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ABSTRACT

We evaluated the performance of circular optimal trade-off SDF (OTSDF) and distance classifier correlation filters (DCCFs) as rotation-invariant correlation filters. Because the filters are designed using different parameters we compared the filter's performance in terms of an equivalent effect of probability of error. The use of OTSDF and DCCF filters as circular filters allows their calculation to be greatly simplified when compared to using rotated views of an object to create filters. We found that both types of filters can be used for rotation-invariant object recognition in a noisy environment. In addition, the filters generated were real-valued so they may be implemented on a variety of spatial light modulators.

keywords: circular filters, correlator, distance-classifier correlation filters, optimal trade-off filters, rotation-invariance

1. INTRODUCTION

There are several methods using correlation filters to perform rotation-invariant object recognition.[1-8] Recent advances have created correlation filters that can identify many views of an object with one or a small number of filters. One popular approach has been the use of circular harmonic filters (CHFs), which provide full rotation and shift invariance.[1,2] The first CHF used a circular harmonic from an input image. More advanced versions of CHFs use linear combinations of circular harmonics of a training set of images, and minimize the average correlation energy.

Rotation-invariance may be obtained in a straightforward way by using rotated versions of an input image as training images to a generalized distortion-invariant filter. Using the original synthetic discriminant function filter (SDF), rotated objects can be made to have the same correlation peak value. [9] However, the SDF is limited because it constrains one value in the correlation plane. The MACE filter is a type of SDF filter that attempts to control the entire correlation plane.[10] Generally, the MACE filter lacks noise tolerance and is sensitive to intra-class variations. The MACE filter is actually a special case of an optimal trade-off SDF (OTSDF) filter. In these filters, a performance measure is optimized while holding others constant and satisfying the correlation peak constraints.[11,12] To determine an OTSDF filter, an energy function, which is the weighted sum of performance measures is minimized. The filter provides the best trade-off between the performance measures for the specified weights.

Rotation-invariance may also be obtained in a straightforward way using distance classifier correlation filters (DCCFs). These filters are used with more than one class of objects and measure the difference between objects and ideal references.[13] One disadvantage of using the SDF-based and DCCF filters is that as the angular spacing of rotated views of an object decreases and the number of different objects increases, the computational demand for filter generation significantly increases. In addition, the resulting filters are often complex-valued which limits the devices on which they can be applied.

As the angular spacing of the training images used in the OTSDF and DCCF filters decreases, the resulting filter will tend to be appear more circularly-symmetric. When the angular spacing is very small, the filters will be circularly-symmetric and consist of concentric rings. Circular filters are those with circular symmetry about the origin; the

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frequency domain of an optical correlator can be thought of in polar coordinates with only the radius as a variable. Using this concept a genetic algorithm was used to determine the radial magnitudes of a binary circular filter.[14] This approach used a performance criterion of a weighted sum of other performance criteria. This approach is useful because it generates filters that can be implemented on binary spatial light modulators (SLM)s as opposed to the generally complex values of the former filters.

We also used circular filters for rotation invariance; however, we combined them with the concept of OTSDF and DCCF filters to obtain filters with theoretical advantages while reducing the complexity of the filter design. In addition, the circular OTSDF and DCCF filters are real-valued so they may be implemented on a variety of SLMs. Because the filters use different parameters in their design and sometimes different performance measures, we compared the filters' performance in terms of an equivalent effect of probability of error.

2. CIRCULAR CORRELATION FILTERS

Circular symmetric filter design eliminates the distortion induced by rotated input objects. In contrast to traditional approaches where multiple views of an object are used as a training set for the filter, we summed the Fourier transform of an object across each angle for a particular radius as

$$\mathbf{x}_i = \sum_{\theta} X_i(r,\theta), \tag{1}$$

where $X_i(r,\theta)$ is the Fourier transform of the *ith* input image in polar coordinates, and $\mathbf{x}_i$ is a vector which contains the sum of the Fourier transform as a function of radius r. Using the values of $\mathbf{x}_i$ in a circular filter is equivalent to using many closely-spaced images for a training set. This approach requires only one image and the resulting filter values are contained in a vector. Because the filter is circularly symmetric, the phase values cancel and the filter will be real-valued.

