Pattern recognition with adaptive morphological composite filters

Abstract

Adaptive morphological composite correlation filters for robust and distortion-invariant pattern recognition are proposed. The filters are designed with an iterative algorithm to reject a background noise and to achieve a desired discrimination capability. The recognition performance of the proposed filters is compared with that of linear composite filters in terms of noise robustness and discrimination capability. Computer simulation results are provided and discussed.

1 INTRODUCTION

Correlation-based filters have been an area of extensive research over past decades. The classical matched spatial filter (VanderLugt, 1964) is optimal if an input image is corrupted by additive Gaussian noise. However, many real images are corrupted by non-Gaussian noise. Composite filters based on synthetic discriminant functions (SDF) (Hester, 1980) can be used for multiclass pattern recognition. SDF filters utilize a set of training images to synthesize a template that yields prespecified correlation outputs in response to training images. A drawback of SDF filters is appearance of false peaks on the correlation plane. A partial solution of this problem is to control the whole correlation plane by minimizing the average correlation energy (MACE) (Mahalanobis, 1987).

Common correlation-based filters use a linear correlation. Minimization of the mean absolute error (MAE) leads to a nonlinear morphological correlation, which is computed as a sum of minima. This criterion is more robust when the noise has even slight deviations from the Gaussian distribution, and produces a sharper peak at the origin (Maragos, 1989).

In this paper we design morphological adaptive composite filters for distortion-invariant pattern recognition. Section 2 provides the design of composite morphological filters. Section 3 describes the iterative algorithm used for rejection of a background noise. In section 4, computer simulations are provided and discussed. Section 5 summarizes our conclusions.

2 MORPHOLOGICAL COMPOSITE FILTERS

We wish to design a nonlinear composite filter, which is invariant to geometrical distortions, robust to noise, cluttered background, and false objects. The filtering is a locally adaptive signal processing in a moving window. The window is referred to as the *W*-neighborhood. The shape of the *W*-neighborhood is similar to the region of support of the target. The size of the neighborhood is referred to as $|W|$. Let $\{T(k,l)\}$ and $\{S(k,l)\}$ be a target image and a test scene respectively, both with Q levels of quantization. The local nonlinear correlation derived from the MAE criterion between a normalized input scene and a shifted version of the target can be defined as

$$C(k,l) = \sum_{m,n \in W} MIN\left[a_{kl} S(m+k, n+l) + b_{kl}, T(m,n)\right], \quad (1)$$

where the sum is taken over the *W*-neighborhood. a_{kl} and b_{kl} take into account illumination and a bias of the target, respectively. The coefficients can be computed by minimizing the mean squared error between the window signal and the target as

$$a_{kl} = \frac{\sum_{m,n \in W} T(m,n) \cdot S(m+k,n+l) - |W| \cdot \bar{T} \cdot \bar{S}(k,l)}{\sum_{m,n \in W} \left(S(m+k,n+l)\right)^2 - |W| \cdot \left(\bar{S}(k,l)\right)^2}, \quad (2)$$

$$b_{kl} = \bar{T} - a_{kl} \cdot \bar{S}(k,l), \quad (3)$$

where $\bar{T}$ and $\bar{S}(k,l)$ are the averages of the target and local window signal over the window at the (k,l)'th window position, respectively. According to the threshold decomposition, a gray-scale image $X(k,l)$ can be represented as a sum of binary slices:

$$X(k,l) = \sum_{q=1}^{Q-1} X^q(k,l),$$

where $\left\{X^q(k,l), q = 1, \dots Q-1\right\}$ are binary slices obtained by decomposition of the image with a threshold q as

$$X^q(k,l) = \begin{cases} 1, & if \quad X(k,l) \geq q \\ 0, & otherwise \end{cases}.$$

Now, assume that there are N objects from the true class $\{T_i(k,l), i = 1...N\}$ and M objects to be rejected $\{P_i(k,l), i = 1...M\}$ (the false class). We construct N reference images as combinations of the training images:

$$\hat{T}_i(k,l) = \sum_{q=1}^{Q-1} T_i^q(k,l) \bigcap \left[\overline{\bigcup_{j=1}^{M} P_j^q(k,l)} \right], \quad i = 1...N, \qquad (4)$$

where $\{T_i^q(k,l), q = 1,...Q-1, i = 1,...N\}$ and $\{P_i^q(k,l), q = 1,...Q-1, i = 1,...M\}$ are binary slices obtained by threshold decomposition from corresponding training images of true and false classes respectively. $\bigcup$ and $\bigcap$ represent the logical union and intersection, respectively. The nonlinear composite correlation is computed by

$$\hat{C}(k,l) = MAX\left(\left\{ \frac{u}{t_i} C_i(k,l), i = 1...N \right\} \right). \qquad (5)$$

where $\hat{C}(k,l)$ is the composite correlation, $C_i(k,l)$ is the i'th correlation between the input scene and the i'th reference image, $MAX\ (X_i)$ is the maximum value among all the X_i, u is the desired value at the correlation output, and

$$t_i = \sum_{k,l \in W} \sum_{q=1}^{Q-1} T_i^q(k,l) \bigcap \left[\overline{\bigcup_{j=1}^{M} P_j^q(k,l)} \right]. \qquad (6)$$

One can show that the composite correlation yields the value u at output correlation for objects belonging to the true class, while the output correlation peaks for the false objects are zeros.

