Automated Classification of Generic Terrain Features in Digital Elevation Models

Abstract

Using digital elevation models (DEMs), it is possible to automatically replicate the manual classification of elevated terrain features, or mounts, in certain physiographic regions. Results of the automatic classification, which uses percent slope and critical point information, are compared to a manual classification of the same area using computer-generated synthetic stereo images.

Success of the automated classification appears to be limited by the algorithm, the nature of the regional terrain, and the quality of available digital elevation data. However, regional and local knowledge about the area may improve the classification results.

Introduction

Most terrain classification to date has been manually intensive, using aerial photographs or topographic maps as the primary data source (Way, 1973; Mintzer and Messmore, 1984). However, using advanced computer capabilities and digital elevation data, automated classification of certain terrain features is possible.

Several automated terrain classification methods have been developed to address categorizations of broad areas of terrain (Dikau, 1989; Pike and Thelin, 1989; Rives and Besaw, 1990), whereas other methods have been proposed to classify more specific features, such as drainage networks and drainage basins (Band, 1986; Jenson and Domingue, 1988; Seemuller, 1989).

Two related areas of automated terrain classification have been largely unexplored. One area is automated methods to replicate the manual classification of specific geomorphologic landforms, such as drumlins and alluvial fans. The second, and perhaps easier, area is the identification of more commonly recognized generic or basic-level terrain features, such as hills and plains (Graff, 1991).

This study implements the first stage of a divide-and-conquer approach to automated terrain classification. This approach simplifies the complex problem of terrain classification by defining two generic terrain feature categories – mount and non-mount. Mount refers to terrain features – such as hills, mountains, and ranges – that are elevated from the surrounding terrain. All remaining areas are classified as non-mount.

Classification

Due to the subjective nature of many commonly recognized generic terrain terms, such as hill and plain, most terrain classification systems employ specific geomorphologic terms used by Earth scientists, such as drumlin and alluvial fan (Hoffman, 1985; Frank *et al.*, 1986; Lay, 1991). However, work in cognitive categorization theory shows that it is often easier to classify generic objects than it is to provide a more specific classification (Rosch *et al.*, 1976; Rosch, 1978).

Rosch *et al.* (1976) and Rosch (1978) proposed a categorization system that provides various levels of classification ranging from general or superordinate, at the uppermost level, to specific or subordinate, at the bottom level. This theory of categories and set theory has been used with cartographic abstraction principles to develop a conceptual framework for features in geographic information systems (GIS) (Usery, 1993).

Evident at all levels of classification are "prototype" objects which are the "best examples" of a particular category. In general, objects that are atypical or differ greatly from the prototype are more difficult to classify than those that closely resemble the category prototype (Jolicoeur *et al.*, 1984). This is especially important when dealing with terrain features which often differ greatly from the textbook examples and from each other.

Central to the system proposed by Rosch *et al.* (1976) are basic-level categories and objects. Basic-level objects are basic in perception, function, communication, and knowledge organization (Lakoff, 1987). According to Jolicoeur *et al.* (1984), the typical pattern of categorization, followed by most people, is identification at the basic level first, followed some time later by subordinate- and superordinate-level identification.

Hoffman (1985) uses the concept of basic-level objects and categories in his treatment of "generic" topographic terms. He states that these terms, which include hill and plain, are rooted in perception, judgement, and experience and are frequently used to communicate the perceptual form of terrain.

The terrain categorization system used in this study is based on generic, basic-level terrain features (Table 1). An attempt is made to differentiate "mount" from "non-mount" areas. The term "mount" is adapted from the U.S. Geological Survey's (USGS) proposed Digital Line Graph-Enhanced (DLG-E) definition as "a landmass that projects conspicuously above its surroundings" (Guptill *et al.*, 1990, p. A-97).

