Recognition of Multiple Objects with Adaptive Correlation Filters

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Abstract. A new method for reliable optical pattern recognition of multiple objects in a cluttered background and consequent classification of the detected objects is proposed. The method is based on an adaptive composite correlation filter. The filter is designed with the help of an iterative algorithm exploiting a modified version of synthetic discriminant function filter. The impulse response of the filter contains information needed to localize and classify objects belonging different classes. Computer simulation results obtained with the proposed method are compared with those of known correlation based techniques in terms of performance criteria for recognition and classification of objects.

1 Introduction

A number of techniques and algorithms based on different criteria have been proposed to solve effectively one of the two different recognition tasks: detection of targets and classification of given objects. However, in real applications often these two problems cannot be separately considered. For instance, several objects and their geometrically distorted versions are embedded into a cluttered noisy background. Basically, heuristic digital systems based neural networks and evolutionary algorithms use two-step processing: segmentation and classification. Such the systems are not able correctly to detect and perform segmentation of distorted objects, which are embedded in cluttered noisy scenes. Correlation-based methods possess a good mathematical basis to detect and localize (estimation of the target position) objects. Many correlation filters optimized with respect to different detection criteria have been proposed [1]. Note that detection and classification of multiple objects are computation-intensive processing tasks. Correlation filters can be implemented optically or by the use of hybrid (optodigital) systems at a high rate [2]. Optical correlators are inherently shift invariant, producing correlation peaks that indicate both presence and location of input objects. In order to detect and classify objects with the use of correlation operation the following methods are proposed: (i) time-sequenced filtering [3], in which multiple filters (one for each version of the input object) are sequenced rapidly in and out of the filter plane, yielding a sequence of output correlation re-

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sponses; (ii) space multiplexed [4] or spatial frequency multiplexed [5] filtering, in which all filters are presented simultaneously in the filter plane, yielding an array of multiple correlation responses; (iii) combination filtering, in which several filters are combined to form a composite filter that yields a detectable output correlation response for any set of input objects [6]. The last method may be utilized to construct a bank of composite filters that can be used as time-sequenced or multiplexed filters. Note that time-sequenced and space-multiplexed filtering requires a large number of correlations, because a single filter for each object and each its distorted version is used. To reduce the number of filters Braunecker et al. [7] proposed to carry out only $\log_2(N)$ correlations by forming primitive composite filters from similar patterns, where N is the number of patterns to be recognized,. A drawback of this method is that it works only with binary images. Billert and Singher [8] suggested to reduce the number of correlations by employing different composite filters, each of them is able to recognize a set of training images. The filters possess a good tolerance to additive noise at the input scene. Nevertheless, the filters work well only with binary-segmented 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. Yaroslavsky [9] suggested a correlation filter with a minimum probability of anomalous errors (false alarms) and called it the optimal filter (OF). 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) [10]. The POF produces sharp correlation peaks but possesses a poor performance in terms of the DC for noisy and cluttered scenes. An attractive approach to distortion-invariant pattern recognition is based on synthetic discriminant functions (SDF) filters [11]. A conventional SDF filter is composed by a linear combination of training images. It is able to control only one point at the correlation plane for each training image. As a result, the SDF filters often have a low discrimination capability. Mahalanobis, et al, [12] suggested the minimum average correlation energy (MACE) filter. The MACE filter produces sharp correlation peaks by minimizing the average of correlation energy in the correlation plane. However, the MACE filter is not tolerant to input noise, and it is more sensitive to interclass variations than other composite filters. The main efforts in correlation filter research are focused to the problem of recognition and localization of objects, and commonly ignoring the problem of classification. This paper is devoted to the design of new correlation filters for solving the following two problems: reliable recognition and correct classification of all desired objects, which are embedded into a cluttered noisy background. These problems may be solved with the help of adaptive correlation filters [13], [14]. In order to obtain the impulse response of an adaptive filter an iterative algorithm is used. At each iteration, the algorithm suppresses the highest sidelobe at the correlation plane. Therefore, it increases monotonically the DC until a prespecified value is reached. The object classification is carried out using the phase information at the origin of the correlation peak for each target. The proposed method requires only one correlation to detect and classify all needed objects. This paper is organized as follows. Section 2 presents a basic description of pattern recognition based on conventional SDF filters, as well as a modified SDF approach proposed for object classification. The proposed algorithm of the adaptive filter design is given in Section 3. Computer simulation results obtained with the proposed filter are presented and discussed in Section 4. Finally, Section 5 summarizes our conclusions.

