

Engineering Physics and Mathematics Division

Mathematical Sciences Section

**ARE BILINEAR QUADRILATERALS BETTER
THAN LINEAR TRIANGLES?**

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E. F. D'Azevedo

Abstract

This paper compares the theoretical effectiveness of bilinear approximation over quadrilaterals with linear approximation over triangles. Anisotropic mesh transformation is used to generate asymptotically optimally efficient meshes for piecewise linear interpolation over triangles and bilinear interpolation over quadrilaterals. The theory and numerical results suggest triangles may have a slight advantage over quadrilaterals for interpolating convex data function but bilinear approximation may offer a higher order approximation for saddle-shaped functions on a well-designed mesh.

1. Introduction

This paper compares the theoretical effectiveness of bilinear approximation over quadrilaterals with linear approximation over triangles. The novelty is in the use of anisotropic mesh transformation to generate asymptotically optimally efficient meshes in the comparison. This work is a basic study on optimal meshes with the intention of gaining insight into the more complex meshing problems in finite element analysis. The theory and numerical results suggest triangles may have a slight advantage over quadrilaterals for interpolating convex data functions but bilinear approximation may offer a higher order approximation for saddle-shaped functions on a well-designed mesh.

We consider the problem of interpolating a given smooth data function with continuous piecewise linear triangles or bilinear quadrilaterals over a domain to satisfy a given error tolerance. A mesh that achieves this error tolerance with the *fewest* elements is defined to be optimally efficient. Intuitively, one would expect smaller and denser elements in regions where the function has sharp peaks or large variations. Since each convex quadrilateral can be split across either one of the diagonals into two triangles, one can imagine embedding a refined triangular mesh within the quadrilateral mesh. A question arises as to whether the bilinear approximation over quadrilaterals or linear approximation over triangles is more effective.

To make a fair comparison, we need to compare bilinear approximation over an "optimal" quadrilateral mesh versus linear approximation over an "optimal" triangular mesh. Indeed, §5 contains an example where the way quadrilaterals are decomposed into triangles may yield different interpolation accuracies. Provably optimal triangular meshes [2,4] have been produced by anisotropic mesh transformation.

Anisotropic mesh transformation is emerging as an effective technique for unstructured grid generation where the vertex distribution is highly non-uniform. The central idea is to control the element shapes and sizes by specifying a symmetric metric tensor that measures the approximation error. The metric tensor determines the corresponding anisotropic transformation. The anisotropic mesh is then the image of a uniform mesh of optimal shape elements under the anisotropic transformation. Simpson [8] gives a survey on anisotropic meshes.

Nadler [6], D'Azevedo and Simpson [3,4], and D'Azevedo [2] have studied *local* anisotropic transformation for the generating of optimally efficient triangular meshes. Peraire et al. [7] applied anisotropic transformation in mesh generation for dynamic remeshing in solving compressible flow problems. In these works, piecewise linear approximation of a quadratic function is used as the model for local analysis. In this paper we extend a similar analysis to bilinear approximation on quadrilateral patches.

An outline of the paper follows. In §2, we review the key ideas in [2] for generating optimally efficient triangular meshes. In §3, we consider error properties of bilinear interpolation. We

consider the optimal geometry for quadrilateral patches in §4. We compare the effectiveness of quadrilaterals versus triangular meshes using the local quadratic model in §5. Section 6 contains extensions to hexahedral bricks in three dimensions. Numerical experiments and the results are described in §7. Finally §8 gives a brief summary.

2. Triangular Patch

In this section, we review the basic techniques in determining optimal triangle geometry used in [2]. We show a linear transformation of a regular mesh of optimal-shape triangles yields an optimally efficient mesh for interpolating a quadratic function.

2.1. Quadratic Model

Given the data values at the three vertices of a triangle, the piecewise linear interpolant

$$p_t(x, y) = p_0 + p_1x + p_2y, \quad p_t(x_i, y_i) = f_i$$

can be determined by solving the 3×3 system of linear equations,

$$\begin{bmatrix} 1 & x_1 & y_1 \\ 1 & x_2 & y_2 \\ 1 & x_3 & y_3 \end{bmatrix} \begin{bmatrix} p_0 \\ p_1 \\ p_2 \end{bmatrix} = \begin{bmatrix} f_1 \\ f_2 \\ f_3 \end{bmatrix}$$

Note the determinant of the above matrix is two times the area of the triangle, hence we have a nonsingular system for a nondegenerate triangle.

We shall consider a local analysis where we assume the data function $f(x, y)$ is well approximated by its quadratic Taylor expansion,

$$f(x + dx, y + dy) \approx f(x, y) + \nabla f(x, y)[dx, dy] + \frac{1}{2}[dx, dy]H(x, y)[dx, dy]^t. \quad (1)$$

Let the error formula be $E_T(x, y) = p_t(x, y) - f(x, y)$. By our assumption, $E_T(x, y)$ is a quadratic function and level curves for $E_T(x, y) = c$ form a family of conics with a common center at (x_c, y_c) . They form a family of ellipses if $\det(H) > 0$, and hyperbolas if $\det(H) < 0$. Note by the interpolation condition, the curve $E_T(x, y) = 0$ passes through all vertices of the triangle. If $\det(H) > 0$ (conic is ellipse) then $E_T(x, y)$ attains the local maximum at the center (x_c, y_c) ; otherwise, $\det(H) < 0$ (conic is hyperbola) the maximum error is attained at the midpoint of an edge. The error at a displacement from the center is given by

$$E_T(x_c + dx, y_c + dy) = \mathcal{E}_T - \frac{1}{2}[dx, dy]H[dx, dy]^t, \quad \mathcal{E}_T = E_T(x_c, y_c). \quad (2)$$

The key insight in [2] is in interpreting the Hessian matrix H in (2) as a symmetric metric tensor. Let the symmetric Hessian matrix be diagonalizable as

$$\begin{aligned} H &= Q^t \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} Q = S^t \begin{bmatrix} 1 & 0 \\ 0 & \epsilon \end{bmatrix} S, \quad \text{where } \epsilon = \text{sign}(\det(H)), \\ S &= \begin{bmatrix} \sqrt{|\lambda_1|} & 0 \\ 0 & \sqrt{|\lambda_2|} \end{bmatrix} Q. \end{aligned} \quad (3)$$

Under this transformation S , the expression $[dx, dy]H[dx, dy]^t$ reduces to $(d\tilde{x})^2 + \epsilon(d\tilde{y})^2$, where $[\tilde{x}, \tilde{y}]^t = S[x, y]^t$. The error function can be rewritten as

$$\begin{aligned} E_T(x_c + dx, y_c + dy) &= \mathcal{E}_T - \frac{1}{2}[dx, dy]H[dx, dy]^t \\ &= \mathcal{E}_T - \frac{1}{2}((d\tilde{x})^2 + \epsilon(d\tilde{y})^2) \\ &= \tilde{E}_T(\tilde{x}_c + d\tilde{x}, \tilde{y}_c + d\tilde{y}), \end{aligned} \quad (4)$$

where $\tilde{E}_T(\tilde{x}, \tilde{y})$ denotes the corresponding error function under transformation S in (\tilde{x}, \tilde{y}) -space. The error expression $\tilde{E}_T(\tilde{x}, \tilde{y})$ has no preferred direction hence we shall call the (\tilde{x}, \tilde{y}) -space the "isotropic" space.

