

A Generalized Hough-like  
Transformation for Shape Recognition

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## ABSTRACT

A generalization of Hough transform techniques is introduced which can be used to recognize shapes independent of their position or orientation in an image. The transform technique is equivalent to certain conventional template matching procedures, but is, on the average, 10-20 times faster. An experimental study on synthetic images is presented, and applications of the technique to object tracking are discussed.

## 1. Introduction

An important problem in dynamic scene analysis is tracking objects from frame to frame after an initial "lock-in" on an object of interest. A variety of factors contribute to making this problem difficult. They include changing backgrounds as the object moves, say, from a homogeneous into a textured background, and partial obscuration when the object moves behind another object in the scene.

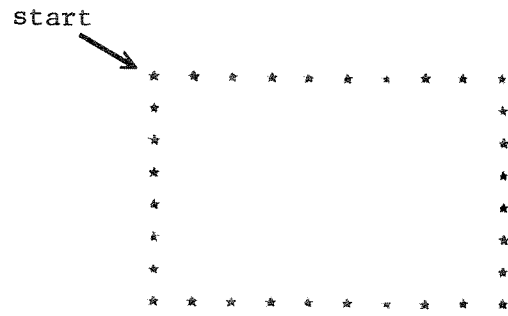
This paper introduces an approach to object tracking which is based on a generalization of Hough transform techniques [1,2] to the recognition of arbitrary planar shapes independent of picture position, orientation and limited scale changes. Section 2 of this paper discusses the technique for position invariant matching. The algorithm described in Section 2 was first introduced in [3]. Section 3 discusses the extension of this approach for orientation and scale invariant matching. Section 4 contains an experimental study which attempts to measure the robustness of the method. It should be noted that ideas similar to the ones presented in this paper have been recently reported in Ballard [4], who in addition discusses utilization of edge slope information (which our algorithms do not) and composite structures based on assemblies of shapes. This report contains some experimental results and a discussion of rotation and size invariant matching which complement the results reported by Ballard [4].

## 2. Position-Invariant Hough Shape Transforms

Let  $B = \{(X_i, Y_i)\}_{i=0}^n$  be a list of boundary points for the shape to be tracked. Let  $P = (X, Y)$  be any point (in practice, a central point such as the centroid of  $B$  will be computationally convenient to use as  $p$ ). Then the Hough-representation of  $B$  using  $p$ ,  $H(B, p)$  is the sequence of vectors  $\{\vec{d}_i\}_{i=0}^n$  where  $dx_i = X - X_i$  and  $dy_i = Y - Y_i$ . Figure 1 contains a simple example for a rectangle shape.

Now, suppose we are given an image,  $f$ , which contains an instance of the shape whose boundary is described by  $B$ . A second array,  $h$ , which is an array of accumulators that is registered with  $f$ , will be used to compute the transform of  $f$  with respect to  $H(B, p)$ . After the transform is computed, points in  $h$  with high values will correspond to hypothetical locations of  $p$  in  $f$ . Of course, once the location of  $p$  is known,  $B$  can be recovered from  $H(B, p)$ . The array  $h$  will be larger than the array of  $f$ , since if the shape is only partly contained in  $f$ , the point  $p$  might be outside of  $f$ .

The transform,  $h$ , is computed by first applying an edge detector to  $f$  to produce an edge map,  $e$ , of  $f$ . Each edge,  $e_i$ , in  $e$  is a potential element of the set  $B$ . Although contrast and orientation information may limit the subset of  $B$  to which any  $e_i$  may correspond, there is, in general, no way to determine to which element of  $B$  any  $e_i$  corresponds without considering the position of all the other  $e_i$ .



