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Recent Results in Rotation Invariant Pattern Recognition

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Introduction

This paper reviews recent progress in rotation invariant pattern recognition; the emphasis is on the work done in our own laboratories, since much of the significant work done elsewhere is described in other papers presented at this conference.

Previous work was described in a previous critical review of technology,[1] and we shall only briefly review this previous material.

In previous years there has been considerable effort expended to develop digital and optical pattern recognition techniques that are invariant to various changes of the objects. The main kinds of invariance are invariance to translations, rotations, contrast, scale, and deformations. Invariance is always obtained at the price of something else: for example, rotation invariance is often accomplished at the cost of discrimination ability or of a decrease in signal-to-noise ratio.

The two main approaches to invariant pattern recognition are matched filtering and invariant moments. The latter, like most other pattern recognition techniques, requires segmentation of the target from the scene, and is difficult to implement optically, whereas the former usually affords invariance to translation as a bonus, because of the linearity of the matched filtering system, and is easy to implement optically by means of optical correlators using holograms as matched filters. In this paper we consider only methods based on matched filtering.

Of particular practical interest is pattern recognition invariant under rotation of the target. There are two kinds of rotations: in-plane and out-of-plane rotation. The easiest kind to implement is in-plane rotation. Although considerable effort has been expended in developing the more difficult out-of-plane rotation invariant methods, no really convincing results have yet been published. We shall consider only in-plane rotation problems.

The main current ideas relevant to in-plane rotation invariant methods involves the use of Circular harmonic filters (CHF) and of composite or synthetic discriminant filters (SDF). Before describing the use of those filters for invariant pattern recognition, we briefly review CHF and composite filters.

Circular harmonic filters

Circular harmonic filters are based on the Circular harmonic decomposition. Any object $f(r,\theta)$ in polar coordinates may be decomposed into a series of circular harmonic components:

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$$f(r,\theta) = \sum_{m=-\infty}^{\infty} f_m(r) \exp(im\theta) \tag{1}$$

where

$$f_m(r) = \int_0^{2\pi} f(r,\theta)\exp(-im\theta)\, d\theta \tag{2}$$

When one component

$$h_m(r,\theta) = f_m(r) \exp(im\theta) \tag{3}$$

is used as a matched filter, a correlation peak whose intensity is invariant to rotations of the object is obtained . If for an unrotated object $f(r,\theta)$, the output correlation with an object $g(r,\theta)$ is $R_{fg}(r,\theta)$. Then for a rotated input $f(r, \theta+\alpha)$, the output correlation will be

$$R_{fg}(r, \theta+\alpha) \exp (im\alpha). \tag{4}$$

This is the foundation of rotation invariant pattern recognition based on Circular harmonic filters. Unfortunately, the unmodified CHC filter does not yield good recognition ability, throws away most of the energy of the target, and is usually associated with high sidelobes, so the method has had to be refined to improve recognition performance.This has been done by combining the CHC idea with other ideas, such as composite filters and phase-only filters.

We briefly review the main CHC filter ideas that have been published.

1) ***Simple CHC filter methods*** involve a single CHC filters or single filters made of combinations of CHC's from different objects. The latter could might be considered as a multiple CHC method. One proposed method involves rotating the filters continuously while the measurements are made (lock and tumbler filter).

2)***Multiple CHC methods*** involve combining the results from more than one CHC filter. The correlation values from different filters are used to create a feature space from the multiple correlation values, then the unknown target is classified using one of the multiple criteria available, such as minimum distance in the feature space.

3) ***Composite CHC filters*** use a single filter made up of a linear combination of filters from different objects that make up the data base of interest. The coefficients may be chosen to discriminate in favor of or against any of the objects that belong to the data base.

3) ***Moment methods*** do not use filters and require much more calculations than the above methods, in addition to requiring segmentation of the targets. However moment methods allow classification of targets not only under changes of position and of orientation, but also under changes of scale. These methods may be more amenable to cases where background is not a problem, as in some tracking problems. Such methods

may not so far be implemented as matched filters, but we mention them for the sake of completeness. Moment methods are described in another paper.