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Table 1. Terrain Categorization System

Superordinate	Basic (Generic)	Subordinate
Terrain	Mount	Drumlin Dune Inselberg
	Plain	Alluvial Plain Outwash Plain Floodplain
	Basin	Kettle Drainage Basin Sinkhole
	Flat	Mud Flat Tidal Flat Playa

Graff, 1991

Mount represents such elevated terrain features as hills, mountains, and ranges. The prototype mount is considered to be "well-defined." A well-defined mount is an isolated, elevated mass with a distinguishable boundary and a summit or peak. To further simplify the classification problem, all features other than mounts, including plains, basins, and flats, are collectively classified as "non-mount."

Information used in manual terrain classification is combined with automated techniques to classify mount/non-mount areas using digital elevation data as the sole data source.

Manual terrain classification often relies on isolating the feature of interest from the surrounding terrain, then measuring attributes associated with the isolated feature. For instance, when using aerial photographs, the boundaries between landforms are often identified by breaks in slope which create apparent tonal and topographic changes (Mintzer and Messmore, 1984). Information such as a break in slope between landforms also can be incorporated into an automated terrain classification scheme.

Automated analysis techniques used in previous studies frequently employ general geomorphometry measures and/or critical points. General geomorphometry is the measurement of landform characteristics over a broad continuous surface (Evans, 1972). Measures used in general geomorphometry often rely on altitude and such derivatives as slope, aspect, and curvature (Evans, 1972; Mark, 1975; Pike, 1988).

Studies using critical points extract information directly from the elevation data without computing derivatives or other measures. Critical points provide the maximum amount of information about a surface. Although called by different names, these points include peaks, pits, ridges, ravines, passes, slopes, break points, and flats (Peucker and Douglas, 1975).

Data

The data are USGS 7.5-minute-based digital elevation models (DEMs) (U.S. Geological Survey, 1990). These data have a 30-metre spacing between *X* and *Y* locations. Each DEM covers an area corresponding to a 1:24,000-scale topographic map.

In order to design mount classification criteria suitable to a wide range of terrain types, five DEMs were chosen as training sites. The results from the training sites were used to tailor the classification algorithm implemented on five DEM test sites.

The training sites are Verona, Wisconsin; Gettysburg, Pennsylvania; Huntsville, Alabama; Mustang Mountains, Arizona; and Paradise Range, California. These sites have a wide range of local relief and contain both well-defined, "prototypical" mounts and poorly defined mounts.

Verona, Wisconsin, and Gettysburg, Pennsylvania, are relatively low-relief areas with 93 m and 117 m of relief, respectively. Verona consists primarily of large areas of undulating hills separated by drainage divides with a few isolated, well-defined mounts. Gettysburg has an overall rolling terrain with several low-relief, isolated hills and a long linear ridge in the northwest corner.

Huntsville, Alabama, has a moderate local relief of 346 metres and several isolated, well-defined mounts with an extensive range along the eastern half of the area. Mustang Mountains, Arizona, has relatively high local relief at 641 m and distinct well-defined mounts. In addition to the more prevalent, well-defined conical mounts, Mustang Mountains also has several low-relief, poorly defined mounts in the southern quarter of the area.

Paradise Range, California, at 800 m, has the highest local relief of all the training sites. This area has an overall rugged topography with the majority of the mounts well-defined and large in extent. There are also a few small, isolated mounts scattered throughout the area. Numerous low-relief coalescing alluvial fans occupy the areas between the mounts.

The five test sites were selected using the same criteria as the training sites. These sites are Oregon, Wisconsin; Post Oak Mountains, Texas; Madison, Alabama; Farley, Alabama; and West of Drinkwater Lake, California.

The lowest relief site at 109 m is Oregon, Wisconsin. In addition to its low relief, this site was chosen because of its poorly defined mounts and overall rolling nature. Post Oak Mountains, Texas, with a local relief of 140 m, was chosen because it has a few isolated, low-relief, flat-topped mounts, in addition to a broad, low-relief, flat-topped range in the southeast quadrant of the DEM.