3 ADAPTIVE FILTER DESIGN

The proposed filtering process controls the correlation output only at the location of cross-correlation peaks. Thus, when a target is embedded into a cluttered background, false peaks may appear everywhere on the correlation plane. In order to improve the discrimination capability it is necessary to reduce false peaks from the correlation output. This can be done with the help of an iterative algorithm. At each iteration the algorithm suppresses the highest false peaks, therefore monotonically increases the value of discrimination capability until a desired value is reached. The discrimination capability (*DC*) is defined as the ability of a filter to distinguish a target from other objects. If the target is embedded into a background, the *DC* can be expressed as follows:

$$DC = 1 - \frac{|C^B|^2}{|C^O|^2}, \qquad (7)$$

where C^B is the maximum in the correlation plane over the background area to be rejected, and C^O is the maximum in the correlation plane over the area of object to be recognized. The area of the object to be recognized is determined in the close vicinity of the target location (the size of the area is similar to the size of the target). The background area is complementary to the object area. Negative values of the *DC* indicate that a tested filter fails to recognize the target. A block-diagram of the iterative procedure is shown in Fig. 1.

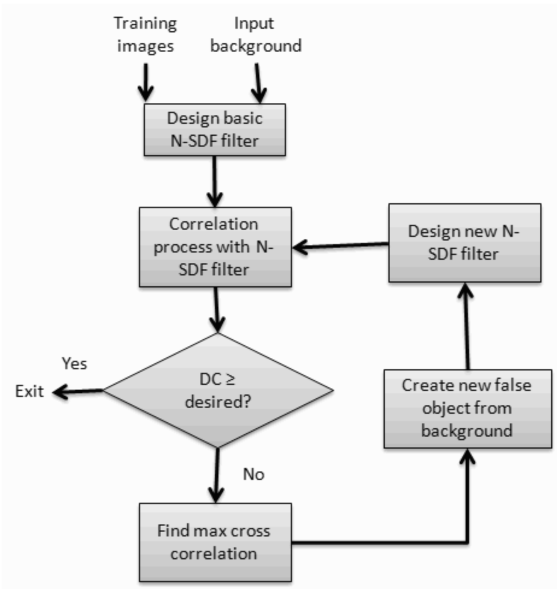

Figure 1: Block diagram of iterative algorithm.

The iterative algorithm consists of the following steps:

1. Design a basic morphological composite filter (N-SDF) with distorted versions of the target and known false objects (Eq. 4).
2. Carry out the nonlinear correlation between the background and the designed filter. Compute the *DC*.
3. If the *DC* is greater or equal to a desired value, then the filter design procedure is finished, else go to the next step.
4. From the background create a new object to be rejected. The origin of the object is at the highest peak in the correlation plane. The object is included into the false class.

5. Design a new N-SDF filter with the true and false classes of objects. Go to step 2.

As a result of the procedure, the nonlinear adaptive filter (NA-SDF) is synthesized. The performance of the filter in the recognition process is expected to be close to that of the synthesis process.

4 COMPUTER SIMULATIONS

In this section with the help of computer simulations we compare the proposed filters with the linear SDF and MACE filters in terms of discrimination capability. Morphological composite filters are optimized with the help of the iterative algorithm described in section 3. To investigate the performance of correlation filters to small geometric distortions of the target and robustness to noise, we carried out three experiments; that is, (i) recognition of a rotated object embedded into cluttered background, and (ii) recognition of a scaled object embedded into a cluttered background.

SDF filters are linear combinations of the training objects. The coefficients of the linear combination are chosen to satisfy a set of constraints on the filter output, requiring a previously specified value for each pattern used in the filter synthesis. Suppose that we have *N* training images, each image contains *d* pixels. The conventional SDF filter can be expressed in spatial domain as

$$\mathbf{h}_{SDF} = \mathbf{R}(\mathbf{R}^{+}\mathbf{R})^{-1}\mathbf{u}. \qquad (8)$$

where $\mathbf{R}$ is a $d \times N$ matrix containing vector versions of training images ordered lexicographically. $\mathbf{R}^{+}$ is the transpose of $\mathbf{R}$. The column vector $\mathbf{u}$ contains N elements, which are the desired values of the output correlation peaks corresponding to each training image. The filter $\mathbf{h}_{SDF}$ is a column vector with d elements. The 2D correlation filter is obtained by reordering the column vector back to a 2D array. Since SDF filters control only the correlation output at the location of cross-correlation peaks, false peaks may appear everywhere on the correlation plane.