2.2. Optimal shape

In the following, we shall determine the best triangle shape that minimizes the interpolation error. We can determine the "efficiency" of the elements by computing their ratio of Error to Area. A small ratio indicates a more efficient element, i.e. one can achieve a lower error tolerance and tile the domain with about the same number of elements.

We consider first the case $f(x, y)$ is convex ($\det(H) > 0, \epsilon = 1$) and level curves or contours of $\tilde{E}_T(\tilde{x}, \tilde{y})$ are concentric circles given by

$$\tilde{E}_T(\tilde{x}_c + d\tilde{x}, \tilde{y}_c + d\tilde{y}) = \mathcal{E}_T - \frac{1}{2}((d\tilde{x})^2 + (d\tilde{y})^2). \quad (5)$$

Let \tilde{T} be the transformed of triangle T over the isotropic space, with vertices at $(\tilde{x}_1, \tilde{y}_1)$, $(\tilde{x}_2, \tilde{y}_2)$ and $(\tilde{x}_3, \tilde{y}_3)$. The circumcircle of \tilde{T} corresponds to the level curve of value zero. Hence the radius of this circumcircle is $\sqrt{2|\mathcal{E}_T|}$ and relates directly to the maximum error attainable (at the center). We can easily see that an equilateral triangle covers the most area for a fixed circumcircle; therefore an equilateral triangle for \tilde{T} is of optimal-shape.

Consider next the case where $f(x, y)$ is not convex but has a saddle-shaped graph ($\det(H) <$

0, $\epsilon = -1$), then we have

$$\begin{aligned}\tilde{E}_T(\tilde{x}, \tilde{y}) &= \tilde{E}_T(\tilde{x}_c + d\tilde{x}, \tilde{y}_c + d\tilde{y}) \\ &= \mathcal{E}_T - \frac{1}{2} ((d\tilde{x})^2 - (d\tilde{y})^2) \\ &= \mathcal{E}_T - \frac{1}{2} ((\tilde{x} - \tilde{x}_c)^2 - (\tilde{y} - \tilde{y}_c)^2) .\end{aligned}\tag{6}$$

We note that the error function $\tilde{E}_T(\tilde{x}, \tilde{y})$ is a harmonic function and attains its extrema on the boundary of \tilde{T} . By calculus, we can show that the local extrema along edge $(\tilde{x}_i, \tilde{y}_i), (\tilde{x}_j, \tilde{y}_j)$ is attained at the midpoint with value

$$\tilde{E}\left(\frac{\tilde{x}_i + \tilde{x}_j}{2}, \frac{\tilde{y}_i + \tilde{y}_j}{2}\right) = \frac{1}{8} |(\tilde{x}_i - \tilde{x}_j)^2 - (\tilde{y}_i - \tilde{y}_j)^2| .$$

The details for finding the optimal-shape triangle in this case are found in [4]. The optimal-shape triangle geometry that minimizes the efficiency ratio (Error/Area) is not unique. The same maximum error is attained at the mid-point of each edge.

From the above two results on optimal-shape triangles, we see that a *regular* mesh of optimal-shape triangles over the isotropic (\tilde{x}, \tilde{y}) -space corresponds to an optimally efficient mesh over the original (x, y) -space. Every triangle attains the same maximum error; moreover, these triangles cover the most area for the error attained and so are optimally efficient. Since the linear transformation S is basically a rotation followed by a rescaling of coordinate axes, we find the areas of triangles are scaled accordingly. Hence the inverse transformation S^{-1} , maps this regular mesh to produce an optimally efficient mesh in the original (x, y) -space.

2.3. Differential Geometry

The *constant* Hessian Matrix H in (1) determines the coordinate transformation S that maps $[\tilde{x}, \tilde{y}]^t = S[x, y]^t$ so that

$$[dx, dy]H[dx, dy]^t = (d\tilde{x}^2 + \epsilon d\tilde{y}^2) .$$

More generally, we may view H as a metric tensor for measuring the interpolation error $[dx, dy]H[dx, dy]^t$. Thus we need to determine $(\tilde{x}(x, y), \tilde{y}(x, y))$, a *continuous* transformation that satisfies $[dx, dy]H[dx, dy]^t = d\tilde{x}^2 + \epsilon d\tilde{y}^2$. The conditions for finding the anisotropic coordinate transformation $(\tilde{x}(x, y), \tilde{y}(x, y))$ are given by a classical result in differential geometry for characterizing a "flat" space [9]: that the Riemann-Christoffel tensor formed from the metric tensor H is identically zero. In our case, a sufficient condition is for $H = \{h_{ij}\}$ to satisfy

$$K_1 h_{11} + K_2 h_{12} + K_3 h_{22} = 0$$

for some constants K_1, K_2, K_3 . The coordinate transformation $(\tilde{x}(x, y), \tilde{y}(x, y))$ may be found by solving an initial value ordinary differential equation. Again, the inverse transformation $(x(\tilde{x}, \tilde{y}), y(\tilde{x}, \tilde{y}))$ maps a regular mesh of optimal shaped triangles to yield an optimally efficient mesh.

3. Quadrilateral Patch

In this section, we derive the error term for bilinear approximation of a quadratic data function. We first consider a rectangle (x_i, y_i) , $i = 1 \dots 4$ with sides aligned along the coordinate axes. To evaluate the bilinear interpolant $p_\ell(x, y)$, we compute

$$\begin{aligned} p &= \frac{x - x_1}{x_4 - x_1} = \frac{x - x_2}{x_3 - x_2}, \quad q = \frac{y - y_1}{y_4 - y_1} = \frac{y - y_2}{y_3 - y_2} \\ p_\ell(x, y) &= (1 - p)[qf_4 + (1 - q)f_1] + p[qf_3 + (1 - q)f_2], \quad \text{where } f_i = f(x_i, y_i). \end{aligned}$$

Note the existence of xy terms from pq and $p_\ell(x, y)$ is linear on each side. The linear function is determined by the function values at the corresponding vertices.

For a *general* quadrilateral, it is impossible to find a polynomial in x and y which reduces to an arbitrary linear form along the four sides [5]. Hence simply solving for the undetermined coefficients in $p_\ell(x, y) = p_0 + p_1x + p_2y + p_{12}xy$ as done for triangles by imposing the interpolation condition

$$\begin{bmatrix} 1 & x_1 & y_1 & x_1y_1 \\ 1 & x_2 & y_2 & x_2y_2 \\ 1 & x_3 & y_3 & x_3y_3 \\ 1 & x_4 & y_4 & x_4y_4 \end{bmatrix} \begin{bmatrix} p_0 \\ p_1 \\ p_2 \\ p_{12} \end{bmatrix} = \begin{bmatrix} f_1 \\ f_2 \\ f_3 \\ f_4 \end{bmatrix}$$

might fail with a singular matrix.

To overcome this limitation, we shall use the isoparametric formulation (commonly used in finite element analysis) by considering basis functions over the normalized (p, q) -space over the unit square, $0 \leq p, q \leq 1$. Basis functions are

$$\begin{aligned} \phi_1(p, q) &= (1 - p)(1 - q), & \phi_2(p, q) &= p(1 - q), \\ \phi_3(p, q) &= pq, & \phi_4(p, q) &= (1 - p)q \end{aligned} \quad (7)$$

Note that $\phi_1(0, 0) = 1$, $\phi_1(p, q) = 0$ at the other corners and the basis functions sum to one, $\sum_{i=1}^4 \phi_i(p, q) = 1$.

