

# Detection of Topographic Characteristics in Digital Images Approximated by Triangular Surfaces

HÉLIO PEDRINI  
WILLIAM ROBSON SCHWARTZ

Federal University of Paraná  
Department of Computer Science  
Curitiba-PR, Brazil, 81531-990

helio@inf.ufpr.br william@pet.inf.ufpr.br

**Abstract.** This paper presents a new method for extracting topographic features from images approximated by triangular meshes. Peaks, pits, passes, ridges, valleys, and flat regions are defined by considering the topological and geometric relationship between the triangular elements. The approach is suitable for several computer-based recognition tasks, such as geographic information systems, rapid prototyping, computer graphics, and reverse engineering. The method has been applied to a wide range of images, producing a good compromise between accuracy and time requirements.

**Keywords:** Topographic features, triangulation, surface shape.

## 1 Introduction

The identification of topographic features in digital images is a primary problem encountered in any general computer vision system. Several computer-based recognition tasks such as navigation of geographic information systems, autonomous vehicles, planetary exploration, reverse engineering, and medical image analysis require the construction of accurate models based on shape descriptors in order to represent surface information in an efficient and consistent way.

Peaks, pits, ridges, valleys, passes, and flat regions are some useful topographic features used in image analysis. A peak is a point such that in some neighborhood of it, there is

no higher point. Similarly, in some neighborhood of a pit, there is no lower point. A ridge correspond to a long, narrow chain of higher points or crest, while a valley correspond to a chain of points with lower elevations. A pass is a low point on a ridge or between adjacent peaks.

As an alternative representation to regular grid models, our method uses triangulated irregular networks to represent the object surface as a mesh of adjacent triangles, whose vertices are the data points. The points need not lie in any particular pattern and the density may vary over space. There are many advantages associated with triangulated irregular networks. First, complex data are com-

monly irregularly distributed in space, therefore, the structure of the triangulation can be adjusted to reflect the density of the data. Consequently, cells become larger where data are sparse, and smaller where data are dense. Second, topographic features can be incorporated into the model. For instance, vertices in a triangulation can describe nodal features such as peaks, pits or passes, while edges can represent linear features such as break, ridge or channel lines. Finally, triangles are simple geometric objects which can be easily manipulated and rendered.

Section 2 provides an overview of the main methods for extracting topographic features from digital images. An improved triangular model is presented in Section 3. The definition of topographic features as descriptive elements of the surface is given in Section 4. Section 5 presents some experimental results and implementation issues. Section 6 concludes with some final remarks and directions for future research.

## 2 Previous Work

Several methods have been proposed to identify topographic features in digital images. The vast majority of the methods are defined in terms of cell-neighbor comparisons within a local window over the image [6, 10, 18] or derived from contour lines of the image [2, 11, 19]. Concepts from differential geometry are

often used in surface feature recognition [1]. For instance, basic surface types can be determined by estimating directional derivatives of the intensity image. Since the computation of surface derivatives is extremely sensitive to noise or other small fluctuations, image smoothing is usually required to reduce the effects of noise. However, such smoothing can also suppress relevant information or cause edge displacement.

Peucker and Johnston [17] characterize the surface shape by the sequence of positive and negative differences as surrounding points are compared to the central point. Peucker and Douglas [16] describe several variations of this method for detecting surface specific points and lines in terrain data.

The method proposed by Johnston and Rosenfeld [10] detects peaks (pits) by finding all points  $P$  such that no points in an  $n$  by  $n$  neighborhood surrounding  $P$  have higher (lower) elevation than that of  $P$ . To find ridges (valleys), their method identifies points that are either east-west or north-south elevation maxima (minima) through a "smoothed" array in which each point is given the highest elevation in a  $2 \times 2$  square containing it.