2.1 OTSDF filters

We considered an example that considers the parameters of discrimiation and noise tolerance as performance values. Additional parameters may be easily incorporated into the filter, but our example demonstrates the circular OTSDF method. In our example, the filter was designed to minimize the effect of additive noise on the correlation output, and the average correlation energy. This is actually a trade-off between MACE and minimum variance SDF (MVSDF)[15] filters. In the MVSDF filter the output correlations are generally broad, while the MACE filter usually has sharp correlation peaks. The general OTSDF design can be described as,

$$\mathbf{h} = \mathbf{T}^{-1}\mathbf{X}(\mathbf{X}^{+}\mathbf{T}^{-1}\mathbf{X})^{-1}\,\mathrm{c} \tag{2}$$

where $\mathbf{X}$ is a matrix and contains the training set of circular filter values $\mathbf{x}_i$ as columns, c is a vector that contains the desired correlation peak of each training image, and the matrix $\mathbf{T}$ contains the weighted sum of performance parameters. The vector $\mathbf{h}$ contains the values of the circular OTSDF filter. In our example, $\mathbf{T} = \alpha\mathbf{P} + (1-\alpha^2\,\mathbf{D}_x)^{1/2}$, where $\mathbf{D}_x$ is a diagonal matrix with that contains the average power spectrum of the circular filter values, and $\mathbf{P}$ is the noise power spectral density which is assumed to be white. The parameter α varies from $0 \le \alpha \le 1$. If $\alpha = 0$ then the resulting filter is the MACE filter, if $\alpha = 1$ the result is the MVSDF filter.

2.2 DCCF filters

The DCCF filter was developed to directly measure the similarity between the shape of the correlation plane and the ideal shape for that class.[13] The DCCF filter was designed to optimally separate classes while making them as compact as possible. In other words, the filter increases the inter-class distances while making each class more compact to simultaneously improve distortion tolerance and discrimination. For two classes, the filter can be described by

$$\mathbf{h} = \mathbf{S}^{-1}(\mathbf{m}_x - \mathbf{m}_y), \tag{3}$$

where $\mathbf{m}_x$ and $\mathbf{m}_y$ are the mean image of class x and class y respectively, and $\mathbf{S}$ is the diagonal matrix,

$$\mathbf{S} = [1/N_x \Sigma(\mathbf{X}_i - \mathbf{M}_x)(\mathbf{X}_i - \mathbf{M}_x)^* + 1/N_y \Sigma(\mathbf{Y}_i - \mathbf{M}_y)(\mathbf{Y}_i - \mathbf{M}_y)^*], \tag{4}$$

where $\mathbf{M}_x$ and $\mathbf{M}_y$ are the diagonal versions of $\mathbf{m}_x$ and $\mathbf{m}_y$, $\mathbf{X}_i$ and $\mathbf{Y}_i$ are the diagonal versions of the *ith* image in class x and y. The 1st summation in Eq. (4) is over class x and the 2nd summation is over class y, and N_x and N_y are the number of images used for each class.

3. SIMULATION RESULTS

We examined the performance of circular OTSDF and DCCF filters by comparing their results from the same sensor imagery. We used two classes, each with five training objects with each object taken from the infrared image shown in Fig. 1. Each object image was 128 x 128 pixels and contained one object. The training sets for the OTSDF and DCCF filters were K1-K5 and B1-B5 for class x (in-class), and class y (out-of-class) respectively. In the approach of Ref. 14, a genetic algorithm determined the radii of the circular filters. In our approach, we considered circular filters with radii of 1 pixel-width resolution.

We compared the performance of the filters using correlation peak data to determine the probability of error of recognition. Without noise the correlation peaks for the OTSDF are shown in Fig. 2. For values of $0 \leq \alpha \leq 0.9$, the correlation peaks had large sidelobes; only for $\alpha > 0.9$ did the correlation responses appear somewhat smooth; therefore we used $\alpha = 0.9$ in our experiments. The results showed that the discrimination among the training set was satisfactory indicated by the large separation between the two sets of correlation heights. The discrimination of objects not in the training set was not as great even though the images appeared similar to the training set. The correlation peaks for the DCCF filter were shown in Fig. 3. For the training set, the two classes were separated, but it did not appear to be as great as with the OTSDF filter. Although the discrimination of the remaining objects appeared to decrease somewhat, it appeared to be greater that for the OTSDF filter. The PCE values for the OTSDF and DCCF filters were 1.84 and 0.77 respectively indicating the OTSDF filter produced sharper correlation peaks.