Mapping from (p, q) to the original (x, y) -space is by

$$\begin{aligned} x(p, q) &= x_1\phi_1(p, q) + x_2\phi_2(p, q) + x_3\phi_3(p, q) + x_4\phi_4(p, q) \\ y(p, q) &= y_1\phi_1(p, q) + y_2\phi_2(p, q) + y_3\phi_3(p, q) + y_4\phi_4(p, q) \end{aligned} \quad (8)$$

that maps vertex $(0,0)$ to (x_1, y_1) , vertex $(1,0)$ to (x_2, y_2) , $(1,1)$ to (x_3, y_3) and $(0,1)$ to (x_4, y_4) . The bilinear interpolant (over (p, q) -space) is given by

$$p_i(x(p, q), y(p, q)) = f_1\phi_1(p, q) + f_2\phi_2(p, q) + f_3\phi_3(p, q) + f_4\phi_4(p, q), \quad f_i = f(x_i, y_i)$$

3.1. Restriction to Parallelogram

The isoparametric formulation maps from the canonical (p, q) -space to the original (x, y) -space. For a general quadrilateral patch, it may be difficult to generate the inverse transformation $(p(x, y), q(x, y))$ from the original (x, y) space to the canonical (p, q) space. From (7) and (8), we have

$$x(p, q) = \boxed{(x_1 - x_2 + x_3 - x_4)}pq + (x_2 - x_1)p + (x_4 - x_1)q + x_1,$$

and a similar expression for $y(p, q)$. The isoparametric map is an affine transformation if and only if $\boxed{(x_1 - x_2 + x_3 - x_4) = 0}$ and $\boxed{(y_1 - y_2 + y_3 - y_4) = 0}$, i.e. the quadrilateral patch has parallel sides. Let the parallel sides be

$$\begin{bmatrix} u_x \\ u_y \end{bmatrix} = \begin{bmatrix} x_2 - x_1 \\ y_2 - y_1 \end{bmatrix} = \begin{bmatrix} x_3 - x_4 \\ y_3 - y_4 \end{bmatrix}, \quad \begin{bmatrix} v_x \\ v_y \end{bmatrix} = \begin{bmatrix} x_4 - x_1 \\ y_4 - y_1 \end{bmatrix} = \begin{bmatrix} x_3 - x_2 \\ y_3 - y_2 \end{bmatrix},$$

then (8) simplifies to the affine transformation

$$\begin{bmatrix} x(p, q) \\ y(p, q) \end{bmatrix} = \begin{bmatrix} u_x & v_x \\ u_y & v_y \end{bmatrix} \begin{bmatrix} p \\ q \end{bmatrix} + \begin{bmatrix} x_1 \\ y_1 \end{bmatrix}. \quad (9)$$

The affine transformation is well defined since the area of the quadrilateral patch is

$$\mathcal{A} = (u_x v_y - u_y v_x) = \det \left(\begin{bmatrix} u_x & v_x \\ u_y & v_y \end{bmatrix} \right) \neq 0.$$

Since we intend to apply coordinate transformation to a *regular* quadrilateral mesh in the generation of asymptotically optimal meshes, the consideration of only parallelograms is not a severe restriction.

4. Optimal Shape

In the following, we shall determine the best parallelogram shape that minimizes the interpolation error. The error function for quadratic interpolation is

$$\begin{aligned} E_Q(p, q) &= p_t(x(p, q), y(p, q)) - f(x(p, q), y(p, q)) \\ &= \mathcal{E}_Q - \frac{1}{2} (\mu_1 dp^2 + \mu_2 dq^2) , \end{aligned} \quad (10)$$

where $[p_c, q_c] = [1/2, 1/2]$,

$$\begin{aligned} \mathcal{E}_Q &= E_Q(p_c, q_c) = \frac{1}{8} (\mu_1 + \mu_2) \\ 0 &= \frac{\partial}{\partial p} E_Q(p_c, q_c) = \frac{\partial}{\partial q} E_Q(p_c, q_c) \\ \mu_1 &= [u_x, u_y] H [u_x, u_y]^t, \quad \mu_2 = [v_x, v_y] H [v_x, v_y]^t . \end{aligned} \quad (11)$$

For a convex function ($\det(H) > 0$), μ_1 and μ_2 are positive, hence the maximum error is attained at the center $[p_c, q_c]$.

Under the anisotropic transformation, we have

$$\begin{aligned} [\tilde{u}_x, \tilde{u}_y]^t &= S[u_x, u_y]^t, & [\tilde{v}_x, \tilde{v}_y]^t &= S[v_x, v_y]^t \\ \mu_1 &= \tilde{u}_x^2 + \tilde{u}_y^2 = L_1^2, & \mu_2 &= \tilde{v}_x^2 + \tilde{v}_y^2 = L_2^2 \end{aligned} \quad (12)$$

The area of the quadrilateral in isotropic space is

$$\tilde{\mathcal{A}} = \tilde{u}_x \tilde{v}_y - \tilde{u}_y \tilde{v}_x = L_1 L_2 \sin(\theta) , \quad (13)$$

where θ is the angle at corner $[\tilde{x}_1, \tilde{y}_1]$. Since the anisotropic transformation S is a rotation followed by a rescaling of coordinate axis (3),

$$S = \begin{bmatrix} \sqrt{|\lambda_1|} & 0 \\ 0 & \sqrt{|\lambda_2|} \end{bmatrix} Q ,$$

the area of quadrilateral over isotropic space is $\text{sqrt}(|\lambda_1 \lambda_2|) = \text{sqrt}(|\det(H)|)$ times the area of the quadrilateral over the original (x, y) space,

$$\tilde{\mathcal{A}} = \mathcal{A} \sqrt{|\lambda_1 \lambda_2|} = \mathcal{A} \sqrt{|\det(H)|} .$$

Note that $\det(H)$ is intrinsic to the data function $f(x, y)$.

A square (in any orientation) with $L_1 = L_2$ and $\sin(\theta) = 1$ minimizes the efficiency ratio

(Error/Area),

$$\frac{\mathcal{E}_Q}{\mathcal{A}} = \frac{1}{8} \frac{\mu_1 + \mu_2}{L_1 L_2 \sin(\theta)} = \frac{1}{8} \frac{L_1^2 + L_2^2}{L_1 L_2 \sin(\theta)} \leq \frac{1}{4},$$

and hence is of optimal shape.

If $f(x, y)$ is saddle-shaped ($\det(H) < 0$) the error expression is still

$$E_Q(p, q) = \frac{1}{8}(\mu_1 + \mu_2) - \frac{1}{2}(\mu_1 dp^2 + \mu_2 dq^2).$$

Under the anisotropic transformation S ,

$$\mu_1 = \tilde{u}_x^2 - \tilde{u}_y^2, \quad \mu_2 = \tilde{v}_x^2 - \tilde{v}_y^2.$$

Both μ_1 and μ_2 vanish for

$$[\tilde{u}_x, \tilde{u}_y] = [L, L], \quad [\tilde{v}_x, \tilde{v}_y] = [-L, L], \quad (14)$$

which correspond to a square rotated by $\pi/4$. The above indicates an "exact fit" ($E_Q(p, q) = 0$) if $\mu_1 = \mu_2 = 0$. This suggests bilinear approximation is a better interpolant than simple linear interpolation and the simple quadratic model is inadequate to fully capture the error properties in this case.

To summarize, a square over the isotropic space in any orientation is optimal for the elliptic case, and a square rotated by $\pi/4$ is optimal for the hyperbolic case.