Paton [13] uses a six-term quadratic expansion in Legendre polynomials fitted to a small disk around each pixel. The most significant coefficients of the second-order polynomial are used to classify each pixel into a

descriptive label. Grender [5] compares the grey level elevation of a central point with surrounding elevations at a given distance around the perimeter of a circular window and the radius of the window may be increased in successive passes through the image.

Hsu, Mundy, and Beaudet [9] use a quadratic surface approximation at every pixel on the image surface. Lines emanating from the central point in the principal axes of this approximation provide natural boundaries of patches representing the surface. The principal axes from some critical points distributed over the image are selectively chosen and interconnected into a network to produce an approximation of the image data. Mask matching and state transition rules are used to extract a set of primitive features from this network.

Toriwaki and Fukumura [20] use two local measures of grey level pictures, connectivity number and coefficient of curvature for classification of each pixel into a descriptive label, which is then used to extract structural information from the image.

Watson, Laffey, and Haralick [7, 21] provide a method for classifying topographic features based on the first and second directional derivatives of the surface estimated by bicubic polynomials, generalized splines, or the discrete cosine transformation. A technique proposed by Gauch and Pizer [14] locates re-

gions where the intensity changes sharply in two opposite directions. The curvature calculation is based on level curves of the image, requiring the evaluation of a large polynomial in the first-, second-, and third-order partial derivatives. They determine curvature extrema of the level curves of the image in order to achieve this. Unfortunately, their calculation requires the evaluation of a large polynomial in the first-, second-, and third-order partial derivatives of the image, where cubic splines are used to calculate the partial derivatives.

A more recent evaluation of some methods for ridge and valley detection is presented by López *et al.* [12]. A survey describing efficient data structures and geometric algorithms for extracting topographic features in terrain models is given in [4].

The method proposed in this paper differs from the majority of the feature detection algorithms found in literature, which are generally based on regular grid models. A disadvantage of regular grids is their inherent spatial invariability, since the structure is not adaptive to the irregularity of the object surface. This may produce a large amount of data redundancy, especially where the topographic information is minimal. The method proposed by Falcidieno and Spagnuolo [3] is the most similar to the one presented here.

### 3 Triangulation Construction

Although many surface representations have been proposed in the literature, polygonal surfaces are the most common choice for representing three-dimensional data sets. They are supported by the vast majority of modeling and rendering packages (such as OpenGL, VRML, VTK, and Data Explorer), and polygonal surface data are widely available. Hardware support for polygon rendering is also becoming more popular.

In the last few years, several polygonal surface simplification algorithms [8] have been proposed in the literature to generate a surface containing fewer polygons. This is important for processing, visualizing, or transmitting larger surface data sets than the available capabilities of software, computers, and networks permit. Additionally, the concept of multiresolution modeling is generally associated with the possibility of representing a geometric object at different levels of detail and accuracy. For a given application, a coarse representation can be used to describe less relevant areas, while high resolution can be focused on specific parts of interest.

The construction of our triangular meshes is performed by an incremental triangulation algorithm [15], which iteratively adds new points to the model, updating it after each point is inserted. An approximation formed by two triangles is initially constructed. This

mesh is then incrementally refined until either a specified error is achieved or a given number of points is reached.

A constrained Delaunay triangulation is used to maintain the topology of the data points, whose vertices lie at a subset of the input data. While most of the traditional triangulation techniques are based on the approximation error as a criterion for the mesh quality, the objective of our approach is to construct triangular meshes that preserve important topographic features in the approximated surface.

A local error metric is proposed to select points to be inserted into the triangulation, which is based on the maximum vertical error weighted by the standard deviation calculated in a neighborhood of the candidate point, given by

$$C = \frac{|h(p) - z(p)|}{\sigma(p)} \quad (1)$$

where  $h(p)$  is the height value of point  $p$ ,  $z(p)$  is the height value of the interpolated surface at point  $p$ , and  $\sigma(p)$  is the standard deviation calculated in a  $3 \times 3$  neighborhood of the candidate point  $p$ .