DXI	DYI
3	4
3	3
3	2
3	1
3	0
3	-1
3	-2
3	-3
3	-4
3	-5
2	4
2	-5
1	4
1	-5
0	4
0	-5
-1	4
-1	-5
-2	4
-2	-5
-3	4
-3	-5
-4	4
-4	3
-4	2
-4	1
-4	0
-4	-1
-4	-2
-4	-3
-4	-4
-4	-5

Figure 1. Hough representation of a simple rectangle

Therefore, each edge element,  $e_i$ , is compared to each vector in  $H(B,p)$  to compute a possible location for  $p$ , and that location is incremented in the transform,  $h$ . That is,  $h$  is computed by the following simple algorithm, MATCH 1, originally reported in [3]:

```

For each  $e_i = (X_i, Y_i)$  in  $e$  do
  For each  $d_j = (dx_j, dy_j)$  in  $H(B,p)$  do
     $h(X_i + dx_j, Y_i + dy_j) :=$ 
       $h(X_i + dx_j, Y_i + dy_j) + 1;$ 

```

Notice that the result of applying this algorithm is exactly the same as correlating a binary image representation of  $B$  with the binary edge map,  $e$  (this was originally pointed out by Sklansky [5]; see Ballard [4]). The correlation, however, is based on considering all points in  $h$  as potential location for  $p$ , and then for each location counting the number of appropriately positioned (according to  $H(B,p)$ ) edges in  $e$ . The advantage of the transform algorithm is computational efficiency. If  $h$  is an  $rxs$  picture, then to compute  $h$  using a standard correlation algorithm requires  $O(rxsxn)$  operations - i.e., for each of  $rxs$  potential location for  $p$ , we must check the  $n$  locations of possible edge points determined by  $H(B,p)$ . Algorithm MATCH 1, on the other hand, requires  $O(|e|xn)$  operations where  $|e|$  is the number of edges detected. Since, in practice, edges account for no more than 5%-10% of any image, algorithm MATCH 1 will result in speed-ups of 10 to 20 over conventional correlation procedures.

To illustrate the procedure, an image was created in which the rectangle described in Figure 1 was inserted at an arbitrary

location. Figure 2 contains the transform of that image. Notice that the peak of the transform occurs at the location of  $p$ .





### 3. Rotation Invariant Matching

In the preceding section we assumed that the orientation of B in f was known. Suppose, on the contrary, that it is not known (this can occur, e.g., while tracking a vehicle, from above, which is moving along an unpredictable path). In this case, when we hypothesize that a particular  $e_i$  corresponds to some  $d_j$ , the strongest conclusion we can draw is that if  $e_i$  were indeed  $d_j$ , then p must lie somewhere on the circle of radius

$R_j = \sqrt{dX_j^2 + dY_j^2}$  centered at  $e_i$ . The following algorithm, algorithm

MATCH 2, accomplishes rotation invariant matching.

For each  $e_i = (X_i, Y_i)$  in e do

For each  $d_j$  in H(B,p) do

$R_j = \sqrt{dX_j^2 + dY_j^2}$   
For  $\theta = 0, 2\pi$ , by  $d\theta$  do begin

$$h_x = R_j * \cos \theta + X_i;$$

$$h_y = R_j * \sin \theta + Y_i,$$

$$H(h_x, h_y) = H(h_x, h_y) + 1$$

end

Unlike algorithm MATCH 1 where the results were identical to what could have been obtained by correlating the binary image e with a binary image representation of B, the results of applying algorithm B are not identical to what would be obtained by individually correlating  $m=2\pi/d\theta$

rotated versions of  $H$  with  $e$ , and then choosing the maximum match amongst the  $m$  correlation planes. Instead, algorithm MATCH 2 adds the  $m$  correlation planes together to obtain a single plane ( $h$ ). The position in this plane having maximum value is then interpreted as the location of  $B$ .

Notice that if prior information is available concerning the orientation of the object in the frame, then this information can be easily taken advantage of by the algorithm. One simply modifies the bounds on the inner FOR loop so that only a circular arc in  $h$ , rather than an entire circle, is incremented. In tracking vehicles moving along roads, e.g., one can ordinarily assume that between the successive frames the vehicle will not make a turn sharper than  $\pi/2$ , since roads do not bend that quickly. Therefore, the bounds on the inner FOR loop can, in this situation, be modified to  $-\pi/2$  to  $\pi/2$ .

Although algorithm MATCH 2 can detect an arbitrarily oriented version of a shape, it does not compute the orientation of the shape. This could be done by maintaining  $m$  separate correlation plans and applying algorithm MATCH 1 to  $m$  rotated versions of  $H(B,p)$ . In practice, however, this approach has unacceptable storage and time requirements.