5. Comparison of quadrilaterals versus triangles

In this section, we apply the geometric interpretation of the maximum interpolation error over the transformed isotropic space. We recall that over the isotropic space and for a *convex* data function ($\det(H) > 0$), the maximum error (\mathcal{E}_T) for a triangle is attained at the center of its circum-circle with $\mathcal{E}_T = R^2/2$, where R is radius of the circum-circle. The maximum error (\mathcal{E}_Q) for a parallelogram is attained at its centroid with $\mathcal{E}_Q = (L_1^2 + L_2^2)/8$ where L_1, L_2 are lengths of the sides.

Case 1. Consider the quadrilateral produced by merging two equilateral triangles of length L (see Fig. 1). Radius of circumcircle of $\triangle ABC$ is $R = L/\sqrt{3}$, thus

$$\mathcal{E}_T = R^2/2 = L^2/6, \quad \mathcal{E}_Q(L^2 + L^2)/8 = L^2/4.$$

Thus $\mathcal{E}_Q > \mathcal{E}_T$, so triangles are more accurate.

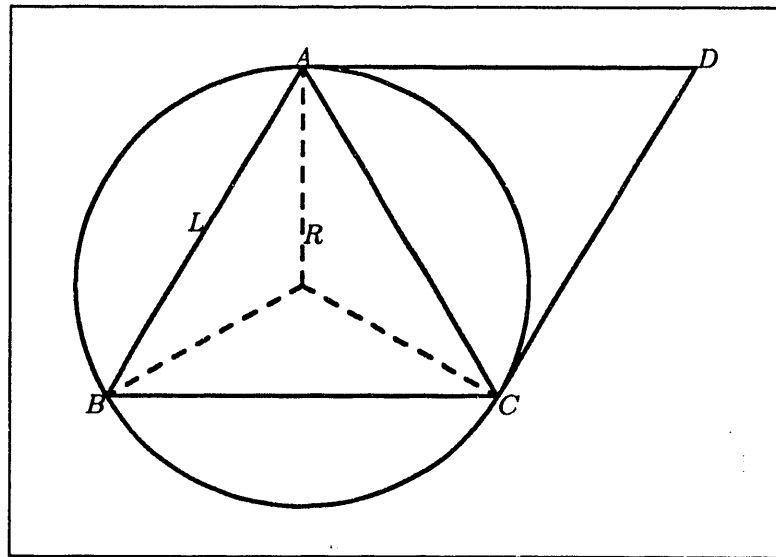


Figure 1: Quadrilateral composed of two equilateral triangles.

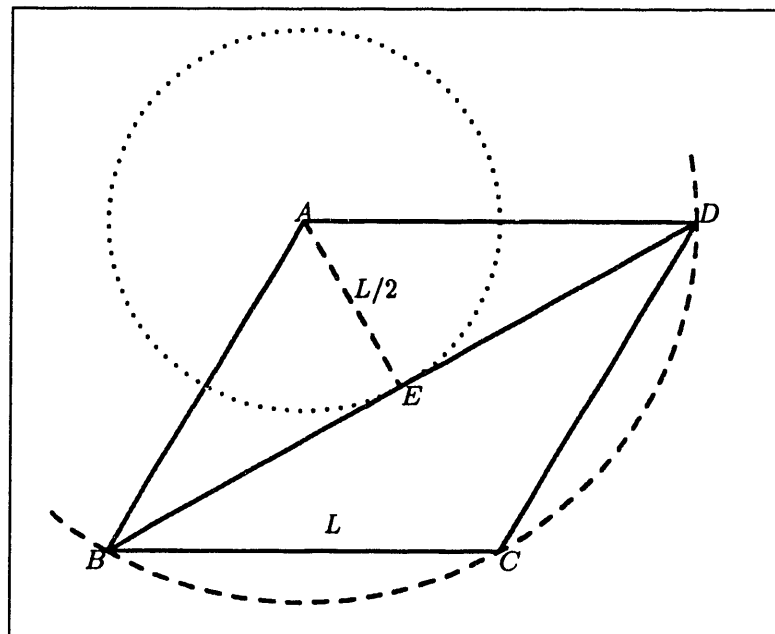


Figure 2: Diagonal BD chosen to decompose quadrilateral.

An earlier work [3] has shown the optimal triangulation incidence is given by the Delaunay triangulation over the isotropic space. If we consider the same quadrilateral with the “wrong” decomposition with diagonal BD (see Fig. 2), the maximum error ΔBCD is attained at vertex E with value $\hat{\mathcal{E}}_T$. Note vertex A is the center of circumcircle for $\triangle BCD$ with radius L . The error attained at vertex E is

$$\begin{aligned}\hat{\mathcal{E}}_T &= \mathcal{E}_T - \frac{1}{2}(d\bar{x}^2 + d\bar{x}^2) \\ &= (L^2/2) - \frac{1}{2}((L/2)^2) = 3L^2/8 .\end{aligned}$$

Thus $\hat{\mathcal{E}}_T = 3L^2/8 > L^2/4 = \mathcal{E}_Q$, and the quadrilateral is more accurate.

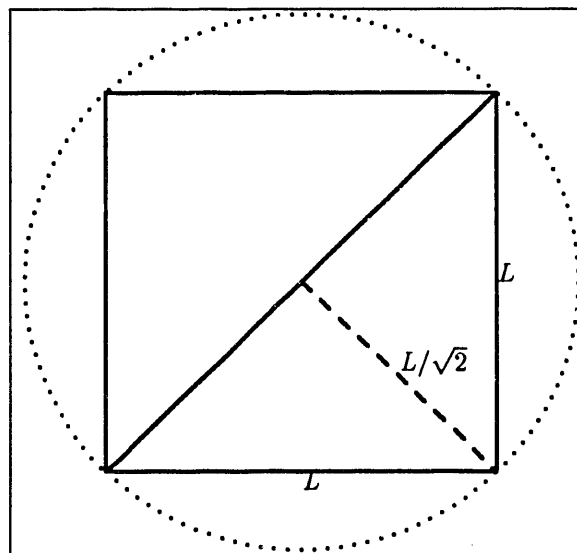


Figure 3: Decomposition of a square.

Case 2. Consider the triangulation produced by decomposing the optimal square configuration for quadrilaterals (see Fig. 3). Radius of circumcircle is $R = L/\sqrt{2}$,

$$\mathcal{E}_Q = (L^2 + L^2)/8 = L^2/4, \quad \mathcal{E}_T = R^2/2 = L^2/4 .$$

Thus $\mathcal{E}_Q = \mathcal{E}_T$.

In fact we can show a stronger result that the refined triangulation will always produce better accuracy for approximating a convex function. Consider the parallelogram in Fig. 4 with $L_1 = |BC|$, $L_2 = |AB|$, $\angle ABC = \theta_1 + \theta_2 \leq \pi/2$ and vertex O is center of circumcircle for

by *element* comparison, the quadrilateral is more efficient. In other words, if we were to approximate a function with either N quadrilaterals or N triangles, quadrilaterals are preferred.

On the other hand, triangles may have advantages over quadrilaterals for finite element computations. Matrix assembly and the solution of the sparse linear equations are commonly the most intensive calculations. If we decompose a quadrilateral mesh into triangles as done above, no extra nodes are introduced. There will be twice as many triangular elements but the resulting assembled matrix has the identical sparsity pattern and the same number of unknowns. Matrix assembly with a general convex quadrilateral usually requires multiple costly evaluations of the Jacobian distortion in numerical quadrature over the isoparametric space, whereas only one preassembled element table is repeatedly reused for all triangles. Thus matrix assembly with triangles may be competitive with assembly with general quadrilaterals. In other words, if computation with N quadrilaterals is as costly as using $2N$ triangles, then triangles are preferred. The actual computation costs may depend on the implementation of the finite element code.

