0	0	0	0	0.08	0.83	0.1	0	0	0	0
A-SDF	0.92	0.87	0.89	0.89	0.88	0.92	0.88	0.89	0.9	0.89	0.93

performance of the OF is worsened rapidly when the standard deviation of background noise increases. The performance of the filters with nonoverlapping colored background noise is similar. Numerical results of the performance of correlation filters for the scenes in Fig. 5 (the standard deviation of white and colored background noise is 40) are provided in Table 2. We carried out 60 statistical trials of the experiment for different positions of the target, nontargets, and different realizations of background noise. With 95% confidence, the DC values for the scenes in Figs. 5(a) and 5(b) are equal to 0.914 ± 0.0062 and 0.932 ± 0.0058, respectively. We can see that the proposed filter yields the best performance in terms of the DC. The performance of the OF is poor because four nontargets incorporated into nonoverlapping background. This leads to a spatially inhomogeneous model of the background. Thus, the filter becomes ineffective. The MSF and the POF in all experiments fail to detect the target.

Now we investigate tolerance of the correlation filters to small geometric image distortions. Several methods have been proposed to improve pattern recognition in the presence of such distortions. These methods can be broadly classified into two groups. The first class concerns formally with 2-D scaling and rotation distortions. Such methods include space-variant transforms and circular harmonic functions. The second class of filters uses training images that are sufficiently descriptive and representative of the expected distortions. The proposed method is based on the second approach. In our experiments, the input scene shown in Fig. 4(a) with an imbedded geometrically distorted object is used. We compare the performance of the A-SDF with those of the OF and the conventional SDF. Sixty statistical trials for each experiment for different positions of a distorted target are carried out. In tables negative values of the DC are substituted by zeros. First, geometric distortion by means of rotation is investigated. The step and the range of object rotation are 1 deg and [0,13], respectively. The conventional SDF is designed with versions of the object rotated by 0, 2, 4, 6, 8, 10, and 12 deg. The A-SDF is trained with two versions of the object rotated by 0 and 8 deg. After 22 iterations, the obtained A-SDF filter yields DC=0.97. Note that the conventional SDF always fails to detect the rotated target in the cluttered background. The performance of the OF and the A-SDF in terms of the DC is given in Table 3. We can see that the performance of the OF degrades rapidly with increasing of the object distortion. The proposed filter adapts well by training to small rotations of the target. Next, tolerance of the filters to scale distortions of the target is investigated. The step and the range of the scale factor are 0.04 and [0.8,1.2], respectively. The conventional SDF is designed with all scaled versions of the object. The A-SDF is trained only with five versions of the object scaled by factors of



(a)



(b)

Fig. 9 Test scenes corrupted by zero-mean additive white noise with σ=40: (a) noisy test scene shown in Fig. 4(b) and (b) noisy test scene shown in Fig. 5(b).

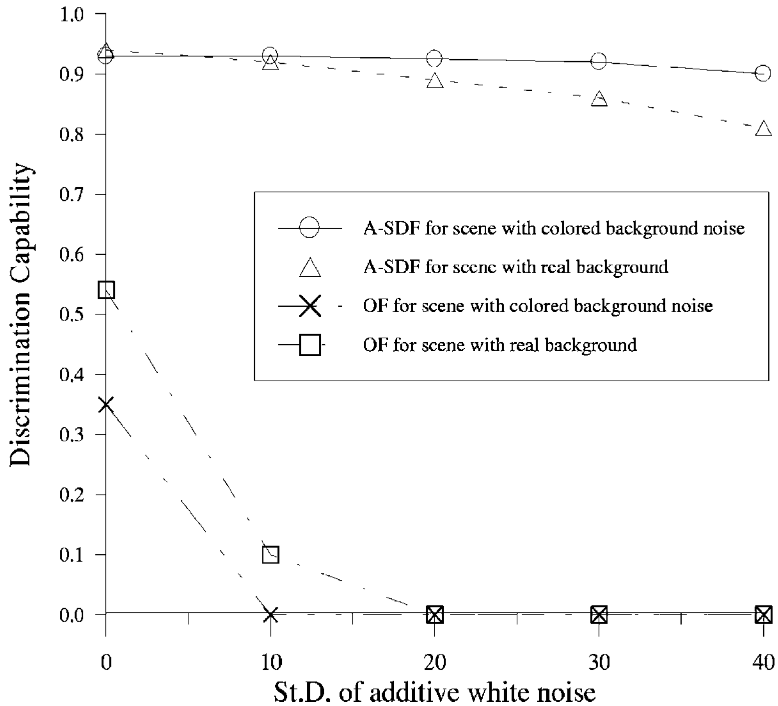


Fig. 10 Tolerance of the OF and the A-SDF to additive white noise. The performance of the filters with the noisy test scenes shown in Fig. 9 in terms of the DC versus the standard deviation (St.D.) of additive white noise.

0.8, 0.9, 1, 1.1, and 1.2. After 120 iterations the obtained A-SDF filter yields DC=0.96. The conventional SDF fails to recognize the scaled target. The performance of the OF and the A-SDF is given in Table 4. One can observe that the OF is very sensitive to scale distortions. The A-SDF always detects the scaled object. Note that in this case, the filter design is much more computationally intensive compared with that of rotation distortion. In a similar manner, the proposed method can be used to design an adaptive filter that can possess a good tolerance to arbitrary geometric distortions. The complexity of the composite filter design depends on the size of training set of used distorted images.

Finally we tested the robustness of correlation filters to additive sensor's noise that is always present in input scenes. Figures 9(a) and 9(b) show, respectively, the scenes in Figs. 4(b) and 5(b) corrupted by additive zero-mean white Gaussian noise with the standard deviation of 40. In a similar way, experiments of pattern recognition with the OF and the A-SDF were conducted while the standard deviation of additive noise was varied. Figure 10 presents the tolerance of the filters to additive noise for the test scenes shown in Fig. 9. Since the synthesis of A-SDF filters takes into account additive noise by training with a noise realization then the filters provide a good robustness to the noise. In contrast, the performance of the OF deteriorates quickly when signal noise fluctuation increases.

5 Conclusion

New adaptive SDF filters were proposed to improve recognition of a target embedded into a known cluttered background. It was shown that the proposed iterative filter design algorithm with a few training iterations helps us to take the control over the whole correlation plane. The computer simulation results demonstrated superiority in the performance of the proposed filters for pattern recognition comparing with that of the MSF, the POF, and the OF. The suggested filters possess high scene-adaptivity and good robustness to additive input noise and to small geometric image distortions. Finally, note that the proposed iterative filter design algorithm can be used to improve the pattern recognition performance of any correlation filter by adapting the filter to a given input scene.

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