4) ***Other methods*** include all methods that do not fall in the preceding three groups. They include methods such as coordinate transformation methods.

phase-only filters

Phase-only filters have been shown to yield sharp correlation peaks and low sidelobes, in addition to improving filter discrimination. Since Circular harmonic filters tend to have large sidelobes, fabricating the filters as phase-only CHC filters can be expected to improve performance.

The phase-only CHC filter is

$$h_m(\rho) = \exp\,[j\alpha_m(\rho) + m\phi] \tag{5}$$

where $\alpha_m(\rho) + m\phi$ is the phase of the Fourier transform of the CHC component of order m. However this filter is not rotation invariant, because the center correlation of the filter with the object from which the filter, which is equal to

$$C_m = \int_0^x |F_m(\rho)|\rho d\rho \exp(jm\phi_0) \tag{6}$$

where ϕ_0 is the rotation angle of the target, becomes for a real filter

$$C_m = 2\pi \int_0^X |F_m(r)| r dr \cos mf_0 \tag{7}$$

which changes with rotation angle ϕ_0. This may be alleviated by using two filters, a cosine filter and a sine filter, but this requires an optical system able to combine two beams, which is less convenient.[2]

A single binary phase-only filter (BPOF) can be made invariant to target rotation by incorporating a carrier frequency into the filter. The targets used in most of the experiments of this paper are shown in Fig. 1. The filters were designed to recognize the three space shuttles with different orientation in positions 1, 6 and 8 of the figure (counting from left to right and from top to bottom).

We have compared unipolar [0,1] and bipolar [1,-1] filters[3] and have found that both yield good response equivalent to the pure phase-only filter: the bipolar filter has a diffraction efficiency of 40% and a space-bandwidth product (SBWP) of 3L, whereas the unipolar filter has a diffraction efficiency of 10% and a SBWP of 4L.

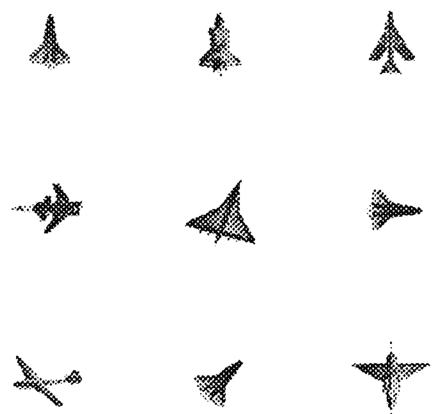

Figure 1: Targets used for recognition experiments.

covariance filter

The filter described next is the result of the combination of two ideas: the CHC rotation-invariant filter and a sidelobe-reducing composite filter. Because the aim of this filter is to eliminate the contribution to the correlation of the mean of the target, we call this filter a covariance filter.[4]

The equation which describes this filter, in the simplified specific case where there is one object to be recognized and one to be discriminated against, is

$$h(x,y) = af(x,y) + bg(x,y) + cu(x,y) \tag{8}$$

where a, b and c are real coefficients to be determined. The function f(x,y) is the object to be recognized, g(x,y) is to be rejected and u(x,y) is a uniform background with a size equal to or greater than f(x,y). Usually, the function u(x,y) is a rectangle, but in rotation invariant filters more complex shapes must be used because a uniform object does not have a CHC decomposition except for the zero order. The values of the constants a, b and c are determined by solving a set of linear equations for x = y = 0

$$R_{fh}(0,0) = aR_{ff}(0,0) + bR_{fg}(0,0) + cR_{fu}(0,0) = R_{ff}(0,0) \tag{9}$$

$$R_{gh}(0,0) = aR_{gf}(0,0) + bR_{gg}(0,0) + cR_{gu}(0,0) = 0 \tag{10}$$

$$R_{uh}(0,0) = aR_{uf}(0,0) + bR_{ug}(0,0) + cR_{uu}(0,0) = 0 \qquad (11)$$

where $R_{fh}(0,0)$, $R_{gh}(0,0)$, $R_{uh}(0,0)$ are respectively the cross-correlation of f(x,y) and h(x,y), g(x,y) and h(x,y) and u(x,y) and h(x,y) at the point (0,0) and where $R_{ff}(0,0)$, $R_{gg}(0,0)$ and $R_{uu}(0,0)$ are respectively the autocorrelations of the functions f(x,y) and g(x,y) at the point (0,0).