Case 3. Consider the approximation of a saddle-shaped function by a square (unrotated) over the isotropic space. The error formula gives

$$\begin{aligned} E_Q(p_c + dp, q_c + dq) &= \frac{1}{8}(\mu_1 + \mu_2) - \frac{1}{2}(\mu_1 dp^2 + \mu_2 dq^2), \quad (p_c, q_c) = \left(\frac{1}{2}, \frac{1}{2}\right) \\ &= -\frac{1}{2}(dp^2 L^2 - dq^2 L^2), \quad \text{where } \mu_1 = L^2 = -\mu_2, \end{aligned} \quad (16)$$

The maximum error is attained at the mid-point of each edge. Let $(dp, dq) = (1/2, 0)$, then $E_Q = L^2/8$. This gives an efficiency ratio of $1/8 = 0.125$. One optimal triangle shape for saddle-shaped function is the triangle with vertices at $(0, 0)$, $(L, 0)$, $(1/2L, \sqrt{5}/2L)$ over the isotropic space [2], which has area $\sqrt{5}L^2/4$. The maximum error is $L^2/8$ and attained at the mid-point of each edge. This gives an efficiency ratio of $1/(2\sqrt{5}) \approx 0.224$. Thus a mesh with N quadrilaterals should yield roughly the same accuracy as $2N$ triangles. This is verified in the numerical experiments.

6. Extensions to three dimensions

The previous results for quadrilaterals easily extend to trilinear interpolation over hexahedral bricks in three dimensions. Again we consider the isoparametric formulation,

$$x(p, q, r) = \sum_{i=1}^{i=8} x_i \phi_i(p, q, r), \quad p_t(p, q, r) = \sum_{i=1}^{i=8} f_i \phi_i(p, q, r). \quad (17)$$

Note that a deformed brick may not have planar faces since the first three points of a face determine a plane and the fourth corner vertex may not in general lie on this plane. Isoparametric

coordinate mapping $(x(p, q, r), y(p, q, r), z(p, q, r))$ in (17) is affine if the hexahedral brick has parallel sides (and hence planar faces). Let the parallel sides be $[u_x, u_y, u_z]$, $[v_x, v_y, v_z]$, and $[w_x, w_y, w_z]$. The error term has the familiar form

$$\begin{aligned} E_Q(p, q, r) &= E_Q(p_c + dp, q_c + dq, r_c + dr) \\ &= p_\ell(p, q, r) - f(x(p, q, r), y(p, q, r), z(p, q, r)) \\ &= \mathcal{E}_Q - \frac{1}{2}(\mu_1 dp^2 + \mu_2 dq^2 + \mu_3 dr^2) \end{aligned} \quad (18)$$

where

$$\begin{aligned} [p_c, q_c, r_c] &= [1/2, 1/2, 1/2], \quad \mathcal{E}_Q = E_Q(p_c, q_c, r_c) = \frac{1}{8}(\mu_1 + \mu_2 + \mu_3), \\ 0 &= \frac{\partial}{\partial p} E_Q(p_c, q_c, r_c) = \frac{\partial}{\partial q} E_Q(p_c, q_c, r_c) = \frac{\partial}{\partial r} E_Q(p_c, q_c, r_c), \\ \mu_1 &= [u_x, u_y, u_z] H [u_x, u_y, u_z]^t, \quad \mu_2 = [v_x, v_y, v_z] H [v_x, v_y, v_z]^t, \\ \mu_3 &= [w_x, w_y, w_z] H [w_x, w_y, w_z]^t, \end{aligned} \quad (19)$$

For a convex data function ($\det(H) > 0$), maximum error is attained at the center $[p_c, q_c, r_c]$ and the optimal shape is a cube.

For a saddle-shaped function ($\det(H) < 0$),

$$\begin{aligned} \mu_1 &= \tilde{u}_x^2 + \tilde{u}_y^2 - \tilde{u}_z^2, \quad \mu_2 = \tilde{v}_x^2 + \tilde{v}_y^2 - \tilde{v}_z^2, \\ \mu_3 &= \tilde{w}_x^2 + \tilde{w}_y^2 - \tilde{w}_z^2, \end{aligned}$$

over the isotropic space. The hexahedral with coordinates

$$\begin{aligned} [\tilde{u}_x, \tilde{u}_y, \tilde{u}_z] &= [L, 0, L], \quad [\tilde{v}_x, \tilde{v}_y, \tilde{v}_z] = [-L/2, -\sqrt{3}L/2, L], \\ [\tilde{w}_x, \tilde{w}_y, \tilde{w}_z] &= [-L/2, \sqrt{3}L/2, L] \end{aligned} \quad (20)$$

has $\mu_1 = \mu_2 = \mu_3 = 0$ with maximal volume of $3\sqrt{3}/2L^3 \approx 2.598L^3$, hence is of optimal shape.

Direct comparison with tetrahedral meshes as performed in §5 is more complicated since the optimal regular tetrahedron cannot tile 3D-space, and a cube can be decomposed in several ways into 5 or 6 tetrahedra. However, it is still relatively easy to show that the subdivision of a cube into 5 tetrahedra over the isotropic space yields the *same* maximum error in approximating a convex function.

7. Numerical Experiments

In this section, we demonstrate that a well designed mesh for bilinear interpolation of a saddle-shaped function may give substantial improvements over a triangular mesh. The examples are taken from [2]. The procedure in [2] for generating optimal triangular meshes is modified to generate optimal quadrilateral meshes. Only elements entirely interior to the unit square are generated to simplify the presentation.

Example 1. Exponential increase along x -axis,

$$f(x, y) = \exp(5x) \sin(5y) .$$

Example 2. A near singularity at $(x_0, y_0) = (0.5, -0.2)$,

$$f(x, y) = \frac{(x - x_0)^2 - (y - y_0)^2}{((x - x_0)^2 + (y - y_0)^2)^2} .$$

Example 3. A more severe near singularity,

$$f(x, y) = \frac{((x - x_0)^2 + (y - y_0)^2)^2 - 8(x - x_0)^2(y - y_0)^2}{((x - x_0)^2 + (y - y_0)^2)^4} .$$

Example 4. Example 4 is Example 2 modified by a rescaling of y -axis,

$$f(x, y) = \frac{(x - x_0)^2 - (\sqrt{10}y - y_0)^2}{((x - x_0)^2 + (\sqrt{10}y - y_0)^2)^2} .$$

The results of the experiments are summarized in Figures 5-8 and Tables 1-4. Mesh I is generated by optimal squares over the isotropic space. Mesh II is generated by optimal squares with a $\pi/4$ rotation over the isotropic space to capture the "super-convergence" behavior. Both meshes have similar element size, element shape and density and differ only in their orientation. The meshes are displayed in Figures 9-16. Results for optimal triangular meshes produced in [2] are included for comparison. Mesh I produces an almost level error profile. This indicates an equilibration of interpolation error evenly over all elements. Error profile for Mesh I is comparable to an optimal triangular mesh with about twice as many triangles. Mesh II displays the "super-convergence" behavior by consistently achieving an error 10-20 times smaller than Mesh I.

Table 5 shows the effect of generating finer meshes over the isotropic space. If we consider the median error, Mesh I shows the expected $O(h^2)$ convergence. From the efficiency ratio (Error/Area), we can also predict the decrease of error is proportional to the number of elements. Results in Mesh II clearly display the higher than $O(h^2)$ "super-convergence" behavior.