We compared the noise performance of the OTSDF and DCCF filters as a function of the SNR of the input images. We compared the performance of the filters for two cases, one was when the 10 test images were those in making the filter, and when the test images contained an additional five images per class from Fig. 1. For each SNR value we used a total of 1000 noisy images (50 versions of each image) containing independent noise samples and measured the histogram of the correlation peaks. Then, we determined the correlation peak value that produced the minimum value of the probability of error P(E), of identifying the two classes. The value of the minimum P(E) for each SNR value is shown in Fig. 4. The results show that the OTSDF filter worked best when only the training set images were used. When all images were used, the error due to the OTSDF significantly increased. Although the error due to the DCCF for the training set was larger than the OTSDF filter, the error did not increase as much when all images were used as inputs. When all images were used as test images, the OTSDF filter had a larger P(E) than the DCCF filter at larger values of SNR, and a smaller P(E) at lower values of SNR.

4. CONCLUSION

The noise performance of the OTSDF filter was superior to that of the DCCF when only images used to make the filter were used as test data. When additional images were used the performance of both filters decreased. The OTSDF filter had a lower probability of error at higher noise levels, and the DCCF filter had a lower probability of error better at lower noise levels. Both types of filters may be used for rotation-invariance; however, the better choice may be application-dependent. The filters generated were real-valued so they may be implemented on a variety of SLMs.

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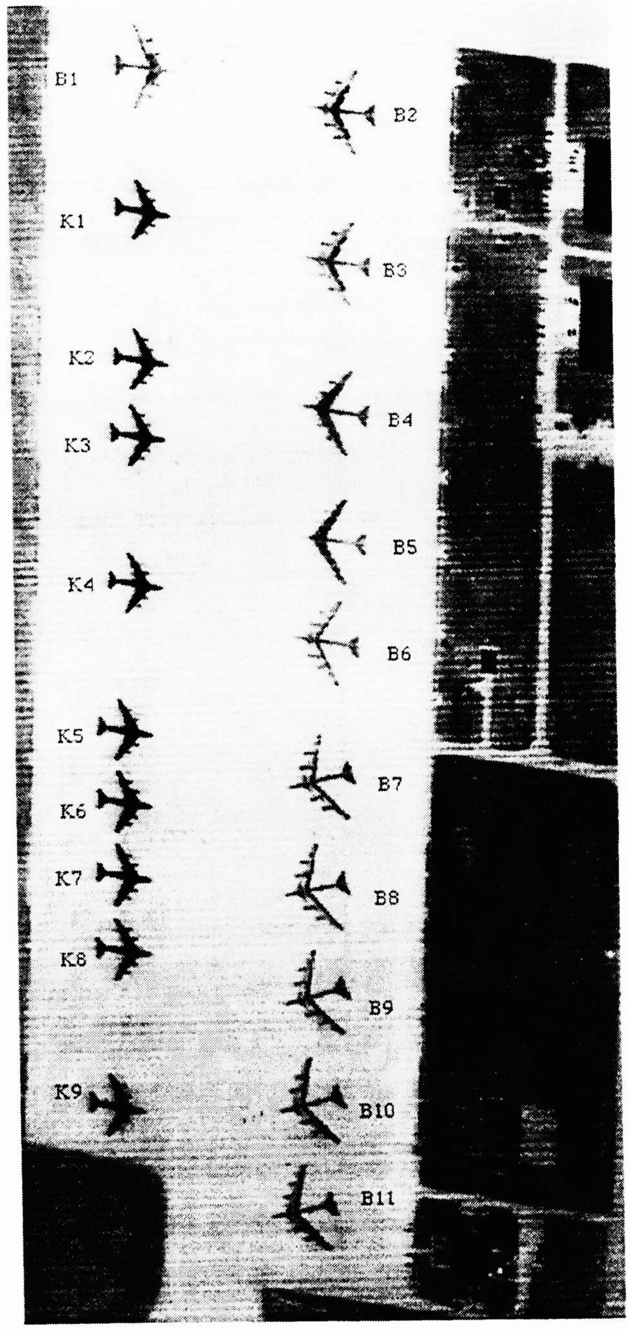