The idea of the above metric is to associate greater importance to the points in regions where the local variability of the data is high, allowing the surface to conform to the local trends in the data. In flat regions, where  $\sigma(p) = 0$ , the algorithm uses only the denom-

inator  $|h(p) - z(p)|$  to select new points.

A priority queue stores the sequence of vertices used to refine the triangulation, ordered by increasing approximation error. For each refinement step, only those vertices affected by the insertion process need to have their approximation error recalculated.

The sequence of local modifications generated during the refinement step is applied to a triangulation until either the desired accuracy of the approximation is achieved or a given number of points is reached. The extraction of a representation of the terrain at a given tolerance level is obtained by using a coarse triangulation and iteratively inserting vertices into the triangulation until the desired precision is satisfied.

#### 4 Identification of Topographic Features

The triangulated surface is defined as graph consisting of vertices, directed edges, and triangles. In our method, the identification of topographic features is directly derived from the triangular models. This can be achieved by analyzing the structure of the triangles in the mesh.

Figure 1 illustrates some of the most common topographic features, which are classified according to the topological and geometric relationship between the triangulation elements. The angle between the normals of adjacent triangles indicates concave, convex,

and planar shapes along the surface.

For each edge  $e$  not belonging to the surface boundary, it is assigned a label according to the information about the angle between the two triangles  $t_1$  and  $t_2$  sharing the edge. The angle between  $t_1$  and  $t_2$  is concave (convex) if for any points  $p_1 \in t_1$  and  $p_2 \in t_2$ , the straight line segment  $p_1p_2$  is located completely above (below) the surface identified by  $t_1$  and  $t_2$ . Otherwise, it is plane. A surface characteristic point  $P$  is classified as peak (pit) if its  $z$  value is greater (smaller) than the  $z$  value of each point belonging to the lines with intersect in  $P$ .

These extracted feature elements, describing nodal features (such as peaks, pits, or passes) and linear features (such as ridges, rivers, roads, channels, or cliffs), are incorporated into the triangulation as constrained vertices and edges, respectively, in a such way that subsequent operations will preserve them.

#### 5 Experimental Results

Our method has been tested on a number of data sets in order to illustrate its performance. Due to space limitations, only three data sets are presented here.

Figure 2(a) shows the USGS Crater Lake DEM, a digital terrain model consisting of  $336 \times 459$  elevation points and 30- by 30-meter data spacing, Figure 3(a) shows the USGS Lake Champlain DEM, consisting of

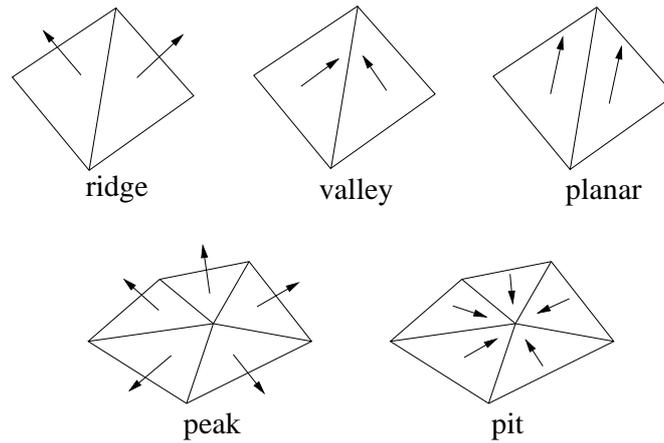


Figure 1: Topographic features in triangular meshes.

600×600 elevation points and 3- by 3-arc-second data spacing, and Figure 4(a) shows the classic *Mona Lisa* image (256×256).

Some results for these images are summa-

For each one of these three images, the corresponding triangular meshes obtained by our triangulation method (Figures 2-4(b)), the extracted peaks (Figures 2-4(c)), the extracted pits (Figures 2-4(d)), the extracted ridges (Figures 2-4(e)), and the valleys (Figures 2-4(f)) are illustrated.