From Eq. (10), g(x,y) is completely rejected by the filter h(x,y). But in many practical cases, the clutter and unwanted objects present in the input scene are unknown a priori. The g(x,y) may therefore not be available for filter design. The composite filter becomes simply

$$h(x,y) = f(x,y) + \alpha u(x,y) \qquad (12)$$

To ensure that the correlation center $|R_{ff}(0,0)|^2$ be a maximum in the output plane, the center used for the CH expansion should be a proper center of the object f(x,y). A rotation invariant covariance filter, which adds rotation invariance to the above filter, is a composite CH filter

$$h_m(r,\theta) = [f_m(r) + \alpha u_m(r)] \exp(jm\theta) \qquad (13)$$

which is a linear combination of the CH component $f_m(r,\theta)=f_m(r)\exp(jm\theta)$ of the f(x,y) and a constant CH function $u_m(r)\exp(jm\theta)$ with

$$u_m(r) = \begin{cases} K & \text{when} \quad R_1 \le r \le R_2 \\ 0 & \text{when} \quad 0 \le r < R_1 \end{cases} \qquad (14)$$

where K is a complex constant, R_2 is the radius of the CH filter $f_m(r,\theta)$ and R_1 is the radius of a small circle inside which $u_m(r)$ is equal to zero. The value of R_1 is determined experimentally. There exists an infinity of objects whose CH functions are equal to $u_m(r)$ described by Eq. (13). One possibility is illustrated in the Fig. 2.

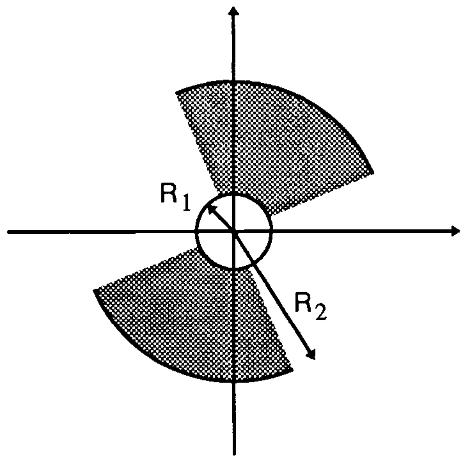

Figure 2. Uniform object (order 2).

The derivation of the binary CH covariance filter is similar to that of the binary CH filter. The Fourier transform of Eq. (13) is calculated. The amplitude of the transform is set to unity throughout the Fourier plane. The resulting filter is then binarized according to Eq. (14) or other. The binary CH covariance filter produces the required impulse response of a continuous phase-only CH covariance filter.

Table 1 shows the correlation peak values obtained by the optical experiments. Objects 1, 6 and 8 were space shuttles rotated by various angles, and the other numbers correspons to other aircraft. All the data were normalized by the peak intensity of image No.1. The filters were made and tested under slightly different conditions so it was difficult to compare absolute values of the peak intensities from different filters. The phase-only filters were encoded as CGHs. The binary CH covariance filter is written directly on photographic film. Their correlation peaks were therefore in the off-axis diffraction orders.

It is easy to see that the covariance filter gave results that were superior to the others from the point of view of discrimination ability.

Table 1. Normalized output peak intensities obtained by optical filtering.