It can be shown [1] the coordinate lines in the isotropic space are mapped to eigen-trajectories

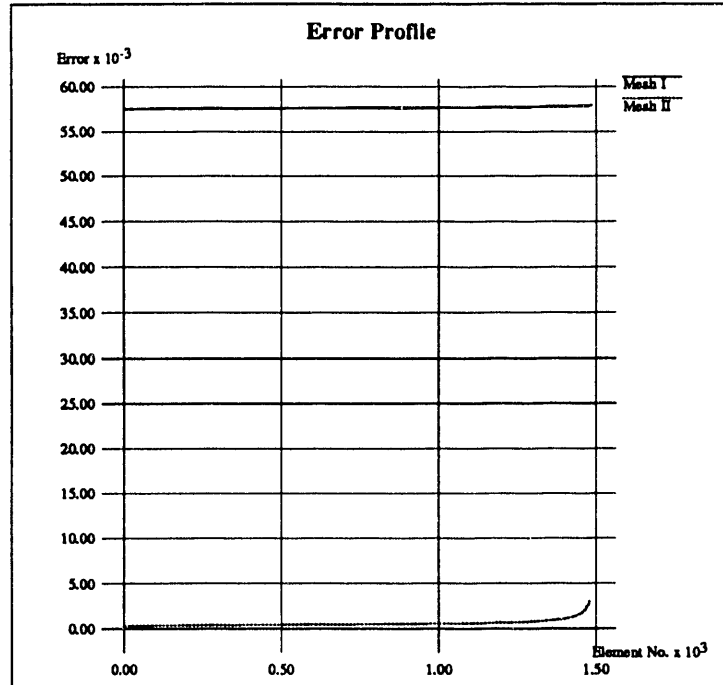


Figure 5: Error profiles for Example 1.

Table 1: Summary of results for Example 1.

	Minimum error	Median error	90 percentile	Maximum error	Number of elements
Triangle	5.27E-2	5.39E-2	5.50E-2	5.74E-2	2923
Mesh I	5.75E-2	5.76E-2	5.78E-2	5.79E-2	1488
Mesh II	2.29E-4	4.62E-4	8.30E-4	3.04E-3	1480

of the Hessian matrix. Thus as the curved element boundaries are poorly approximated by straight edges, the resulting quadrilateral will no longer have parallel sides (Fig. 13, 14). The simple analysis in §3 for parallelograms may not be adequate and this leads to an anomalous increase in the error displayed in Example 3 of a severe singularity (Fig. 7).

8. Summary

We have used a simple locally quadratic model to develop a geometric interpretation of the interpolation error. We determine the optimal element shapes and their efficiency ratio (Error/Area) over the isotropic space. The analysis shows for approximating convex data functions, bilinear quadrilaterals are more efficient. However, for finite element computations, triangles

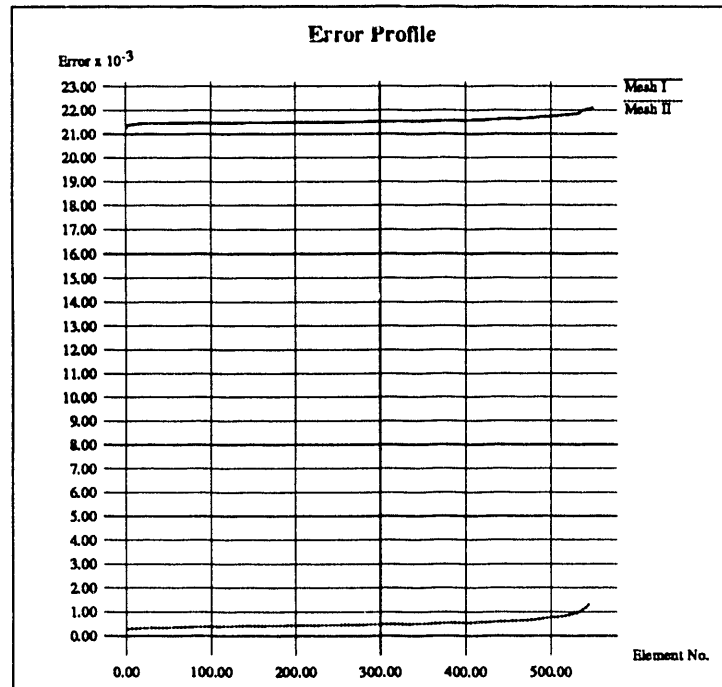


Figure 6: Error profiles for Example 2.

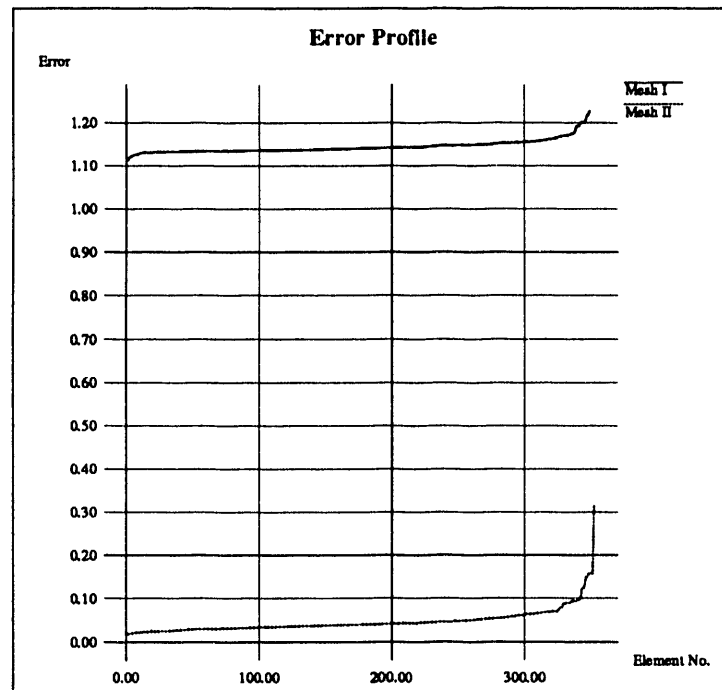


Figure 7: Error profiles for Example 2.

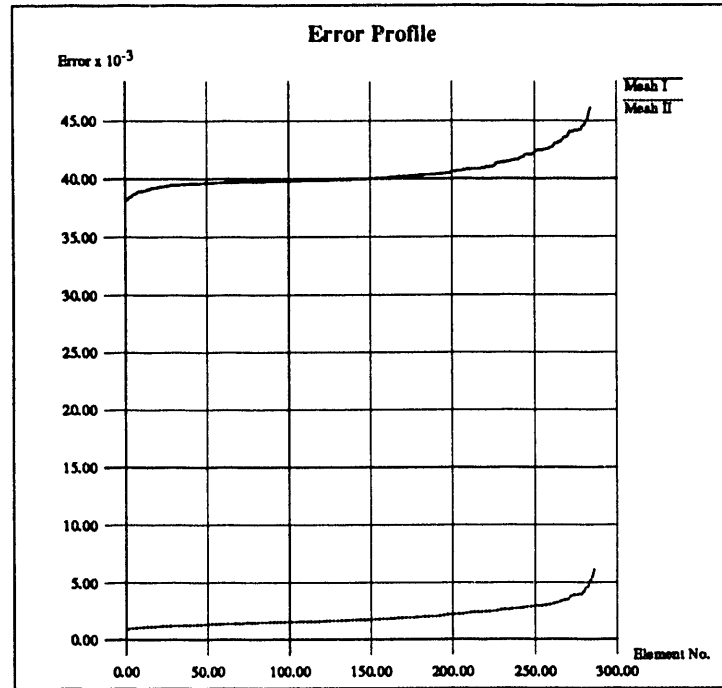


Figure 8: Error profiles for Example 3.