The algorithms were implemented in C++ programming language on Linux platform on an AMD-K6 with a 266MHz processor and 64 Mbytes of main memory.

## 6 Conclusions

Unlike many other approaches which are based on regular grid models, we presented a method for extracting topographic features from images approximated by triangular

rized in Table 1. The number of vertices, RMS error, and execution times for the triangulation construction and topographic feature detection are indicated.

meshes. Characteristic points, lines, and regions are defined by considering the topological and geometric relationship between the triangular elements.

This technique provides an effective compromise between accuracy and time requirements, producing approximations with great flexibility while retaining the most relevant surface features. The method has been applied to a wide range of images containing different properties, achieving encouraging results despite the fact that no additional refinement technique has been performed on the extracted features.

Image	Vertices	RMS Error	Triangulation Time (s)	Ridge/Valley Time (s)	Peak/Pit Time (s)
Crater Lake	5000	2.86	6.03	0.19	0.40
	10000	1.59	7.16	0.34	0.75
	20000	0.86	9.68	0.62	1.46
	30000	0.60	12.00	0.88	2.17
	40000	0.44	14.10	1.17	2.90
	50000	0.36	15.46	1.34	3.62
Mona Lisa	2000	6.66	2.37	0.13	0.22
	3000	5.66	3.01	0.22	0.38
	5000	4.37	3.12	0.33	0.59
	7000	3.50	3.76	0.47	0.83
	9000	2.90	4.10	0.61	1.04
	10000	2.69	4.91	0.69	1.35
Lake Champlain	10000	1.53	15.78	0.47	0.85
	15000	1.12	16.33	0.61	1.20
	20000	0.92	17.97	0.75	2.19
	30000	0.67	20.34	1.04	2.29
	40000	0.55	21.86	1.29	3.01
	50000	0.46	24.10	1.55	3.70

Table 1: Summary of results for sample of images.

## Acknowledgments

Partial support of this work was provided by a grant from Conselho Nacional de Desenvolvimento Científico e Tecnológico, CNPq, Brazil. We would also like to thank the Programa Especial de Treinamento (PET) (Special Training Program) of the Computer Science Department.

## References

- [1] BESL, P. J., AND JAIN, R. C. Segmentation through variable-order surface fitting. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 10 (1988), 167–192.
- [2] CHRISTENSEN, A. H. J. Fitting a triangulation to contour lines. In *Proceedings of the Eighth International Symposium on Computer-Assisted Cartography* (Baltimore, Maryland, USA, 1987), pp. 57–67.
- [3] FALCIDIENO, B., AND SPAGNUOLO, M. A new method for the characterization of topographic surfaces. *International Journal of Geographical Information Systems* 5 (1991), 397–412.
- [4] FLORIANI, L. D., PUPPO, E., AND MAGILLO, P. Applications of computational geometry to geographic information systems. In *Handbook of Computational Geometry* (1999), J. Sack