	CHF	POCHF	CHCF	POCHCF	BCCHCF
1	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
2	0.91	*1.01*	0.58	0.77	*0.90*
3	0.48	0.46	0.41	0.61	0.55
4	0.85	0.86	*0.66*	0.69	0.54
5	*1.13*	1.00	0.45	*0.79*	0.83
6	**0.99**	**0.92**	**0.86**	**0.77**	**0.86**
7	0.57	0.67	0.46	0.66	0.41
8	**0.99**	**1.01**	**1.00**	**1.00**	**0.98**
9	0.87	0.80	0.60	0.71	0.81

coordinate transformation

An alternative invariant pattern recognition method is to use a coordinate transformation system. The problem was that existing optical coordinate transforming systems do not yield very good results, so we decided to develop our own rectangular to polar coordinate transformation system. The idea we used is to have an array of cells where each cell redirect the light to a new corresponding cell in the transformed plane. In the first experiments, we used a periodic array of cells . This was a computer simulation, and it illustrated one of the problems of coordinate transformations: non-uniform sampling. The samples in the transform plane were not equally spaced.

So we devised a non-uniform sampling grid that is nonuniform in both the object plane and in the coordinate-transformed plane, which results in a much more acceptable sampling. This device is shown in Fig. 3, and the coordinate-transformed samples are shown on the right.

The device was calculated by computer, and was printed by a high-resolution commercial laser printer. The device is used by placing it behind an object, and the light from each elementary cell of the object is diffracted into the corresponding area on the transform plane. Note that the device is object-independent and can be used for any object. Its resolution is about 32x32 pixels, but this could be increased by an order of magnitude using diffractive optics techniques.

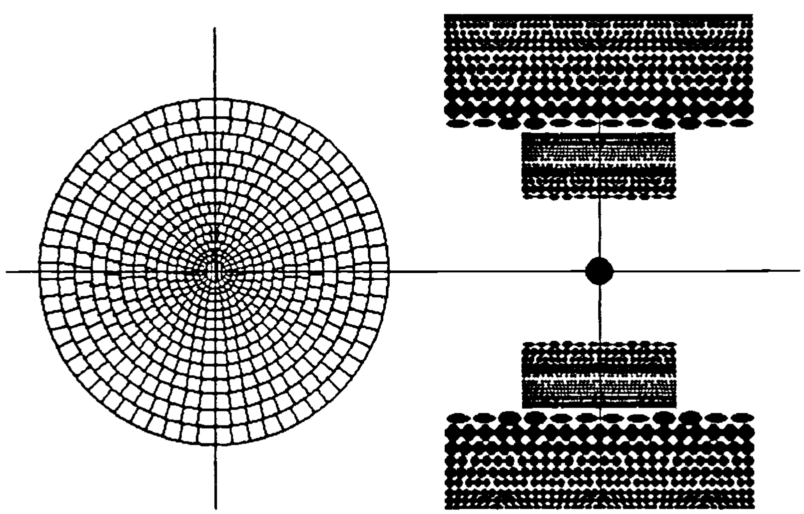

Figure 3
Coordinate transformation with a nonuniform sampling grid and its output

The coordinate transformer was then used in the optical system shown in Fig. 4.

