Voting scheme nonlinearity-based binary composite filter

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ABSTRACT

A voting scheme for the design of composite filter is proposed here. Different types of synthetic discriminant function (SDF) filters, like minimum average correlation energy (MACE), minimum variance SDF (MVSDF), and optimal tradeoff SDF (OTSDF) have been proposed recently for the distortion-invariant recognition. Discretization of these filters is necessary to realize them using the available spatial light modulator (SLM), which limits the efficiency of the continuous domain filters. In this report, we address this SLM-constraint of the composite filter design. Our design starts with a binary SLM. In particular, binary modulation capability of the SLM is incorporated in the composite filter design as a constraint in the form of voting scheme nonlinearity.

Keywords: composite filter, distortion-invariance, discretization, voting scheme.

1 INTRODUCTION

Composite filter design for distortion invariance is attempted primarily in three different ways. In the synthetic discriminant function (SDF) filter approach,[1,2] a number of distorted patterns are trained to design a filter, which is expected to perform well under all other possible distortions. Minimum variance synthetic discriminant filter (MVSDF),[3] minimum average correlation energy (MACE) filter[4] and optimum trade-off SDF (OTSDF)[5] are examples of such composite filter formulations. In the second approach, geometric invariance properties are used in the filter formulation.[6–9] For example, circular harmonic filter expansion for rotation invariance has been proposed. Here, the images distorted by rotation are represented in polar coordinates using circular harmonic components. Use of filter modulation in SDF construction has also been proposed[10–13] to improve the invariance performance.

The above mentioned filters work well in the continuous domain with various degree of success. But their performance degrade with the discretization of the filter. In this work, we particularly emphasize our focus to this problem. The proposed filter synthesis uses the modulation limitation of the available SLM's in the very formulation of the filter, thus leading to a readily-realizable composite filter in a practical SLM. The technique is validated through a simulation for rotation-invariant character recognition.

2 VOTING SCHEME NONLINEARITY FOR COMPOSITE FILTER

Let us discuss the construction of an invariant composite filter to be realized in a binary SLM. A number of representative filter-features $F_1, F_2, \cdots, F_k, \cdots, F_M$ from a possible range of distortion of the target is first determined. Here, we use pjase-only filter (POF) feature. In general, one could have started with any desirable filter modulation to come up with the training set of filters.[10,12] A voting scheme using these features is then employed in the design of the desired composite filter, H. Each pixel of a training feature, $F_k(i,j)$ is assigned a vote for the corresponding pixel, $H(i,j)$ of the desired composite filter. The cast vote is a *yes* $(+1)$ if the pixel value is greater than a threshold value, else it is a *no* (-1).

$$H(i,j) = \begin{cases} \text{H(i,j) } +1, & \text{if } \Re[F_k(i,j)\, exp(j\frac{\pi}{4})] > 0 \\ \text{H(i,j) -1}, & \text{otherwise.} \end{cases} \tag{1}$$

Votes from each of the training features are thus collected. The final filter is determined by counting the votes obtained for each pixel. If majority of the training features say *yes* (+1) to a filter element, then that element is set to +1. Otherwise, it is set to −1. Because of the fact that the votes could be either +1 or −1, for the reason mentioned earlier, this majority-granted scheme can be formulated in the following way.

$$H(i,j) = \begin{cases} +1, & \text{if } H(i,j) >= 0 \\ -1, & \text{otherwise.} \end{cases} \tag{2}$$

Now since, $H(i,j)$ corresponds to majority of $F_k(i,j)$, therefore, the term $H(i,j) - F_k(i,j)$ is zero for majority of the training filters, thus yielding a minimal Euclidean distance. As evident from the previous description, the success of this method depends heavily on the choice of the training set of filter-features. We discuss the effect of two different types of training set selection techniques:

Uniform distribution: The training features are taken uniformly with an uniform interval from the whole distortion range. In typical SDF approaches, the choice of this interval is usually very crucial which is found to be less critical in the present technique.