2 Pattern Recognition and Classification with SDF Filters

Assume that we have a set of objects (including distorted versions) to be recognized. For simplicity, we consider a two-class recognition problem. Let us define the true class as different versions of an object to be recognized. The false class consists of all non-desired objects to be rejected including a cluttered background. The impulse response of a SDF filter is as a linear combination of training images. Let $\{s_i(x, y) \mid i = 1, \ldots, N\}$ be a set of linearly independent training images each with M pixels. The SDF filter in a matrix-vector notation can be expressed as follows:

$$\mathbf{h} = \mathbf{S}\,\mathbf{a}, \tag{1}$$

where **S** is a matrix with N columns and M rows, and its ith-column is given by the vector version of $s_i(x,y)$, **a** represents a column vector of the weighting coefficients $\{a_i \mid i = 1, \ldots, N\}$. The vector **a** must be determined in order to satisfy the following constraints:

$$\mathbf{c} = \mathbf{S}^{+}\mathbf{h}. \tag{2}$$

Here, the superscript ”+” means conjugate transpose. Substituting Eq. (1) into Eq. (2), and if the matrix $\mathbf{R} = (\mathbf{S}^{+}\mathbf{S})$ is non-singular, the vector solution of the equation system is given by

$$\mathbf{a} = (\mathbf{S}^{+}\,\mathbf{S})^{-1}\,\mathbf{c}, \tag{3}$$

and finally, the filter vector is

$$\mathbf{h} = \mathbf{S}\left(\mathbf{S}^{+}\mathbf{S}\right)^{-1}\mathbf{c}\,. \tag{4}$$

To recognize distorted versions of the desired class and to reject all objects of the false-class, we set up the elements of **c** corresponding to the desired and non-desired objects to unity and zero, respectively,

$$\mathbf{c} = [1, 1, \ldots, 1, 0, 0, \ldots, 0]^{T}. \tag{5}$$

This approach can be easily extended to any number of classes.

2.1 Pattern Classification with a Modified SDF Filter

In order to design a SDF filter for multiclass pattern recognition, we can set up for each class different real values in the vector **c**. These values must be within the range of [0, 1]. However, the use of values less than unity in the vector **c** for different true-classes affects severely the discrimination capability. In other words, the correlation peaks of objects belonging to a true-class will be lower than the maximum value. This means that false alarms become very likely. We propose to set the filter output as complex values in a unitary circle as follows:

$$\mathbf{c} = \{\exp(i\,\beta_j) \mid j = 1,\ldots, K;\ \beta_j \in \mathbb{R}\}, \tag{6}$$

where K is the number of true-classes. In this way, we can obtain the maximum intensity correlation peak for each target-object. Note that information about the classes is contained in the phase distribution of the complex correlation plane at the coordinates of the maximum intensities. Using such a filter for multiclass pattern recognition, we expect that the correlation peak intensities of targets will be close to unity for all true-classes, whereas the cross-correlation peak intensities of non-desired objects will be close to zero, i.e.,

$$c = [\exp(i\,\beta_1),\ \ldots,\ \exp(i\,\beta_K),\ 0,\ldots,\ 0]^{\mathrm{T}}. \tag{7}$$

3 Design of Adaptive Correlation Filters for Pattern Recognition and Classification

Commonly, correlation filters are designed to be optimum with respect different performance criteria. The discrimination capability is one of the most important metrics. It is defined as the ability to a filter to distinguish a target among other different objects. The DC can be expressed as follows:

$$DC = 1 - \frac{\left|C^B(0,0)\right|^2}{\left|C^T(0,0)\right|^2}, \tag{8}$$

where $|C^B|^2$ is the maximum intensity in the correlation plane over the area of a background to be rejected, and $|C^T|^2$ is the maximum intensity in the correlation plane over the target position. The area of target position is determined in the close vicinity of the actual target location. The area of background is complementary to the area of the target position. The impulse response of an adaptive correlation filter can be obtained with the help of an iterative algorithm shown in Fig. 1. The proposed algorithm is given as follows.

1. Assign all targets (including distorted versions) belonging to various true-classes to different regions in a unitary circle according to Eq. (6).
2. Create a SDF filter trained only with targets (including distorted versions) using Eqs. (4) and (7).
3. Carry out independently correlations between the adaptive SDF filter and all objects including the background.
4. Calculate DC using Eq. (8).
5. If DC is greater or equal to the desired value, the procedure is finished, else go to the next step.