With the purpose of suppress false correlation peaks, MACE filters minimize the average energy of the correlation output for a set of training images, satisfying at the same time the correlation peak constraints at the origin. Suppose that there are *N* training images, each image with *d* pixels. First, the 2D Fourier transform is performed for each training image and converted into 1D column vector. Next, a matrix $\mathbf{X}$ with N columns and d rows is constructed. The columns of $\mathbf{X}$ are given by the vector version of each transformed image. The frequency response of the MACE filter can be expressed as

$$\mathbf{h}_{MACE} = \mathbf{D}^{-1}\mathbf{X}(\mathbf{X}^{+}\mathbf{D}^{-1}\mathbf{X})^{-1}\mathbf{u} \ , \qquad (9)$$

where the column vector $\mathbf{u}$ contains desired correlation peak values of the training images. $\mathbf{D}$ is a *dxd* diagonal matrix contains the average power spectrum of the training images. First, distortion invariance to rotation is tested. Fig. 2 (a) shows a set of rotated objects to be recognized (true-class). Rotation angles are -8, -4, 0, 4, and 8 degrees. The size of the window containing the filter is 33x49 pixels. The signal range of all images is [0-255]. With the help of the iterative algorithm we design the adaptive nonlinear filter NA-SDF. The filter includes all true-class objects. The mean value and standard deviation of the objects are 143 and 11, respectively. Figure 2 (b) shows a background to be rejected.

Figure: 2 (a) Set of objects used in experiments, (b) background to be rejected.

The size of the test scene is 256x256. The mean value and standard deviation of the background are 116 and 40, respectively. Next, the target versions rotated from -8 to 8 with a step of 2 degrees are embedded into the test scene. The obtained results are shown in Fig. 3.

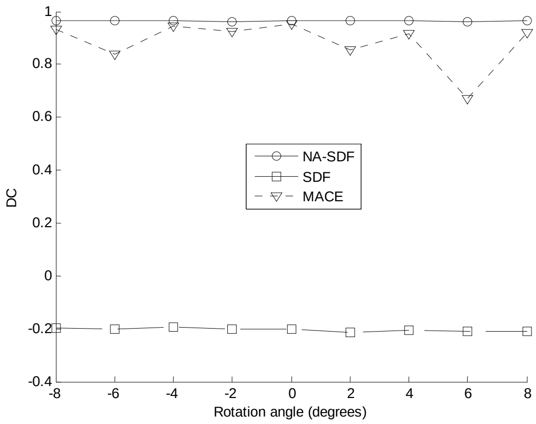

Figure: 3 Discrimination capability as a function of rotation angle.

Note that the SDF filter is unable to recognize the target (DC<0) in all cases. The MACE filter recognizes objects, but its performance decreases for objects that are not included in the training set. The NA-SDF yields the best performance in terms of the DC for all objects. Now we investigate distortion invariance to object scaling. Scale factors are 0.8, 0.9, 1, 1.1, and 1.2. With scaled objects we design an adaptive nonlinear filter. The target versions are scaled from 0.8 to 1.2 with a step of 0.05 and embedded in the scene. The recognition performance of the tested filters is shown in Fig. 4. The obtained results are similar to those of the rotation test. The performance of the NA-SDF is the best among the tested filters. The SDF filter is unable to detect the target. The performance of the MACE filter is low for objects that are not included in the synthesis process.

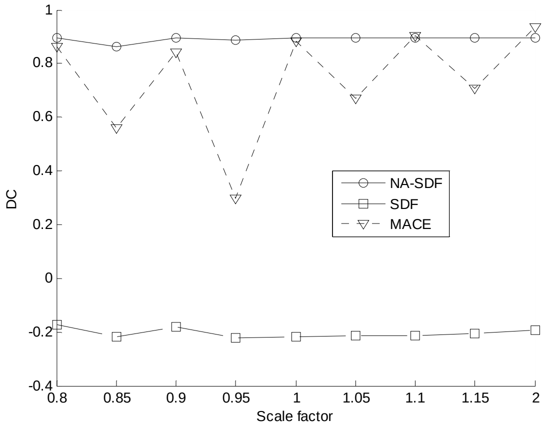

Figure: 4 Discrimination capability as a function of scale factor.

The obtained results are similar to those of the rotation test. The performance of the NA-SDF is the best among the tested filters. The SDF filter is unable to detect the target. The performance of the MACE filter is low for objects that are not included in the synthesis process.

5 CONCLUSION

Adaptive morphological composite filters for distortion-invariant pattern recognition were proposed. The filters for detection of rotated or scaled objects embedded into cluttered background were designed. The performance of the morphological filters was compared with that of conventional SDF and MACE filters in terms of discrimination capability. The adaptive morphological composite filters proved to be distortion-invariant and robust to additive noise when a target is embedded into a cluttered background.

Reference

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