Weighted vote: Here, the voting weights are determined from the correlation coefficients of the training filters, with respect to a reference filter. This reference filter (F_r) is taken to be the filter corresponding to the distorted image having a distortion, which lies in the middle of possible distortion range. This is motivated by the fact that the voting scheme is biased to the mid-range distortion values. The voting weight w_k of the training filter F_k is, therefore,

$$w_k = \frac{\sqrt{(\sum\sum {F_r}^2)(\sum\sum {F_k}^2)}}{\sum\sum F_r * F_k}. \tag{3}$$

The above formulation ensures that the reference filter has a voting weight of 1. Some hard threshold might actually be necessary to limit the weights obtained with the above formulae, to some desired range.

3 SIMULATION RESULTS

The performance of the proposed method is verified for the rotation-invariant character recognition. Three binary characters, E, F, and P, as shown in Fig. 1, are considered.

These characters are chosen, because of their similar enough shape characteristics. In the simulation, each of the characters is treated as target, while the other two are considered as non-target. For example, when the composite filter is constructed for the target character E, then the other two test characters F and P are taken as non-targets. The individual characters are 12×9. In the correlation, these are zero padded to 32×32.

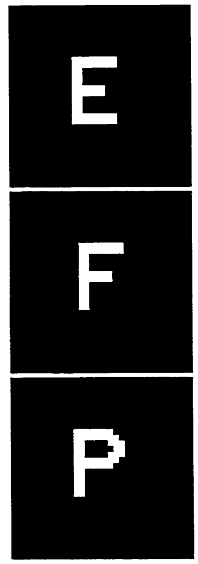

Figure 1: Test character images: E, F, and P.

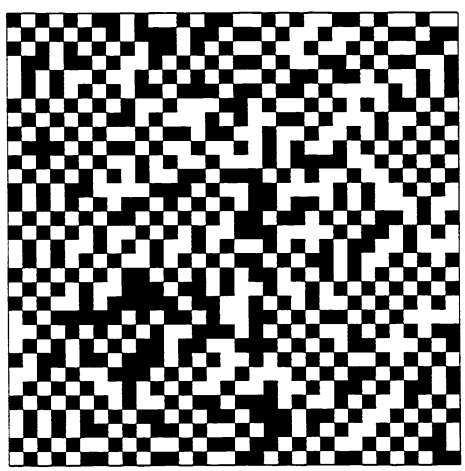

Figure 2: Binary composite filter for the test character F (distortion range of 0-30 degree)

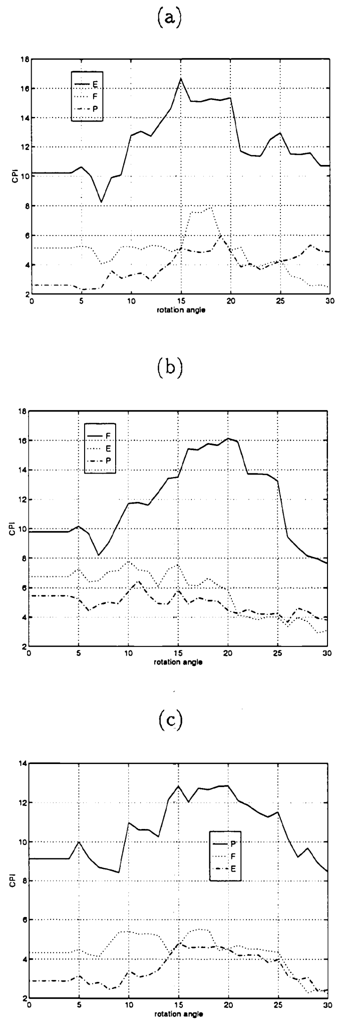

Figure 3: CPI response using uniform interval method in the distortion range of 0-30 degree with composite filter designed for: (a) E, (b) F, and (c) P.