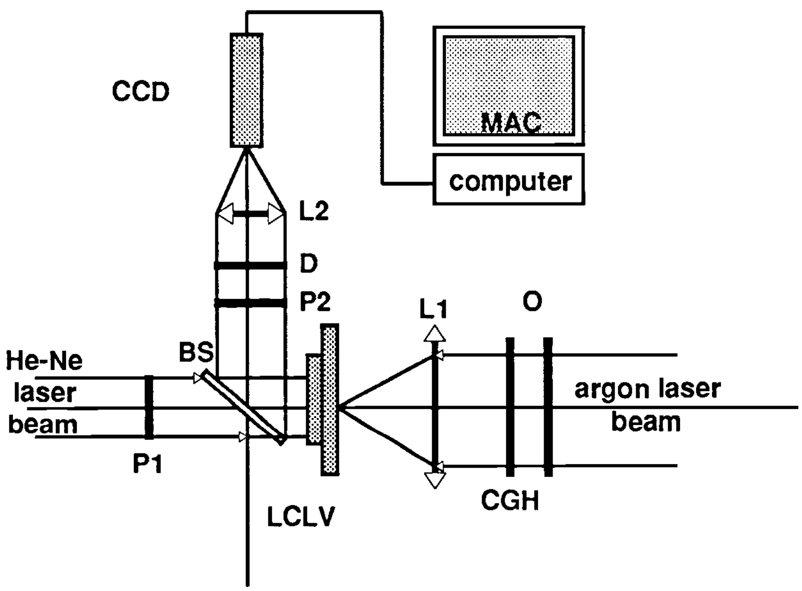

Figure 4: Coordinate transforming pattern classification system

The Object O on the right is transilluminated by an argon laser, and the coordinate-transformed pattern appears on the liquid-crystal light valve (LCLV); the He-Ne laser beam from the left gathers the information on the LCLV and Fourier transforms the pattern by means of lens L_2. P_1 and P_2 are crossed polarizers required to transform the polarization-coded output of the LCLV into amplitude variations.A CCD camera then inputs the Fourier data into a computer for classification.

Although the system was successfully used for invariant recognition, we found that better results were used if a cylindrical lens was used for L_2 instead of a spherical lens. Table 2 shows some of the results obtained for the three letters A, B, and C using a cylindrical lens.

The numbers in the left-hand column correspond tothe orientations of the letters; the other numbers correspond to the normalized differences between the measured results, so larger values correspond to larger differences. A value of one in the table means that there was no difference measured between the input object and the unrotated input object. Perfect recognition would mean that all the rotated values for one object would yield ones, and the table shows that this is indeed the case. In addition, there were no false alarms, since all the cross-values are larger than 1.33. Experiments using more letters were also carried out with similar results. For letters that are difficult to discriminate such as L and I, more refined techniques will have to be used than the simple difference method used here.

Table 2: Experimental results

	a000	b000	c000
a275	**1.00**	2.02	3.30
a315	**1.00**	3.07	5.14
a045	**1.00**	2.71	4.42
a085	**1.00**	2.29	3.75
b275	1.47	**1.00**	2.12
b315	2.07	**1.00**	2.60
b045	1.81	**1.00**	2.44
b085	1.35	**1.00**	1.86
c275	1.75	1.33	**1.00**
c315	2.30	1.71	**1.00**
c045	2.02	1.52	**1.00**
c085	1.64	1.28	**1.00**

Circular sampling filter

Another rotation invariant system using a coding somewhat similar to the previous coordinate transformation system is shown in Fig. 5.

A grating is coded onto concentric circular rings so the light from each ring is diffracted in a different direction. The light from each ring is then focused onto a different element of an array of points; each point corresponds to the total intensity of the light going through one ring. The object or its Fourier transform is put before the device. The device performs an operation similar to a ring-wedge detector, but without the need for any electronics except for a detector array at the point array (we used a CCD camera). The ensemble of intensities of the array of points is characteristic of the object, and is invariant under rotation of the object.After we built this system, we found that a similar system had been proposed by Casasent et al.; [5] however these authors had only shown the diffraction pattern used, and had not studied their capability for pattern classification.

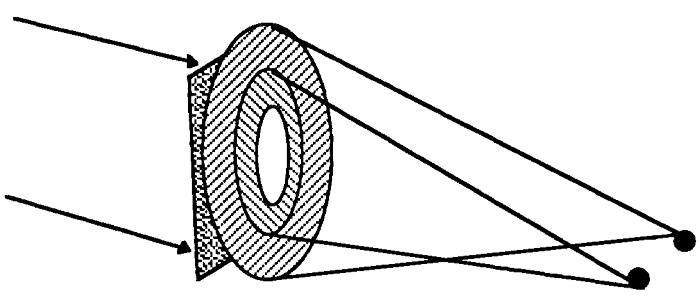

Figure 5. Circular sampling filter

The previous authors had also considered the problem of nonparallel light inherent when the Fourier transform is put before the device instead of the object itself. They had proposed using a liquid-crystal light valve in a manner similar to Fig. 4 to generate parallel light, but had not implemented it. In our experiments, we did this and obtained god results slightly better than those of Table 1.

M-r image

In all the methods using Circular harmonic components previously used, only the information from a restricted set of CHC components is used. We have devised a method that uses all the information from all the CHC components.