The Madison and Farley, Alabama, data sets have moderate local relief. The Madison site, with a local relief of 220 m, consists of several relatively isolated, well-defined mounts and an overall irregular topography. Farley has a local relief of 325 m. Similar to Post Oak Mountains, this site was chosen because of several isolated well-defined mounts and an extensive, relatively flat-topped range.

The fifth test site, West of Drinkwater Lake, California, has the highest local relief of 605 m. This site combines both low- and high-relief terrain features. In addition to several well-defined "prototypical" mounts and high-relief ranges with definite peaks, this site also possesses numerous lower relief topographic features such as alluvial fans and alluvial plains.

Method

All training and test sites were classified both manually and automatically. Manual classification of the training sites identified critical parameters for algorithm development. Manual mount/non-mount identification for all sites established ground truth against which the automated technique was compared.

Manual Classification

Manual classifications for the ten DEMs were performed using shaded relief, synthetic stereo images (Batson *et al.*, 1976) created from software written at the U.S. Army Topographic Engineering Center (TEC). Four volunteer subjects, all scientists at TEC, examined synthetic stereo images of the training sites. They were asked to verbally identify the phys-

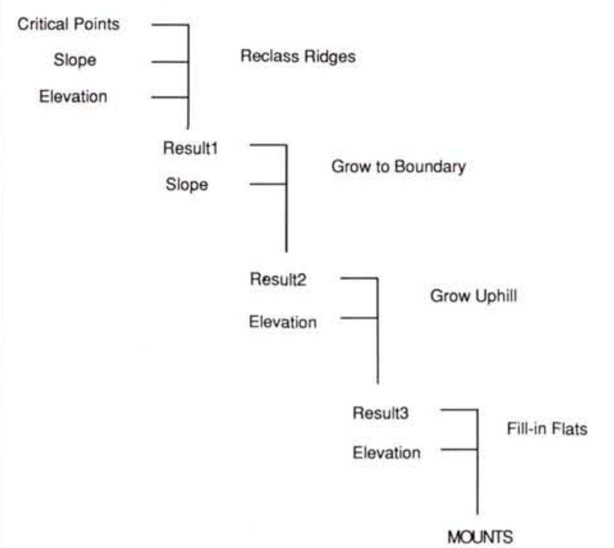


Figure 1. Steps in automated classification method.

ical and perceptual attributes of the mounts in each area, as well as the cognitive attributes of mounts in general.

The most common attributes listed were (1) the mounts were identifiable because they were noticeably higher in relief than the surrounding terrain, (2) the boundary between "mount" and "non-mount" was placed at a noticeable break in slope, and (3) most mounts possess a summit or peak.

The subjects were also asked which mounts were considered to be well-defined and poorly defined and why. The subjects tended to agree that the well-defined mounts were relatively easy to distinguish and possessed sharp breaks in slope at the boundary between mount and non-mount areas. These most closely represent the "prototype" members of the mount classification.

Boundaries between the poorly defined mounts and the non-mount areas, on the other hand, were much more subjective and varied widely from subject to subject. The attribute information from the training site examination was used to develop the mount classification algorithm.

Polygonal boundaries, between mount and non-mount areas, were plotted in a graphics plane overlaying the stereo images using the software that displays the stereo images. One set of boundaries was plotted for each of the five training sites.

The manually classified boundaries were overlayed with the computed data layers and automatically classified mounts for each of the training sites. Results from this process were used to iteratively refine the automatic classification algorithm prior to implementation on the test sites.

For each of the five test sites, four sets of boundaries were plotted, one for each subject. In each case, the mount was identified as either well-defined or poorly defined.

Automated Classification

The method to automatically classify mounts requires three layers of information. These layers include percent slope, critical points, and the original elevation data.

Preprocessing

Several mount attributes, similar to those used in manual terrain classification, are obtained in the preprocessing step. Mount attributes noted by the subjects included surface altitude, slope (gradient), and critical points. Because surface altitude is provided by the elevation values directly, no additional processing is required to obtain this information.