Instead, it is possible to construct a second transform of  $B$ , but with respect to a different point,  $p'$ . If  $(i,j)$  is the point in the transform of  $H(B,p)$  having maximal value, and if  $(i',j')$  is the point in the transform of  $H(B,p)$  having maximal value (notice that these values must, in principle, be identical), then the direction from  $(i,j)$  to  $(i',j')$  gives the direction from  $p$  to  $p'$  in  $f$ . Points  $p$  and  $p'$  should be chosen to be sufficiently far apart so that small errors in the locations of the

maxima in the transforms  $h$  of  $H(B,p)$  and  $h'$  of  $H(B,p')$  do not lead to large errors in the computed orientation of  $B$ .

One last modification to the matching algorithms worth mentioning is the incorporation of a "smoothing" step. The purpose of this is to overcome the slight mispositioning of edges by the edge detection algorithm; this will tend to distribute the contribution from the detected edges of the shape to a small neighborhood around the actual location of  $p$ . To overcome this, rather than simply incrementing a single location,  $(h_x, h_y)$  in  $h$ , one can increment a  $k \times k$  neighborhood (with  $k$  ordinarily 3) of  $h(h_x, h_y)$ . Notice that this is equivalent to applying either of the match algorithms, and then replacing  $h(h_x, h_y)$  by the sum of its  $k \times k$  neighborhood. However, performing the neighborhood increment in the match algorithm requires only an additional  $8|e|$  operation (for  $k=3$ ), while applying the summation as a post-process to  $h$  requires  $4n^2$  operations (using a fast square neighborhood summation algorithm). Since, as mentioned previously,  $|e|$  is no more than  $.05n^2 - .1n^2$ , the former approach is computationally less costly.

Notice that the algorithms can also be modified in a straightforward way to deal with a limited range of scale information. Suppose, e.g., it is known that the object in the image is  $S$  times the size of the model, with  $S \in [S_1, S_2]$  (note  $S_1 < S_2$  and  $0 < S_1$ ). Then, in algorithm MATCH 1 rather than just incrementing a single point at distance  $d = \sqrt{d_x^2 + d_y^2}$  from an edge point, one marks all points in direction  $\tan^{-1} d_y/d_x$  and with

distances  $d' \in [S_1 d, S_2 d]$ . For rotation invariant matching, rather than incrementing a circle (or a circular arc if constraints on the orientation are available) one increments a ring of inner radius  $S_1 d$  and outer radius  $S_2 d$  (or the intersection of the ring with a wedge). Again, different correlation planes can be maintained for different values of the scale, but this increases the storage and computational requirements of the matching algorithms. Note that this idea was employed by Davis [6] to detect circles of various sizes using Hough transform techniques.

#### 4. Experimental Study

A simple experiment using synthesized images was designed and performed to measure the robustness of the shape recognition procedures. In the first experiment orientation was controlled, while in the second experiment orientation was allowed to vary.

The data generated were binary images which are intended to represent the result of applying an edge detection procedure to a grey-scale image. The rectangle shown in Figure 1 was used as the shape to be detected. The images are generated by choosing a random angle for rotating the shape (for experiment 1 the angle was fixed at 0) and then choosing an arbitrary image position for point  $p$  and "painting" the shape around that position. The unreliability of the edge detector is modeled by then randomly reversing  $100 \times p$  percent of the image points from 0 to 1 or 1 to 0. Figure 3 a-d shows representative images obtained for  $P=.40$  and  $.50$ .

The transform at the degraded binary image is then computed and the shape was defined to be correctly matched if the location of the peak of the transform is within one pixel of the actual location of the shape. Figures 4 a-d contain the transforms for Figures 3 a-d. For each value of  $P$ , 15 images were constructed. Tables 1-2 list the probability of error as a function of  $p$  for fixed orientation (Table 1) and orientation invariant matching (Table 2).