- and J. Urrutia, Eds., Elsevier Science, pp. 333–388.
- [5] GRENDER, G. C. TOPO III: A Fortran program for terrain analysis. *Computers & Geosciences* 2 (1976), 195–209.
- [6] HARALICK, R. M. Ridges and valleys on digital images. *Computer Vision, Graphics, and Image Processing* 22 (1983), 28–38.
- [7] HARALICK, R. M., WATSON, L. T., AND LAFFEY, T. J. The topographic primal sketch. *The International Journal for Robotics Research* 2 (1983), 50–72.
- [8] HECKBERT, P. S., AND GARLAND, M. Survey of polygonal surface simplification algorithms. Technical Report CMU-CS, Carnegie Mellon University, Pittsburgh, Pennsylvania, USA, May 1997.
- [9] HSU, S., MUNDY, J. L., AND BEAUDET, P. R. WEB representation of image data. In *Proceedings of the Fourth International Joint Conference on Pattern Recognition* (Kyoto, Japan, 1978), pp. 675–680.
- [10] JOHNSTON, E. G., AND ROSENFELD, A. Digital detection of pits, peaks, ridges, and ravines. *IEEE Transactions on Systems, Man, and Cybernetics* 5 (1975), 472–480.
- [11] LO, S. H. Automatic mesh generation and adaptation by using contours. *International Journal for Numerical Methods in Engineering* 31 (1991), 689–707.
- [12] LÓPEZ, A. M., LUMBRERAS, F., S., J., AND VILLANUEVA, J. J. Evaluation of methods for ridge and valley detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 21 (1999), 327–335.
- [13] PATON, K. Picture description using Legendre polynomials. *Computer Graphics and Image Processing* 4 (1975), 40–54.
- [14] PAUL, J. G., AND PIZER, S. Multiresolution analysis of ridges and valleys in grey-scale images. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 15 (1993), 635–646.
- [15] PEDRINI, H., AND SCHWARTZ, W. R. Topographic feature identification based on triangular meshes. In *Proceedings of 9th International Conference on Computer Analysis of Images and Patterns* (Warsaw, Poland, 2001), pp. 621–629.
- [16] PEUCKER, T. K., AND DOUGLAS, D. H. Detection of surface-specific points by local parallel processing of discrete terrain elevation data. *Com-*

- puter Graphics and Image Processing 4* (1975), 375–387.
- [17] PEUCKER, T. K., AND JOHNSTON, E. G. Detection of surface-specific points by local parallel processing of discrete terrain elevation data. Technical Report 206, University of Maryland, 1972.
- [18] SKIDMORE, A. K. Terrain position as mapped from gridded digital elevation model. *International Journal of Geographical Information Systems 4*, 1 (1990), 33–49.
- [19] TANG, L. Automatic extraction of specific geomorphological elements from contours. In *Proceedings 5th International Symposium on Spatial Data Handling* (Charleston, South Carolina, USA, 1992), IGU Commission on GIS, pp. 554–566.
- [20] TORIWAKI, J., AND FUKUMURA, T. Extraction of structural information from grey pictures. *Computer Graphics and Image Processing 7* (1978), 30–51.
- [21] WATSON, L. T., LAFFEY, T. J., AND HARALICK, R. M. Topographic classification of digital image intensity surfaces using generalized splines and the discrete cosine transformation. *Computer Vision, Graphics, and Image Processing 29* (1985), 143–167.

### Author's Biographies

**Hélio Pedrini** received his B.Sc. and M.Sc. degrees in computer science from the State University of Campinas, Brazil, and the Ph.D. degree in electrical engineering from the Rensselaer Polytechnic Institute, United States. He is currently a professor in the Computer Science Department at Federal University of Paraná, Curitiba-PR, Brazil. His research interests include image processing, computer graphics, computational geometry, and computer vision.

**William Robson Schwartz** is finishing his B.Sc. in computer science at Federal University of Paraná, Curitiba-PR, Brazil. His research interests include image processing, computer graphics, neural networks, geographic information systems, and computer vision.

