# MATH 590: Meshfree Methods Chapter 37: RBF Hermite Interpolation in MATLAB

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Clustered Lagrange Interpolation vs. Hermite Interpolation



# Outline



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We now illustrate the symmetric approach to Hermite interpolation with a set of numerical experiments for first-order Hermite interpolation (i.e., to positional and gradient data) in 2D using the MATLAB program RBFHermite\_2D.m listed below.



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Since derivatives of both the RBFs and the test function need to be included in the program we use the function

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The RBF used in this set of experiments is the multiquadric with shape parameter  $\varepsilon = 6$ .



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- If the same as above, but with q = 0.01h (see the right plot below).



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- 2 Lagrange interpolation to function values at 3*N* clustered points with separation distance q = 0.1h, where *h* is the fill distance of the set of equally spaced points (see the left plot below).
- **(3)** The same as above, but with q = 0.01h (see the right plot below).
- Hermite interpolation to function value, and values of both first-order partial derivatives at the *N* equally spaced points used in the first experiment.



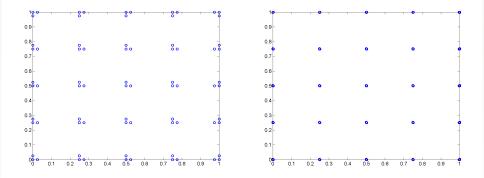


Figure: Clustered point sets with N = 25 basic data points. Cluster size h/10 (left) and cluster size h/100 (right).



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Lagrange interpolation at clustered data sites was accomplished by the same program by adding the following lines to RBFInterpolation2D.m (see RBFInterpolation2Dcluster.m):

```
q = 0.1/(sqrt(N)-1);
grid = linspace(0,1,sqrt(N));
shifted = linspace(q,1+q,sqrt(N)); shifted(end) = 1-q;
[xc1,yc1] = meshgrid(shifted,grid);
[xc2,yc2] = meshgrid(grid,shifted);
dsites = [dsites; xc1(:) yc1(:); xc2(:) yc2(:)];
```



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This is done for the MQ basic function on lines 1–6.



## Program (RBFHermite\_2D.m)

1	rbf = @(e,r) sqrt(1+(e*r).^2); ep = 6; % MQ RBF						
2	dxrbf = @(e,r,dx) dx*e^2./sqrt(1+(e*r).^2);						
3	dyrbf = @(e,r,dy) dy*e^2./sqrt(1+(e*r).^2);						
4a	dxxrbf = @(e,r,dx) e^2*(1+(e*r).^2-(e*dx).^2)./						
4b	(1+(e*r).^2).^(3/2);						
5	$dxyrbf = @(e, r, dx, dy) -e^4 dx dy. / (1 + (e + r) ^2) (3/2);$						
6a	dyyrbf = @(e,r,dy) e^2*(1+(e*r).^2-(e*dy).^2)./						
6b	(1+(e*r).^2).^(3/2);						
7	tf = Q(x, y) (tanh(9*(y-x))+1)/(tanh(9)+1);						
8	$tfDx = @(x,y) 9*(tanh(9*(y-x)).^{2-1})/(tanh(9)+1);$						
9	$tfDy = @(x,y) 9*(1-tanh(9*(y-x)).^2)/(tanh(9)+1);$						
10	<pre>N = 289; dsites = CreatePoints(N,2,'u'); ctrs = dsites;</pre>						
11	<pre>M = 1600; epoints = CreatePoints(M, 2, 'u');</pre>						
12	<pre>DM_eval = DistanceMatrix(epoints,ctrs);</pre>						
13	<pre>dx_eval = DifferenceMatrix(epoints(:,1),ctrs(:,1));</pre>						
14	<pre>dy_eval = Differencematrix(epoints(:,2),ctrs(:,2));</pre>						
15	<pre>DM_data = DistanceMatrix(dsites,ctrs);</pre>						
16	<pre>dx_data = DifferenceMatrix(dsites(:,1),ctrs(:,1));</pre>						
17	<pre>dy_data = DifferenceMatrix(dsites(:,2),ctrs(:,2));</pre>						

```
Program (RBFHermite 2D.m (cont.))
18a rhs = [tf(dsites(:,1),dsites(:,2)); ...
18b
           tfDx(dsites(:,1),dsites(:,2)); ...
18c
           tfDy(dsites(:,1),dsites(:,2))];
19
   exact = tf(epoints(:,1),epoints(:,2));
20
  IM = rbf(ep, DM data);
21
   DxIM = dxrbf(ep,DM data,dx data);
22
   DyIM = dyrbf(ep,DM_data,dy_data);
23
   DxxIM = dxxrbf(ep,DM_data,dx_data);
24
   DxyIM = dxyrbf(ep,DM_data,dx_data,dy_data);
25
   DyyIM = dyyrbf(ep,DM_data,dy_data);
26a IM = [IM - DxIM - DyIM];
26b
         DxIM -DxxIM -DxvIM;
26c
         DyIM -DxyIM -DyyIM];
27
   EM = rbf(ep, DM eval);
28
   DxEM = dxrbf(ep,DM_eval,dx_eval);
29
   DyEM = dyrbf(ep,DM_eval,dy_eval);
30
   EM = [EM - DxEM - DyEM];
31
   Pf = EM * (IM \ rhs);
32
   maxerr = norm(Pf-exact, inf)
```