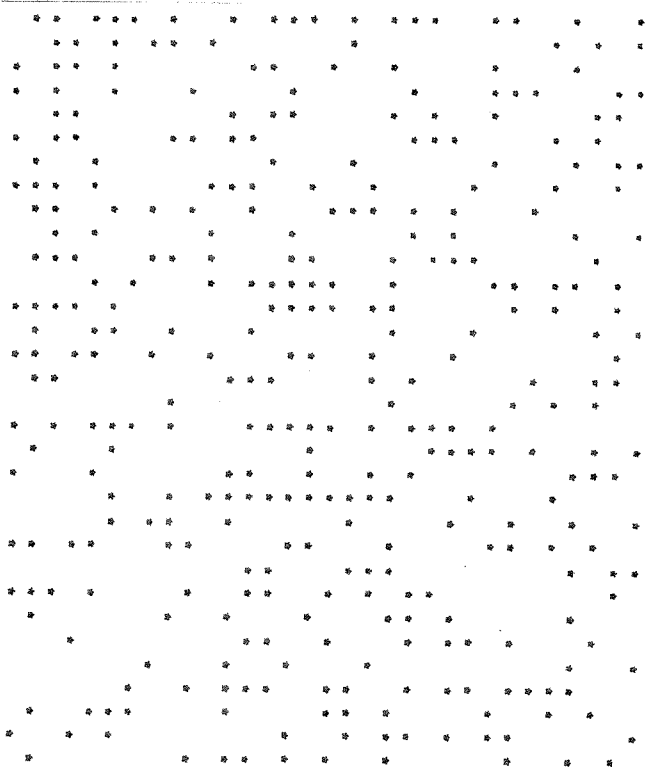


Figure 3a - p=40, orientation fixed

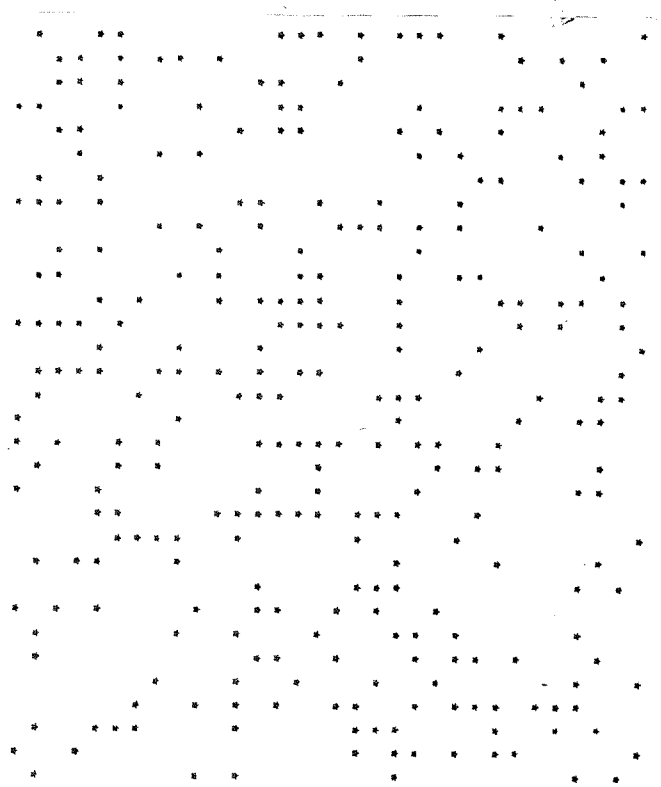


Figure 3b - p=40, orientation random

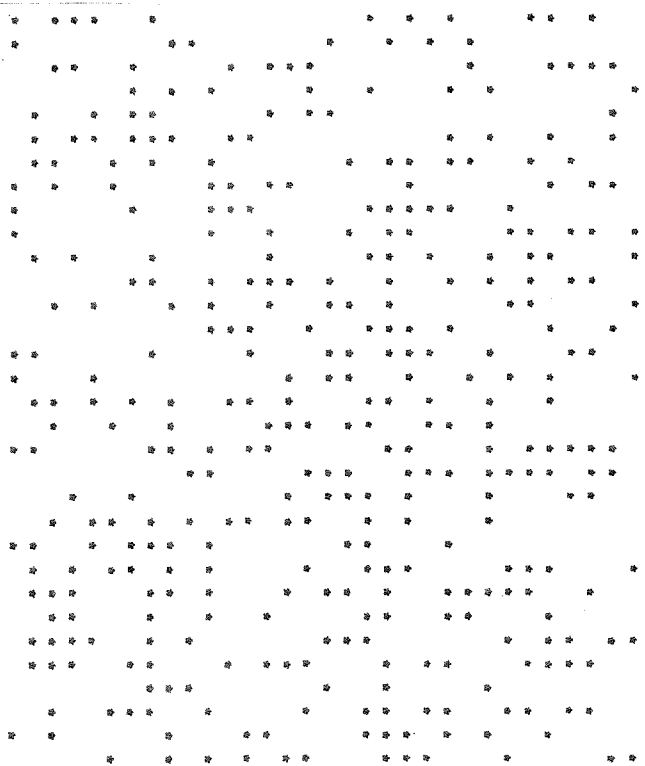


Figure 3c - p=50, orientation fixed

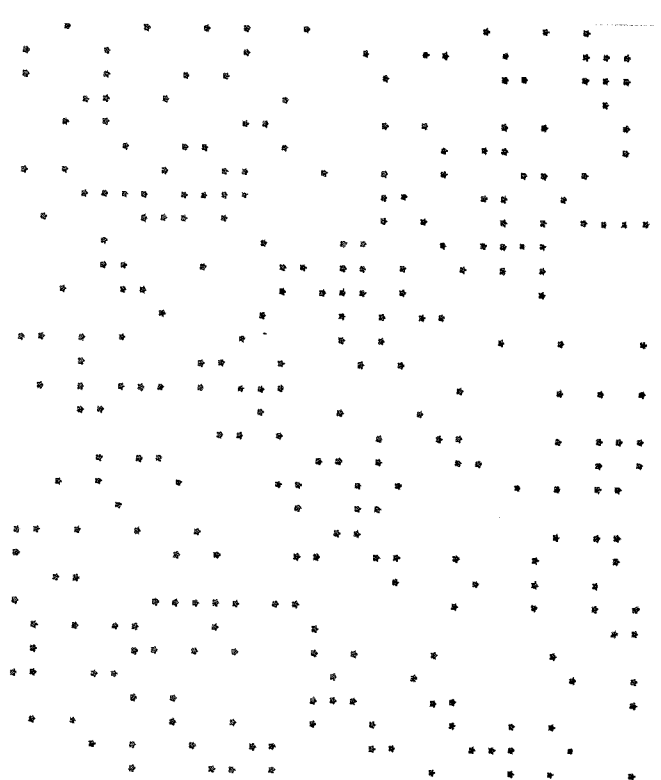


Figure 3d - p=50, orientation random

Figure 3. Noisy shapes in noise background

DELETED POINT OF INTEREST IS (	16,	15),	MAXIMUM =	21
3	5	5	2	5
3	4	4	2	4
3	4	5	2	4
7	3	7	5	6
7	3	8	6	7
3	10	10	8	10
5	7	9	7	9
5	6	6	7	8
6	9	8	7	8
6	9	8	7	8
5	4	4	10	10
5	4	4	11	11
7	7	7	11	11
7	8	8	12	12
3	8	8	10	10
3	8	8	11	11
3	8	8	12	12
3	2	2	16	16
3	2	2	17	17
6	7	7	15	15
6	6	6	15	15
6	6	6	16	16
6	6	6	17	17
3	10	10	12	12
3	10	10	13	13
3	10	10	14	14
3	10	10	15	15
3	10	10	16	16
3	10	10	17	17
3	10	10	18	18
3	10	10	19	19
3	10	10	20	20
3	10	10	21	21
3	10	10	22	22
3	10	10	23	23
3	10	10	24	24
3	10	10	25	25
3	10	10	26	26
3	10	10	27	27
3	10	10	28	28
3	10	10	29	29
3	10	10	30	30
3	10	10	31	31