Prior to creation of the slope and critical point data layers, the elevation data are smoothed twice using a 3 by 3 Gaussian mask. Studies show this to be the optimum number of times to smooth the data without losing excessive detail while still removing noise that may result from the data collection process or from the data source used to produce the elevation matrix (Seemuller, 1989; Lee *et al.*, 1992).

Percent slope is computed from the DEMs by applying a Sobel operator to 3 by 3 neighborhoods of elevation values (Rives and Besaw, 1990). This measure is used to provide a boundary between mount and non-mount areas, the value of which is related to the local relief of the area. Final analysis of all training and test sites determined a boundary slope between mount and non-mount of 10 percent in areas with local relief equal to or greater than 250 m and 6 percent in lower relief areas.

Critical point analysis initially focused on peaks which are defined as a center elevation in a 3 by 3 neighborhood that is greater than all eight surrounding elevations. However, overlay of the peaks with the manually defined mounts showed that the identification criteria were too strict to extract many peaks.

Ridge points, which are considered to be a local maximum compared to its cardinal neighbors in a north-south or east-west direction, were examined in the same manner. Due to the less restrictive criteria for ridge points, it was found that more ridge points than peaks were identified. A higher correspondence between the manually defined mounts and the location of ridge points also resulted.

Mount Classification Algorithm

The mount classification algorithm has four steps. Each step uses the classification of the previous step as input (Figure 1):

(1) *Reclass Ridges.* Assign a boundary slope between mount and non-mount based on the local relief of the area, then classify all ridge points with a slope greater than the boundary slope as mounts and all other points as non-mounts.

(2) *Grow to Boundary.* Examine the mounts classified in Step 1 using a 3 by 3 window of percent slope to "grow" the mounts from the ridge points to the boundary slope. If the center of the 3 by 3 window is a non-mount and its slope is greater than the boundary slope and any of its eight neighbors are a mount, then reclassify the center as mount. This step is repeated, using the results from the previous Step 2 iteration as input, until no more reclassifications are made.

(3) *Grow Uphill.* Continue to "grow" the mounts by examining corresponding rows of original elevation data and mounts classified in Step 2 to look for uphill trends in the data. If a non-mount is encountered after an uphill trend is established, then it is reclassed as mount. The entire area is processed first from left to right, then from right to left.

(4) *Fill-in Flats.* Apply a region-growing algorithm to a 3 by 3 window of original elevation data and mounts classified in Step 3 to fill in remaining non-mounts located in mounts. If all three neighbors to the north, south, east, or west of the center non-mount value are classed as mount and the elevation of the central value is greater than its closest mount neighbor, then reclassify the center from non-mount to mount. This step is repeated, using the results from the previous iteration, until no more reclassifications are made.

Postprocessing

Initial results of the manually derived boundaries with the automatic classifications of the training sites showed that, in some areas, the classification algorithm produced many small isolated mounts. The result of the automatic classification is postprocessed to eliminate all mounts less than 25 cells (150 m by 150 m) from the final classification.

Results

Visual and numerical map comparison techniques were applied to both the training sites and the test sites. Automatically classified mounts were compared visually with the boundaries obtained in the manual classification by overlaying and displaying the files. The mounts in each site were identified as either well-defined or poorly defined based on the manual classification.

For the numerical analysis, the interiors of the manually derived boundaries were filled to form polygons representing mounts. Areas of all the mounts were computed. The coefficient of areal correspondence, which evaluates the overlap of areal patterns, was used to quantitatively compare the manual and automatic classifications (Unwin, 1981). The coefficient of areal correspondence varies from 0 to 1. Patterns that are completely separate give a value of 0 while exactly coincident patterns give a value of 1.

Training site comparisons were performed between mounts manually classified by one of the authors and the automatic classification, resulting in a single visual and numeric classification for each site. The classification algorithm was revised based on the visual and numerical results of the training sites.