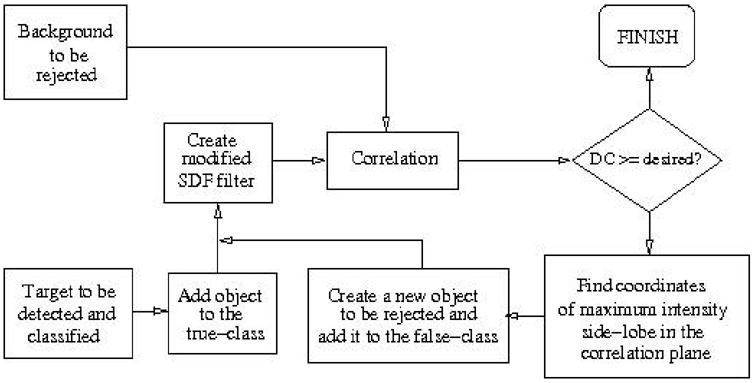


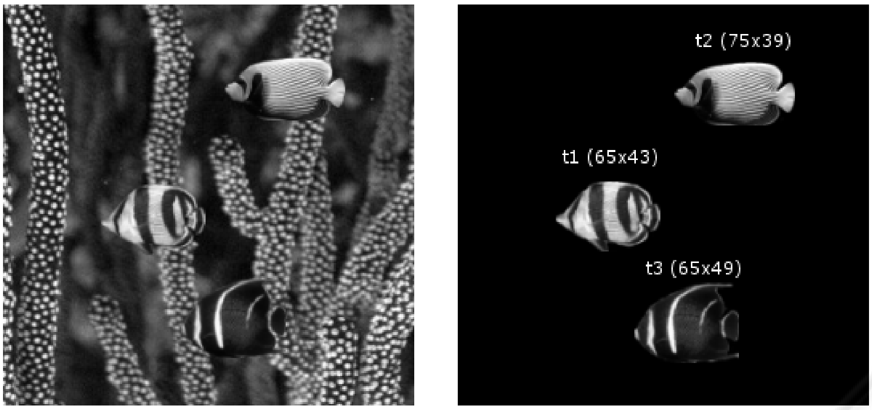
Fig. 1. Block-diagram of the iterative algorithm for the filter design.

6. Create a new object to be rejected. The origin of the object is taken at the coordinates of maximum intensity in the correlation plane. The region of support of the new object is the union of shapes of all targets. This new object is included into the false-class.
7. Create a new adaptive SDF filter utilizing the multiclass recognition problem. The true-classes contain all targets and the false-class consists of objects to be rejected. Go to step 2.

4 Computer Simulations

In this section, results obtained with the adaptive SDF filter are presented. Fig. 2 shows an input scene containing three different fish-targets (t1, t2, t3). Four geometrically distorted versions for each target were used. We utilized two versions rotated with -5 and 5 degrees, and two versions scaled by factors of 0.9 and 1.1. All images used in simulations are monochrome with a signal range of [0, 255]. The size of the images is 256x256 pixels. The targets are located at unknown coordinates in an inhomogeneous background. The goal of our simulation is to design an adaptive SDF filter that is able to recognize the target (and its geometrically distorted versions) and correctly classifies them.

We compare the performance of the proposed filter in terms discrimination capability and classification efficiency with a modified time-sequenced method [3] employing banks of the following filters: the matched spatial filter (MSF) [15], the POF, the OF, and the SDF. The postprocessing algorithm for classification of all objects can be illustrated with three objects as follows: (i) design a correlation filter F1 to detect t1 and to reject t2 and t3; (ii) design a filter F2 to detect t2 and to reject t1 and t3; (iii) design a filter to detect t3 and to reject t1 and t2; (iv) carry out the correlation between the input scene and F1, F2, and F3 obtaining the correlation planes C1, C2, and C3, respectively; (v) localize the maximum intensity values in each correlation plane



(a) (b)

Fig. 2. (a) Test input scene, and (b) three targets.

obtaining MAX_{C1}, MAX_{C2}, and MAX_{C3}; (vi) if $MAX_{C2} < MAX_{C1} > MAX_{C3}$, then the input object is t1, if $MAX_{C1} < MAX_{C2} > MAX_{C3}$, then input objects is t2, finally, if $MAX_{C1} < MAX_{C3} > MAX_{C2}$, then input object is t3. Note that this technique requires the number of correlations equal to the number of patterns. In our simulation the procedure of detection and classification based on the *MSF*, the *POF*, and the *OF* requires 5 correlations for each target, whereas the method using the SDF filters requires one correlation per a target.