3	10	10	32	32
3	10	10	33	33
3	10	10	34	34
3	10	10	35	35
3	10	10	36	36
3	10	10	37	37
3	10	10	38	38
3	10	10	39	39
3	10	10	40	40
3	10	10	41	41
3	10	10	42	42
3	10	10	43	43
3	10	10	44	44
3	10	10	45	45
3	10	10	46	46
3	10	10	47	47
3	10	10	48	48
3	10	10	49	49
3	10	10	50	50
3	10	10	51	51
3	10	10	52	52
3	10	10	53	53
3	10	10	54	54
3	10	10	55	55
3	10	10	56	56
3	10	10	57	57
3	10	10	58	58
3	10	10	59	59
3	10	10	60	60
3	10	10	61	61
3	10	10	62	62
3	10	10	63	63
3	10	10	64	64
3	10	10	65	65
3	10	10	66	66
3	10	10	67	67
3	10	10	68	68
3	10	10	69	69
3	10	10	70	70
3	10	10	71	71
3	10	10	72	72
3	10	10	73	73
3	10	10	74	74
3	10	10	75	75
3	10	10	76	76
3	10	10	77	77
3	10	10	78	78
3	10	10	79	79
3	10	10	80	80
3	10	10	81	81
3	10	10	82	82
3	10	10	83	83
3	10	10	84	84
3	10	10	85	85
3	10	10	86	86
3	10	10	87	87
3	10	10	88	88
3	10	10	89	89
3	10	10	90	90
3	10	10	91	91
3	10	10	92	92
3	10	10	93	93
3	10	10	94	94
3	10	10	95	95
3	10	10	96	96
3	10	10	97	97
3	10	10	98	98
3	10	10	99	99
3	10	10	100	100