To quantify the simulation results, we consider two performance metrics. The first one is the average discrimination ratio (ADR) which is defined as the ratio of the average peak value of the auto-correlation intensity to the average peak value of the cross-correlation intensity. This gives an overall performance measure of the SDF filters, although it is not necessarily a good metric for recognition applications. Autocorrelation, here is the correlation of a distorted version of a target character with the target filter. Crosscorrelation, on the other hand, is the correlation of any non-target with the target filter. The other metric, which is more meaningful is a modified version of signal-to-noise ratio (SNR). Let $< H, F_i >$ denote the correlation plane of the filter H with the input image F_i. Then,

$$SNR = \frac{min[\ max[< H, F_t >]]}{max[\ max[< H, F_n >]]} \tag{4}$$

where F_t represents any distorted target, *i.e.*, $F_t \in$ target class, and $F_n \in$ non-target class. This metric is therefore the ratio of the minimum autocorrelation peak intensity to the maximum crosscorrelation peak intensity. SNR

must be greater than 1 for the detection of all possible distorted target inputs. When it is less than 1, then it is decided that the constructed filter H cannot discriminate well between target and non-target.

With the uniform interval method, we consider an interval of 5 degrees in the distortion range. Figure 2 shows the binary-valued filter for the character "F" designed for a distortion range of 0-30 degree. Figure 3(a) shows the variation of correlation peak intensity (CPI) with respect to the rotation angle. Here, the composite filter is constructed for the character E and the correlation result is obtained for all three characters.

Table 1: Correlation Performance with weighted-vote training patterns

Target	ADR		SNR	
Filter	0-30	0-90	0-30	0-90
E	2.8	2.24	1.04	0.69
F	2.2	1.67	0.98	0.49
P	2.7	1.89	1.52	0.32

As seen from Table 1, the SNR values are greater than 1 for filter E and P, but it is less than 1 for the filter of character F. The correlation performance degrades with increasing distortion range, as is summarized in Table 1.

Next, we use the weighted vote training set selection method. The weight values are constrained to fall in the range of $1 <= w_k <= 2$. The resulting correlation performances are shown in Figs. 4. Note carefully that the overall discrimination performance is better in this case. In particular, filter for target F now has an SNR value of 1.11 against the non-targets F, and P, while it had an SNR value .98 in the previous case.

Note that in the cases where $SNR > 1$, we can set a threshold value for the correlation peak, above which the input can be treated as a target and below which it is a non-target.

4 CONCLUSION

We proposed a composite filter construction which uses a simple voting technique. The number of training filters required herein, do not have any adverse effect on performance, because of the use of majority-granted algorithm. A constant threshold value for the correlation peak response can be utilized to effectively convert the system to a robust recognition system.

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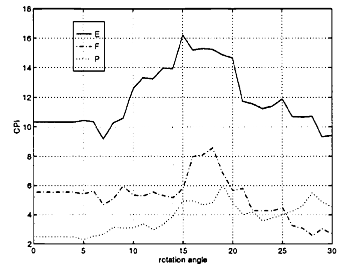
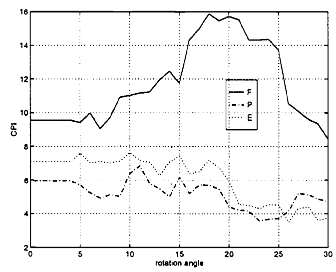
(a)



(b)



(c)

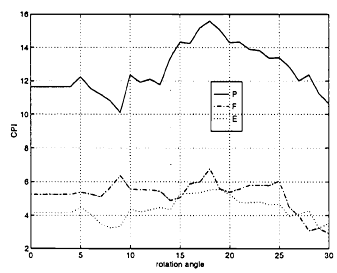


Figure 4: CPI response using weighted vote method in the distortion range of 0-30 degree with composite filter designed for: (a) E, (b) F, and (c) P.

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