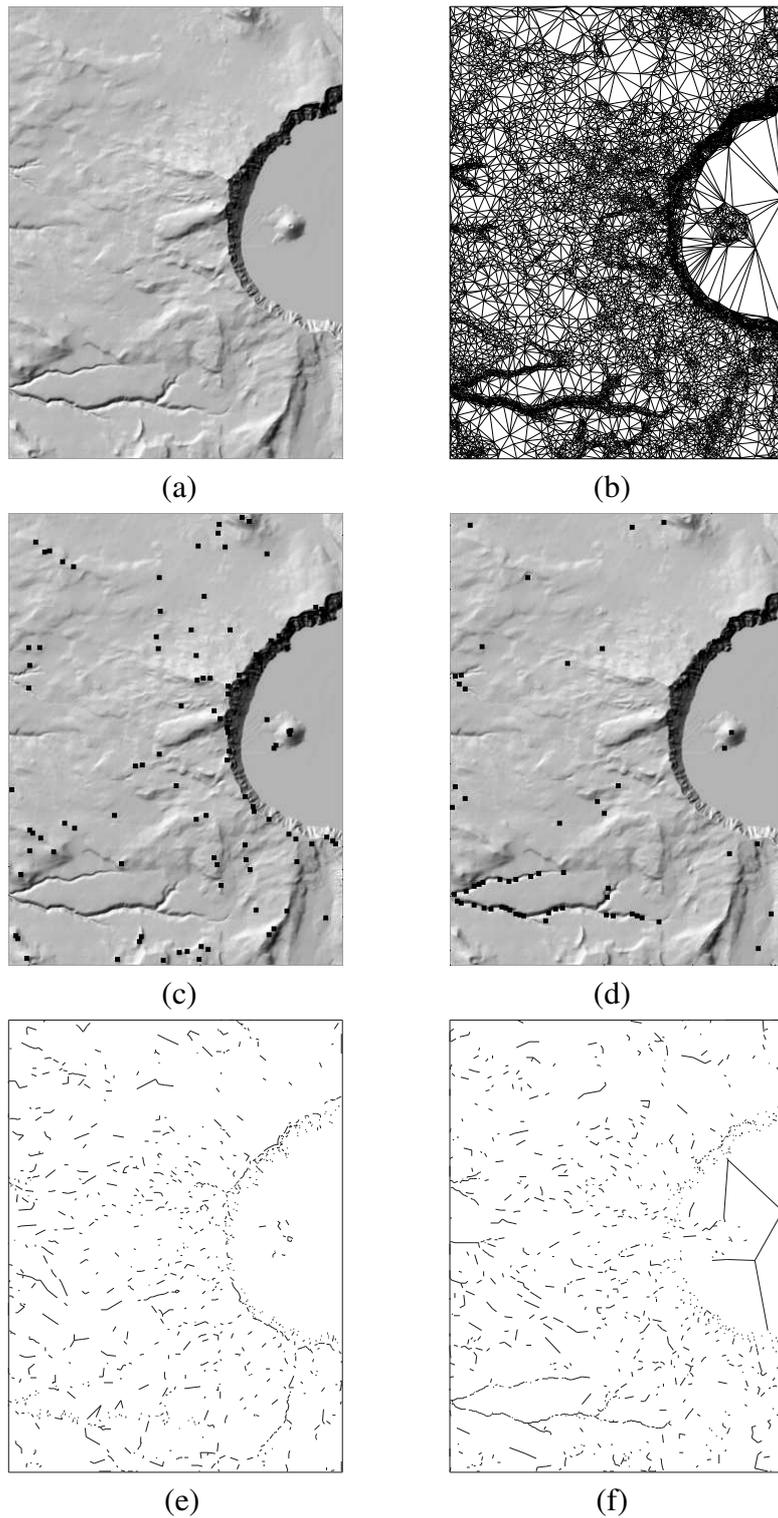


Figure 2: Application of the proposed method to (a) USGS Crater Lake terrain data; (b) triangular mesh obtained by our incremental triangulation technique. The mesh contains only 4% of the original points; (c-d) peaks and pits extracted by using the triangular mesh; (e-f) the extracted ridges and valleys.