Figure 4a -- Transform of Figure 3a.







SKILL:	ORIENTATION	INVARIANCE	DETECTED	POINT OF	INTEREST IS (	16,	15)	MAXIMUM =	438																						
73	78	95	110	132	145	162	180	182	188	175	170	157	182	206	197	186	153	144	149	132	149	203	202	188	176	154	156	124	121	117	102
64	78	87	110	128	151	199	198	185	209	226	209	175	220	234	223	185	163	170	172	168	201	257	242	215	185	159	164	142	132	142	133
68	95	105	129	135	203	212	223	219	210	214	210	210	242	302	285	218	180	208	218	224	241	298	289	220	187	186	172	159	128	167	151
102	118	139	156	207	234	258	233	212	205	215	220	219	276	336	311	247	214	224	235	233	248	323	330	258	197	188	197	180	154	150	155
119	154	186	202	250	276	292	271	229	237	252	248	239	297	362	361	287	226	216	259	248	263	339	358	319	254	213	229	218	185	162	175
123	173	184	220	272	313	336	303	264	261	297	275	285	316	381	371	331	263	273	312	293	311	346	349	310	286	230	237	252	241	211	198
140	169	205	216	261	310	332	318	300	313	343	350	301	329	378	397	350	328	316	355	386	354	340	343	299	267	246	261	300	274	254	196
126	167	182	212	270	304	315	338	333	349	373	376	376	393	414	409	374	331	340	371	406	373	379	352	327	319	325	324	324	311	257	209
123	162	180	219	264	291	303	308	317	353	399	407	419	413	418	427	374	334	352	393	397	382	371	390	411	377	384	383	362	287	225	201
118	148	178	204	255	283	275	296	290	358	401	418	426	426	411	411	374	350	374	407	420	419	385	417	405	423	419	363	342	256	184	150
92	140	182	202	247	267	288	265	277	329	365	384	413	433	412	368	362	377	401	407	433	417	396	403	376	404	401	351	285	243	181	154
107	159	199	236	296	294	254	229	244	275	332	352	393	391	377	384	357	419	424	411	412	436	387	367	363	395	355	348	274	254	191	173
122	176	219	267	315	316	250	234	250	293	308	297	359	362	389	376	390	407	433	423	377	373	401	365	378	359	365	319	260	238	205	177
139	148	201	236	321	322	293	279	300	323	345	335	340	352	374	381	414	401	409	402	370	329	335	350	378	362	353	322	288	231	222	182
112	135	164	209	261	304	323	337	360	358	370	374	359	378	382	406	435	411	422	395	373	329	313	317	340	326	336	323	309	251	228	197
116	96	127	182	223	296	354	389	396	359	365	378	401	395	393	438	427	390	391	388	386	377	334	299	310	321	297	284	277	259	249	219
123	123	148	154	210	289	346	405	408	397	396	412	377	402	381	416	413	388	338	361	384	392	378	356	340	341	317	312	283	251	226	208
142	130	138	191	193	222	315	346	367	376	369	373	363	350	329	364	398	363	332	354	353	386	392	413	371	366	347	294	262	240	219	200
150	157	164	204	192	222	270	291	300	299	291	320	337	308	324	363	371	371	346	334	355	388	398	392	357	371	352	316	261	259	167	173
140	171	219	248	260	227	265	292	274	245	236	298	352	336	324	345	381	371	314	321	368	367	393	376	369	361	374	330	262	231	181	168
154	191	241	276	275	282	306	298	263	258	230	248	316	346	351	308	309	339	320	305	348	373	380	351	336	365	370	326	279	232	209	169
155	214	221	257	274	285	282	311	309	284	241	244	283	309	308	313	298	327	314	334	333	355	333	345	299	333	337	315	257	234	195	174
161	195	216	230	240	268	286	311	308	327	289	263	277	304	303	282	291	340	353	323	307	278	312	320	321	305	318	270	243	207	187	153
168	193	206	222	248	253	272	314	318	299	290	285	292	283	276	293	303	307	330	285	295	272	299	306	337	334	320	312	252	199	168	147
167	194	208	214	241	267	279	286	303	305	299	269	258	244	263	271	292	290	303	306	275	291	318	348	363	356	378	342	289	234	167	150
191	193	188	210	240	263	288	326	337	310	290	251	255	233	244	253	286	301	302	302	325	349	358	361	372	394	388	344	287	243	203	173
186	210	203	200	229	260	280	291	294	320	290	252	222	230	226	268	287	285	280	326	375	380	360	334	337	371	352	344	278	242	208	194
183	214	218	211	207	185	233	262	264	252	234	252	236	208	186	221	251	278	276	319	333	362	317	286	293	336	303	278	244	229	232	208
154	201	199	208	214	219	223	192	201	215	245	261	229	187	178	171	192	219	267	302	311	316	287	233	239	297	305	270	233	203	197	175
117	149	188	197	236	223	198	161	185	194	222	225	209	172	140	109	160	195	218	258	288	261	255	227	201	224	260	222	193	174	182	152
96	128	139	160	186	201	189	147	139	159	184	160	151	140	134	109	109	138	211	215	242	234	237	185	164	174	166	155	162	159	154	131
70	104	132	146	168	167	128	116	118	125	135	141	144	131	122	102	104	123	151	190	201	217	221	187	145	147	157	135	138	135	120	101