We start of the design of the adaptive filter (AF) with assignment centers of classification regions in a unitary circle for t1, t2, and t3 (including distorted versions) as 0, 60, and 120 degrees respectively. Next, the proposed iterative algorithm is used. The performance of the filter during the design process versus the iteration index is shown in Fig. 3. The DC value of 0.9 was reached after 15 iterations. The correlation plane obtained with the adaptive filter for the test scene is shown in Fig. 4. We can see three sharp correlation peaks at locations of the targets. The phase information of the correlation peaks correctly indicates classes of corresponding objects. The computer simulation results are given in Table 1.

Table 1. Performance of correlation filters in terms of DC, number of correctly detected classes, and complexity.

	MSF	POF	OF	SDF	AF
DC	-0.9	-0.2	0.58	0.36	0.85
Number of correctly detected classes	0	0	2	1	3
Number of required correlations	15	15	15	3	1

Line 1 provides the performance of each tested filter with respect to the DC. The negative values of the DC indicate that a tested filter fails to recognize the target. The classification performance of the filters is given in line 2 of Table 1. The computational complexity of the tested techniques in terms of required correlations is shown in line 3 of Table 1. It can be seen that the proposed method yields the best performance with respect to detection, classification, and complexity. The AF adapts well to patterns to be recognized and classified, and to a known background to be rejected.

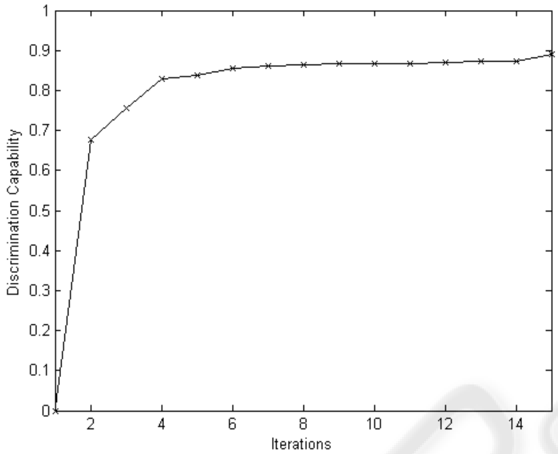
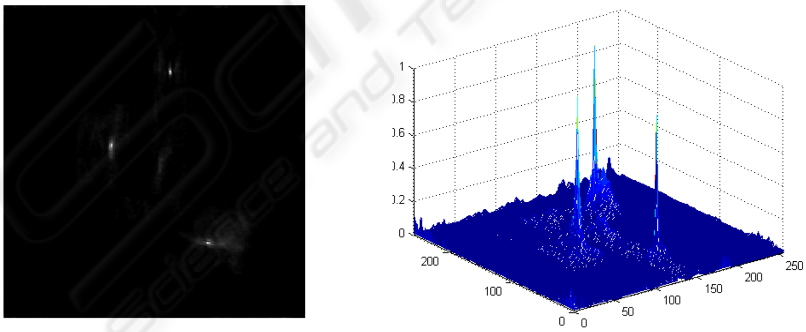


Fig. 3. Performance of the adaptive SDF filter in the filter design process.

To guarantee statistically correct results, 30 statistical trails of the experiment for different positions of the targets were performed. With 95% confidence, the DC of the AF is equal to 0.85 ± 0.03, and the phase estimations at the origin of the correlation peaks for t1, t2, and t3 are equal to 0±5 degrees, 60±4 degrees, and 120.5±2.5 degrees, respectively. This means that all targets can be reliably recognized and classified.



(a) (b)

Fig. 4. (a) Correlation plane for the test scene obtained with the adaptive filter, (b) normalized intensity distribution.

5 Conclusions

A new method based on an adaptive approach and SDF filters was proposed to improve recognition and classification of multiple targets embedded into a known cluttered background. It was shown that the proposed iterative algorithm generates an adaptive filter, which is able to take control over whole correlation plane. With the help of computer simulation, we showed that the proposed filters recognize and classify correctly distorted objects belonging to different classes.

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