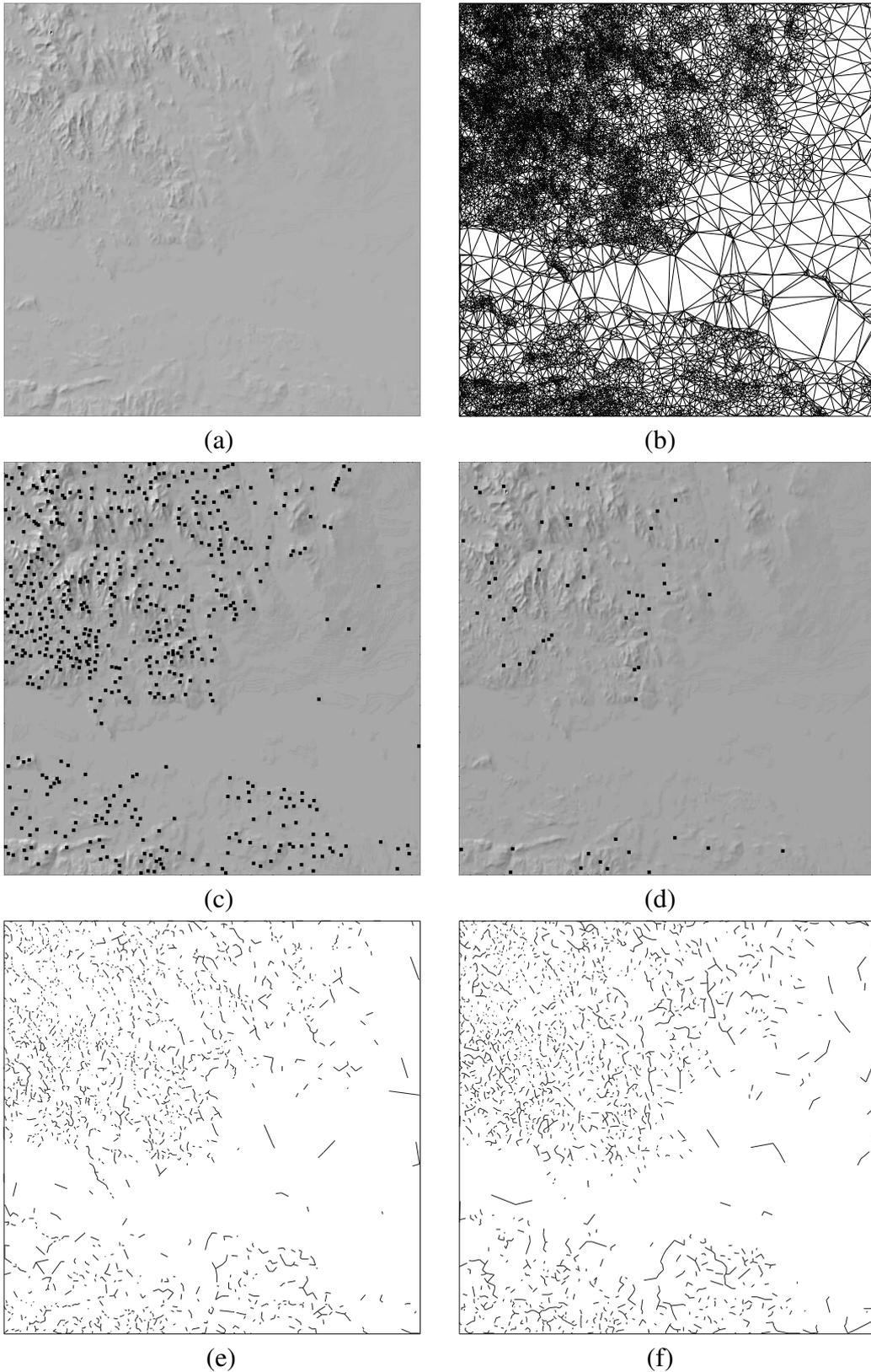


Figure 3: Application of the proposed method to (a) USGS Lake Champlain terrain data; (b) triangular mesh obtained by our incremental triangulation technique. The mesh contains only 4% of the original points; (c-d) peaks and pits extracted by using the triangular mesh; (e-f) the extracted ridges and valleys.