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#### Program (DifferenceMatrix.m)

- 1 function DM = DifferenceMatrix(datacoord, centercoord)
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```
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#### Remark

This code is used in the block matrices IM and EM in RBFHermite\_2D.m. The minus signs used in columns 2 and 3 of the block matrices reflect differentiation of the basic function with respect to its second variable.



Mesh	Laç	grange	Clustered, $q = 0.1h$	
	RMS-error	cond(A)	RMS-error	cond(A)
3 × 3	1.620492e-001	6.078349e+001	8.471301e-002	9.052247e+003
5  imes 5	6.148258e-002	9.464176e+002	2.733258e-002	3.073957e+005
9  imes 9	8.521994e-003	6.523036e+004	2.678543e-003	8.811980e+007
17  imes 17	2.246810e-004	9.017750e+007	3.138761e-005	3.555214e+012
33  imes 33	2.017643e-006	4.799960e+013	2.925784e-007	6.474324e+020

Table: 2D interpolation with clustered data vs. Hermite interpolation (part 1).



Mesh	Clustered	d, $q = 0.01 h$	Hermite	
	RMS-error	cond(A)	RMS-error	cond(A)
$3 \times 3$ $5 \times 5$ $9 \times 9$ $17 \times 17$	9.084939e-002 2.792157e-002 2.687753e-003 3.147808e-005	8.580483e+005 2.829762e+007 8.325283e+009 3.426489e+014	9.128193e-002 2.794943e-002 2.688346e-003 3.148843e-005	1.326346e+002 2.292450e+003 2.185224e+005 2.486624e+009
33 × 33	8.941613e-006	8.943758e+020	5.731027e-009	6.261336e+018

Table: 2D interpolation with clustered data vs. Hermite interpolation (part 2).



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  - This difference has a significant impact on the numerical stability, and the resulting RMS-errors.
  - The Hermite interpolant is more than three orders of magnitude more accurate than the Lagrange interpolant to clusters with q = h/100.

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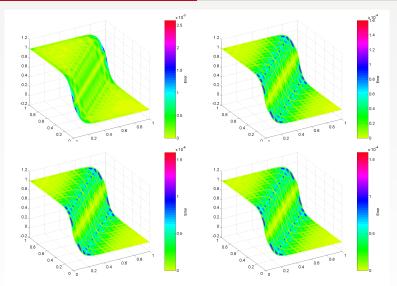


Figure: Fits for clustered interpolants with N = 289 basic data points. Top left to bottom right: Lagrange interpolant, interpolant with cluster size h/10, interpolant with cluster size h/100, Hermite interpolant.

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#### MATH 590 - Chapter 37

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