Test site comparisons were performed by comparing the four test subjects' manual classifications and the automatic classification for each site, resulting in four visual and numeric comparisons per site.

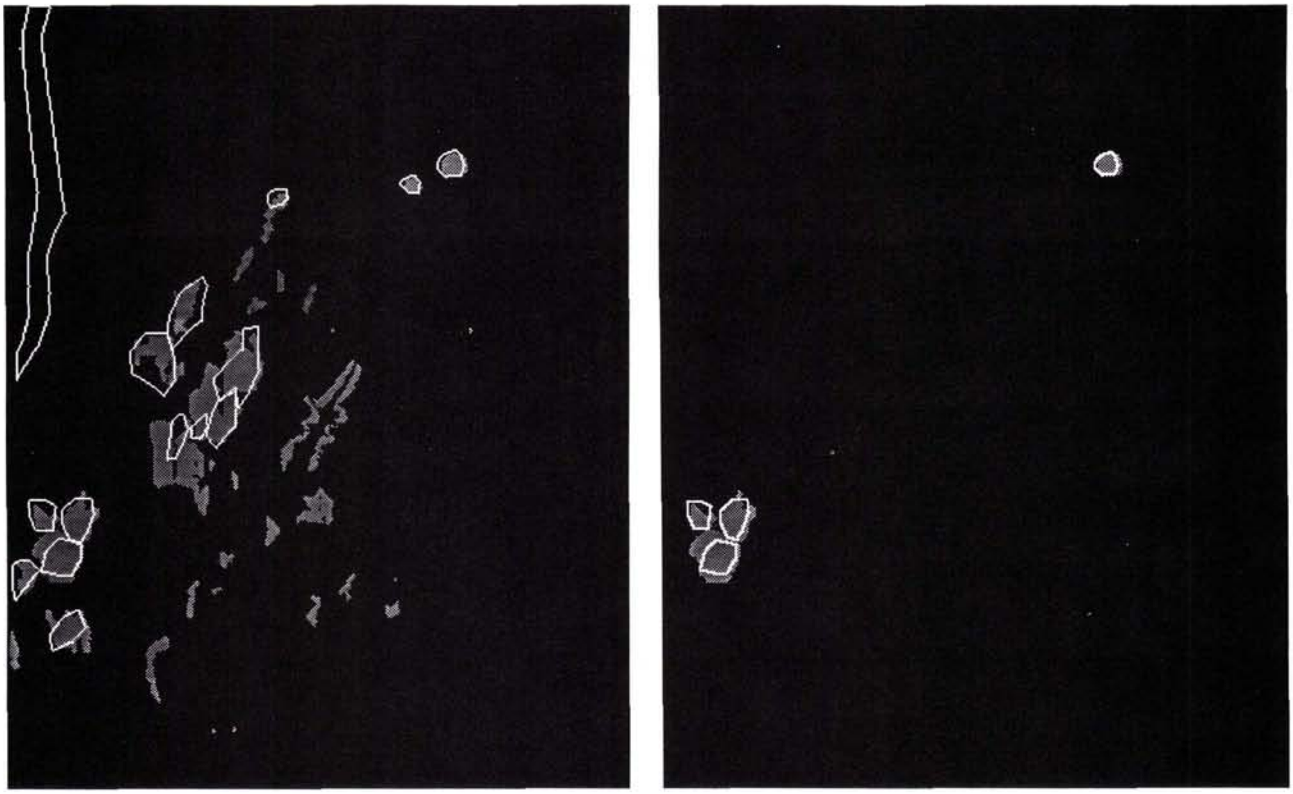
Several figures are used to depict the results for selected training and test sites. Each figure represents an entire DEM.

Training Sites

Visual map comparison of the training sites showed noticeable differences between the manual and automated classifications. These differences included (1) some mounts separated in the manual classification were merged in the automated process; (2) the automatic process produced more mounts; and (3) the boundaries on the manually derived mounts tended to be less detailed than those derived automatically.