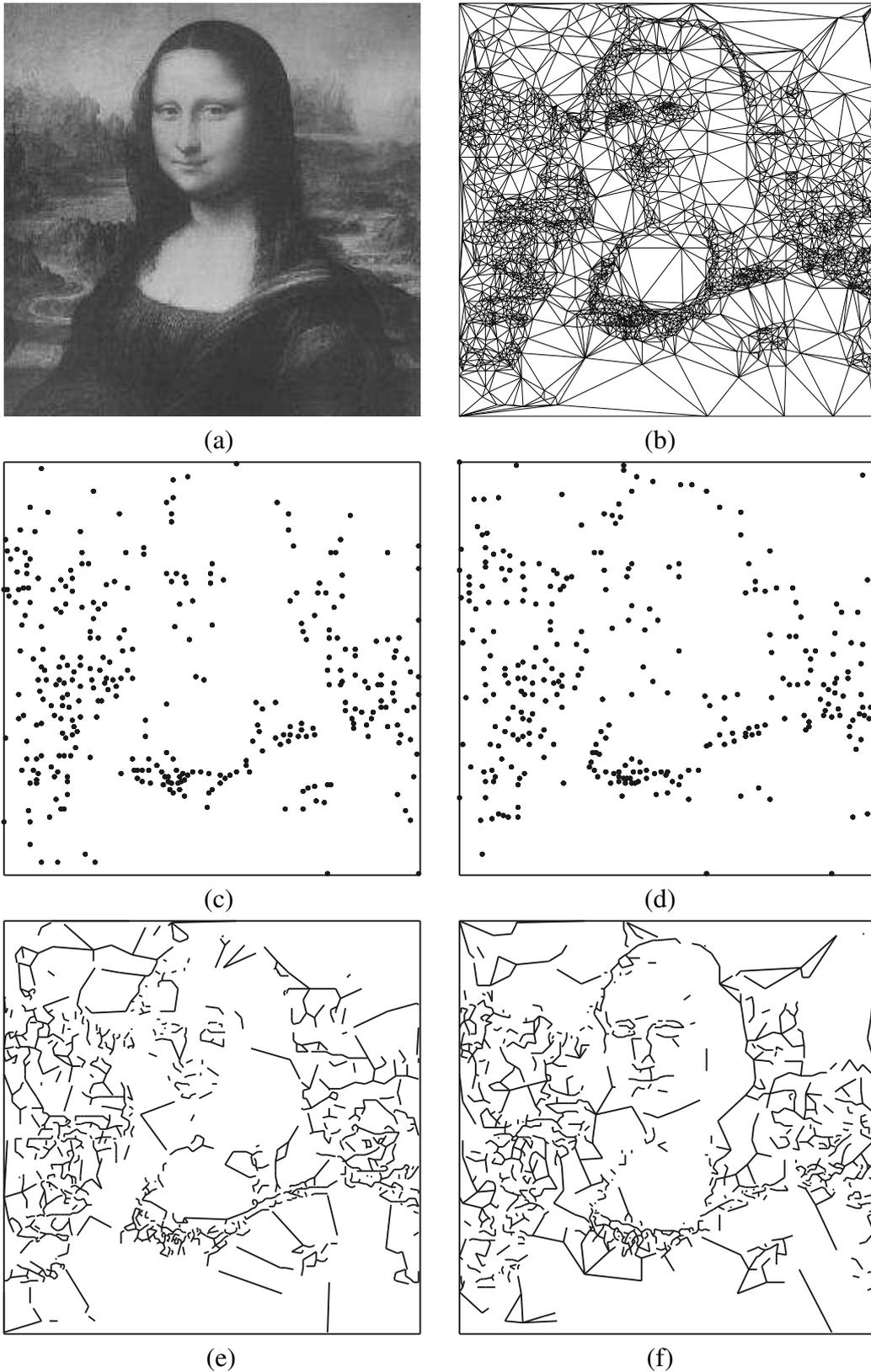


Figure 4: Application of the proposed method to (a) Mona Lisa image; (b) triangular mesh obtained by our incremental triangulation technique. The mesh contains only 4% of the original points; (c-d) peaks and pits extracted by using the triangular mesh; (e-f) the extracted ridges and valleys.