Table 2: Summary of results for Example 2.

	Minimum error	Median error	90 percentile	Maximum error	Number of elements
Triangle	1.87E-2	2.01E-2	2.16E-2	2.57E-2	1072
Mesh I	2.13E-2	2.15E-2	2.17E-2	2.21E-2	550
Mesh II	2.82E-4	4.69E-4	7.33E-4	1.38E-3	546

Table 3: Summary of results for Example 3.

	Minimum error	Median error	90 percentile	Maximum error	Number of elements
Triangle	1.02	1.16	1.32	1.70	650
Mesh I	1.11	1.14	1.16	1.23	349
Mesh II	1.80E-2	3.94E-2	6.75E-2	3.16E-1	352

Table 4: Summary of results for Example 4.

	Minimum error	Median error	90 percentile	Maximum error	Number of elements
Triangle	2.91E-2	3.68E-2	4.61E-2	6.46E-2	608
Mesh I	3.81E-2	4.00E-2	4.24E-2	4.61E-2	284
Mesh II	9.36E-4	1.76E-3	3.04E-3	6.13E-3	286

Table 5: Convergence test on Example 3.

	Minimum error	Median error	90 percentile	Maximum error	Number of elements
Mesh I	11.1E-1	11.4E-1	11.6E-1	12.3E-1	349
Mesh I	3.22E-1	3.23E-1	3.24E-1	3.26E-1	1223
Mesh I	8.03E-2	8.07E-2	8.12E-2	8.23E-2	5063
Mesh I	1.99E-2	2.02E-2	2.04E-2	2.08E-2	20603
Mesh II	1.80E-2	3.94E-2	6.75E-2	3.16E-1	352
Mesh II	2.35E-3	4.22E-3	9.16E-3	6.35E-2	1260
Mesh II	3.10E-4	7.20E-4	1.29E-3	9.41E-3	5244
Mesh II	5.19E-5	1.79E-4	3.78E-4	1.24E-3	21389

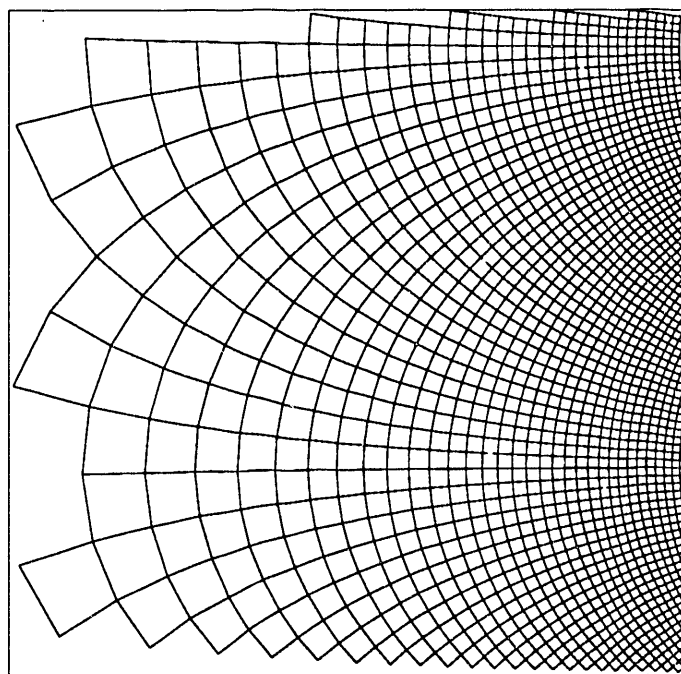


Figure 9: Mesh I for Example 1.

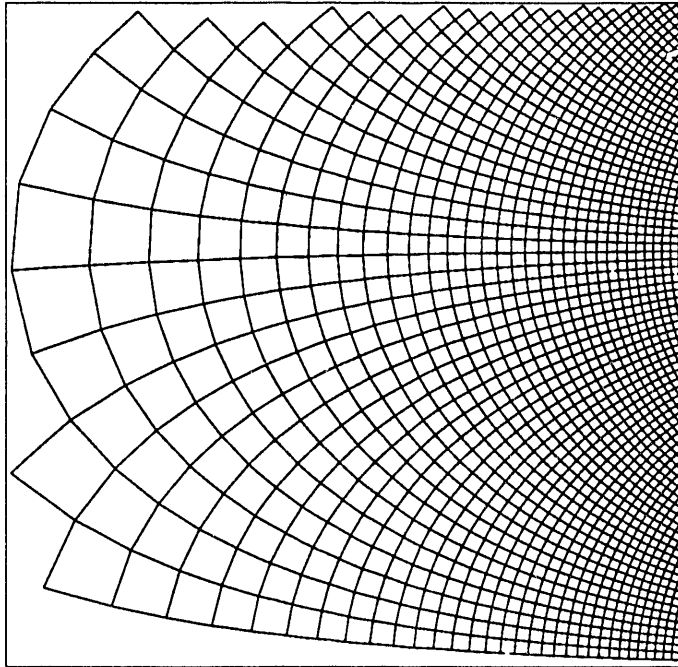


Figure 10: Mesh II for Example 1.

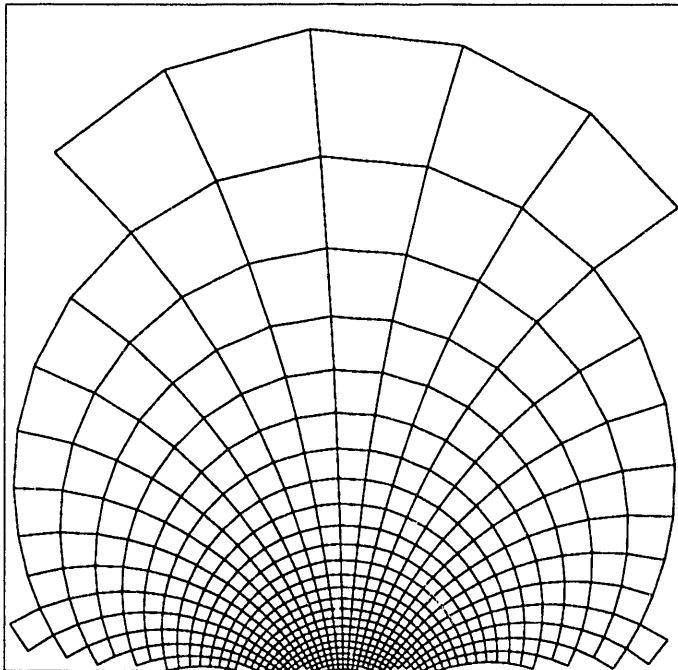


Figure 11: Mesh I for Example 2.