Figure 1 Image used in experiments

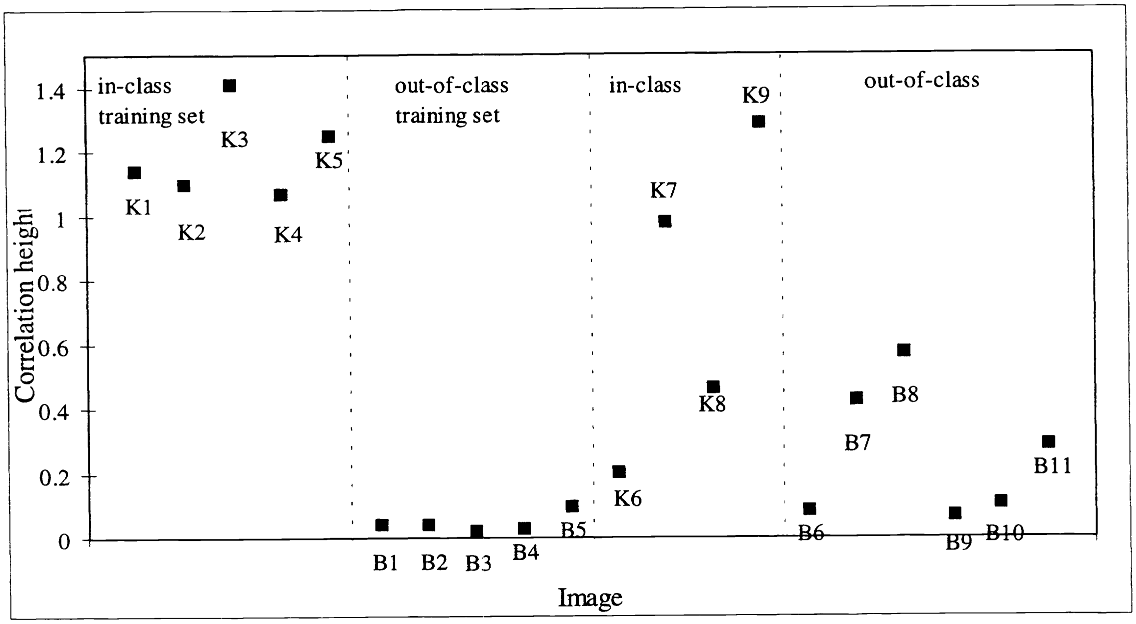

Figure 2 Correlation peaks resulting from OTSDF filter.

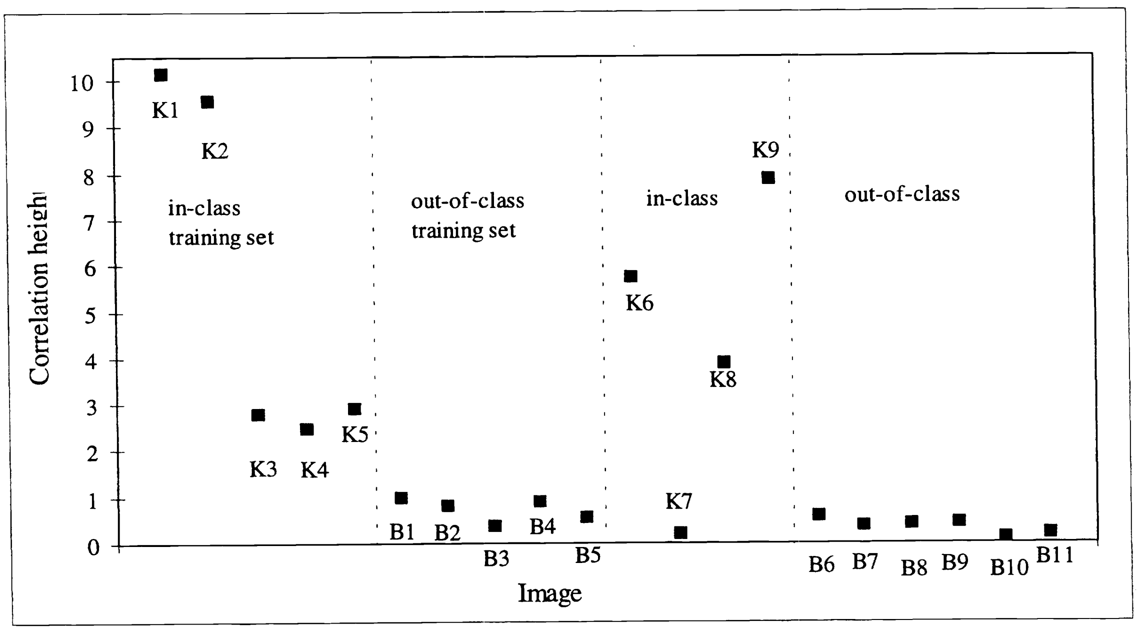

Figure 3 Correlation peaks resulting from DCCF filter.