Figure 4d - Transform of Figure 3d.

<u>P</u>	<u>Prob[error]</u>
.05	0
.10	0
.15	0
.20	0
.25	0
.30	0
.35	0
.40	0
.45	.07
.50	.13
.55	.24
.60	.54

Table 1 - Probability of error for fixed orientation  
shape matching.

<u>P</u>	<u>P(error)</u>
.05	0
.10	0
.15	.07
.20	0
.25	.07
.30	.07
.35	.13
.40	.24
.45	.42
.50	.87
.55	.62
.60	.87

Table 2 - Probability of error for rotation invariant  
matching.

## 5. Conclusion

We have presented a generalization of Hough transform techniques to allow recognition of arbitrary shapes independent of position, orientation and limited scale. The algorithm is an extension of the one presented in [3] and the Hough representation used is similar to, but less general than, the one discussed in [4]. We are currently applying the ideas in this paper to image registration.

References

1. S. Shapiro, "Transformation for the computer detection of curves in noisy pictures," Comp. Graphics and Image Processing, 4, pp. 325-335, 1975.
2. A. Rosenfeld and A. Kak, Digital Picture Processing, Academic Press, N.Y., 1976.
3. P. Merlin and D. Farber, "A parallel mechanism for detecting curves in pictures," IEEEET-Computers, 24, pp. 94-95, 1975.
4. D. Ballard, "Generalizing the Hough Transform to detect arbitrary shapes", Univ. of Rochester Comp. Science, TR-55, Oct., 1977.
5. J. Sklansky, "On the Hough technique for curve detection," IEEEET-Computers, 1977.
6. L. Davis, "Computing the spatial structure of cellular textures," Computer Graphics and Image Processing, II, pp. 111-122, 1979.