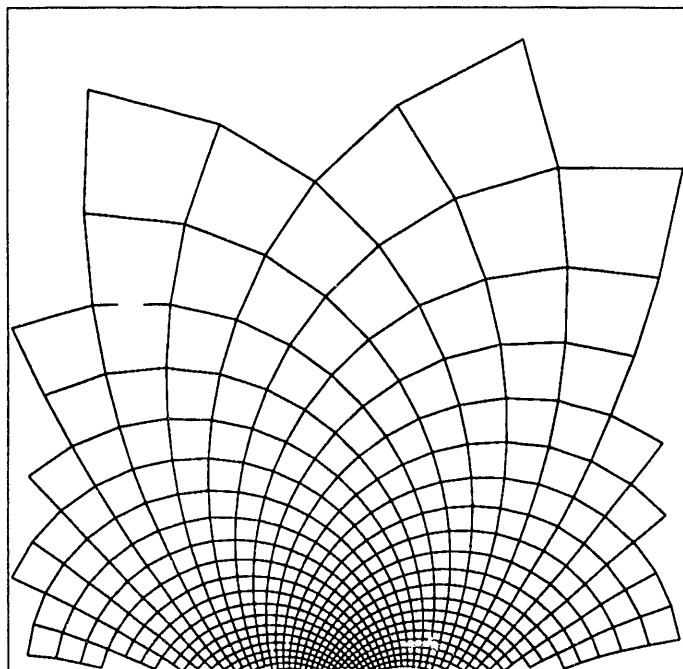


Figure 12: Mesh II for Example 2.

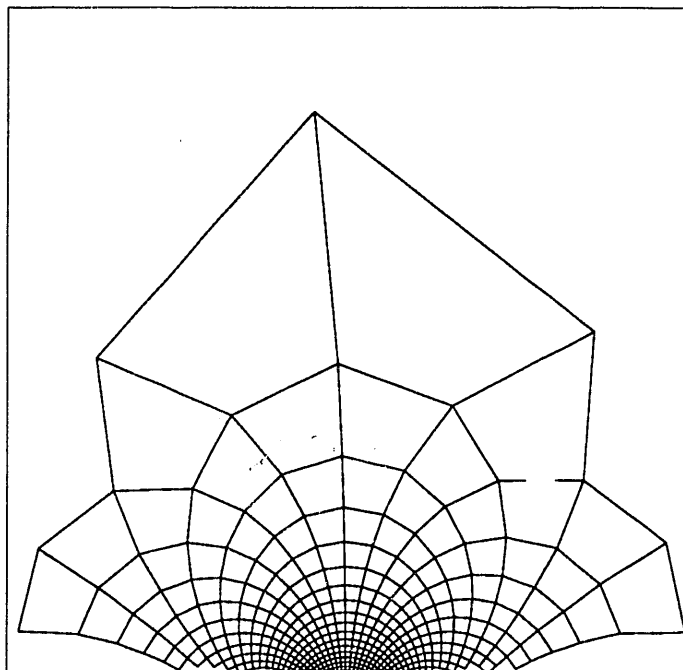


Figure 13: Mesh I for Example 3.

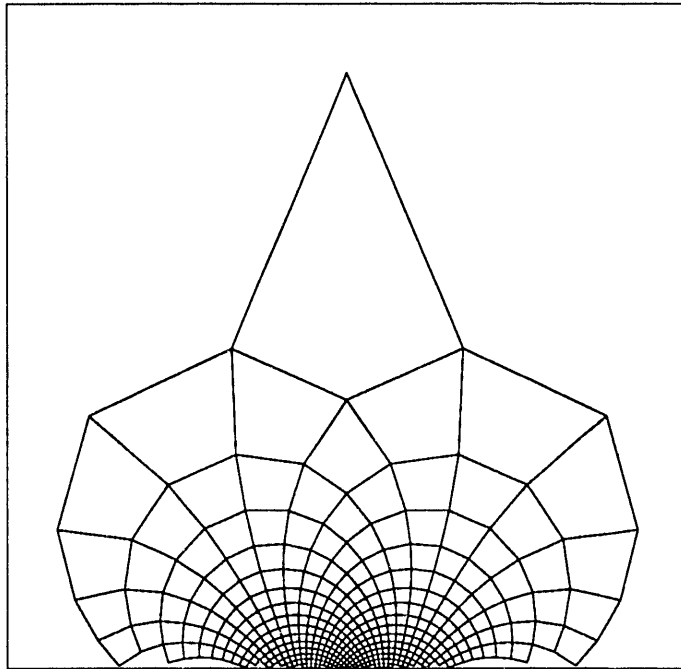


Figure 14: Mesh II for Example 3.

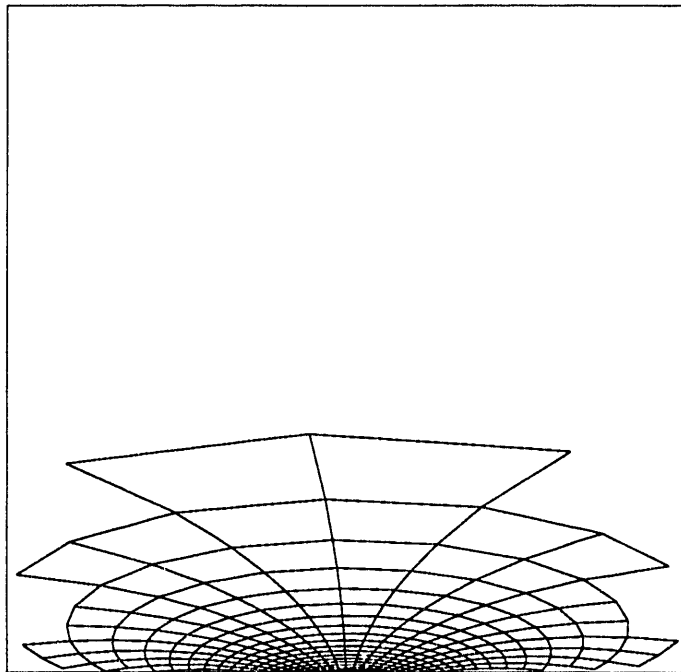


Figure 15: Mesh I for Example 4.

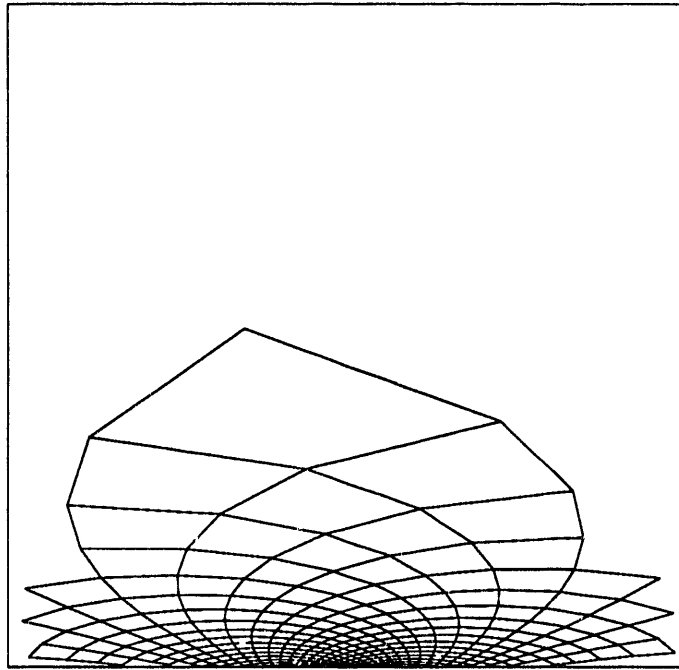


Figure 16: Mesh II for Example 4.

may have a slight advantage. For approximating saddle-shaped data functions, a well designed quadrilateral mesh may show substantial improvements over a triangular mesh. Numerical experiments show good agreement with the analysis. The experiments also show grid orientation may have a significant effect on approximation accuracy.

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