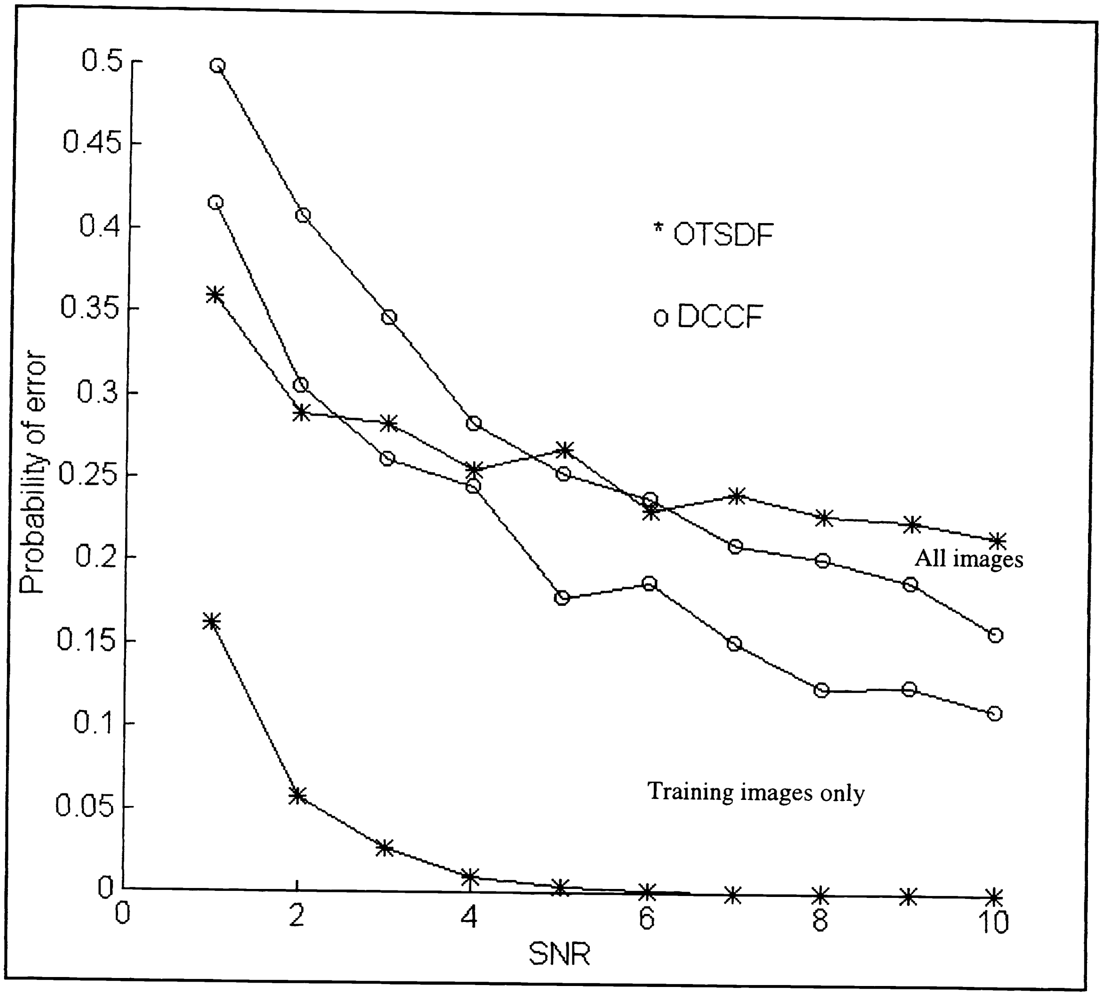

Figure 4 Probability of error of detection for OTSDF and DCCF filters. For each filter, training images, and test and training images are used as inputs. The training image data are the lower two curves.