First it is necessary to generate what we call the m-r image of the object: imagine all the 1-dimensional CHC components set side-to-side in order of increasing order m. This is represented in Fig. 6 as a 3-D plot, where one axis is the radius r, and the other is the CHC order m. The object used was a space shuttle.

Now if this plot is correlated with the m-r image corresponding to an unknown target, the correlation peak obtained will be invariant under rotation of the target, since each CHC component has this invariance. But since all the CHC components are used (in fact we used 32 orders, and because of symmetry, did not use the negative orders), the correlation will be very selective. The results of correlating the m-r image of the space shuttle with the 6 other aircraft and a space shuttle rotated by 90 degrees used in the other experiments are shown in Table 3.

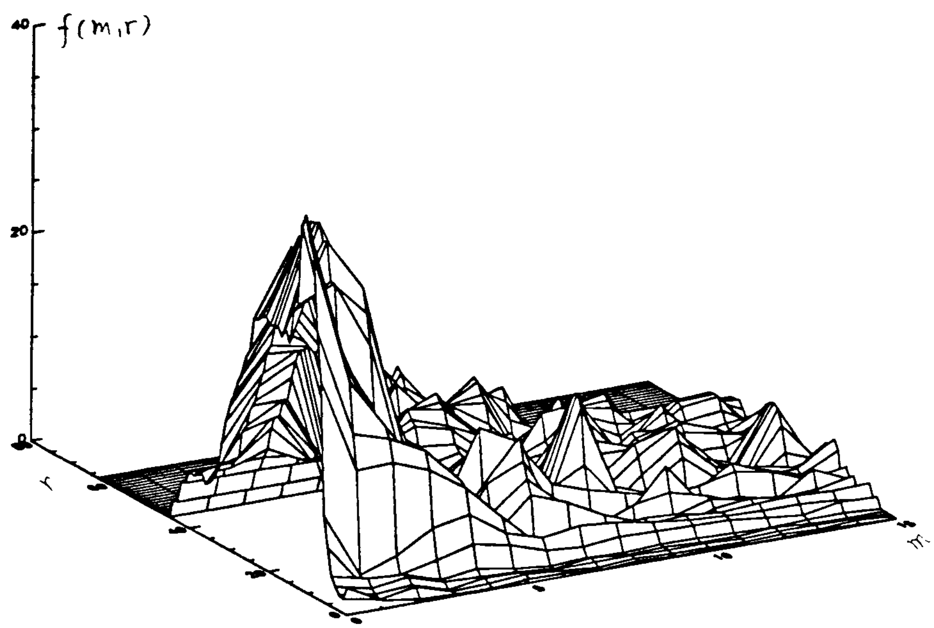

Figure 6. The m-r plot for a space shuttle

Table 3
M-r image correlation results

xf102	xlight	xplan	xsst	Nav090	xx29	xxnav1
-0.0034	0.0744	0.0030	-0.0281	1,000	-0.0087	0.1438

Nav090 represents the rotated space shuttle. the entry xxnav1 corresponds to a space shuttle with the bay doors open, which is considered as a different object because the filter was not designed to recognize it. The table shows that discrimination is extremely good. The disadvantage of this method is that the m-r image of every target must be calculated before carrying out the correlation, which is very time-consuming, but not necessarily prohibitive. The calculation time for this experiment was 30 seconds on a Sun Sparcstation 1. We are investigating ways to speed up the process, including the use of Optics.

Conclusion

We have described some of our recent work in rotation invariant pattern recognition. Some of the other research carried out in our laboratories and involving mostly invariant moments is described in a companion paper by Y. Sheng.

The most promising developments in invariant pattern recognition involving CHC filters involves the use of binary phase-only filters, multiple CHC filters and coordinate-transformation devices. The latter is particularly promising in view of the fact that diffractive optics technology allowing the fabrication of high-quality coordinate transforming devices is becoming available. This technology, combined with techniques described here and in other papers should lead to light, compact and fast invariant pattern recognition systems.

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