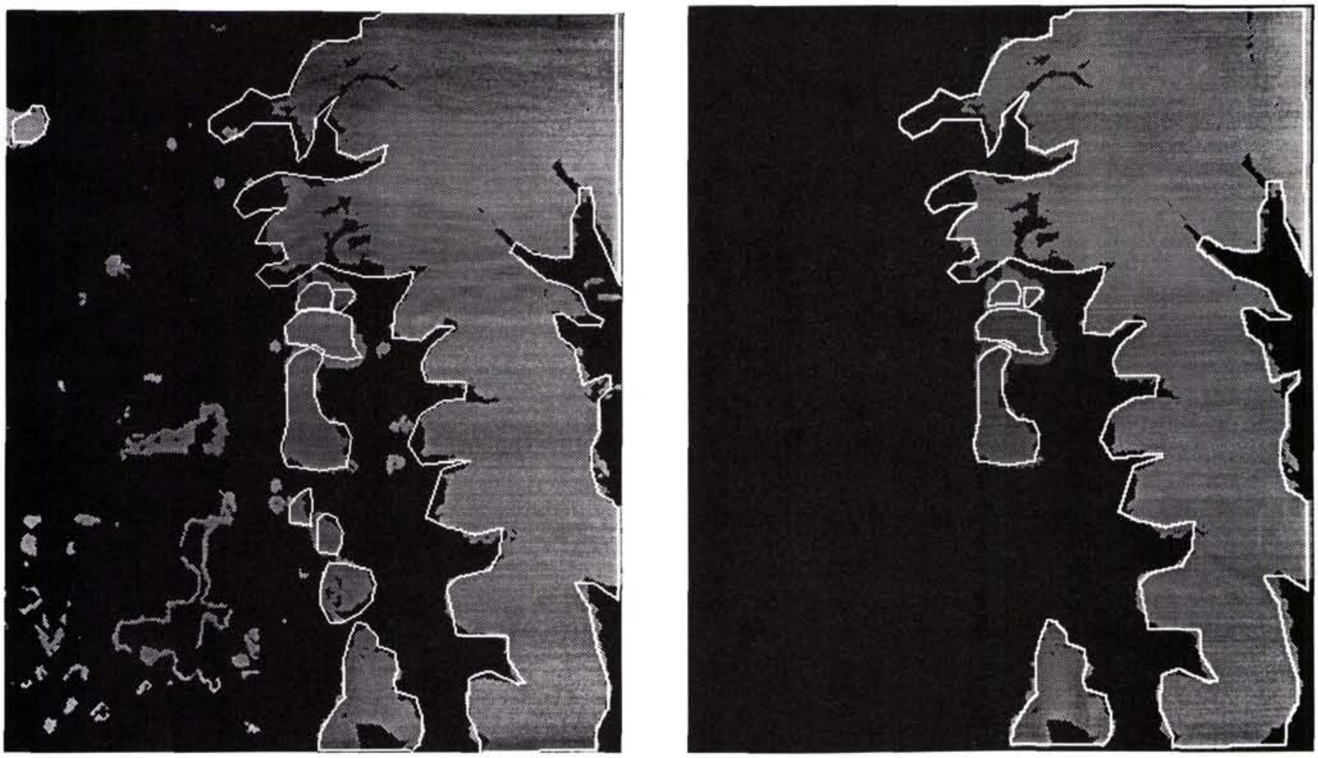
Numerical comparison of all training sites showed overall values that ranged from a low coefficient of areal correspondence of 0.26 to a high of 0.81 (Table 2). The algorithm worked best in areas with a high percentage of well-defined mounts and those with greater local relief.

The lowest overall correspondence was obtained for the Gettysburg area which has a low local relief and few well-defined mounts. In addition, a narrow, linear ridge was quite obvious in the northwest corner in the manual identification and totally missed in the automatic classification (Figure 2). Attempts were made to improve the algorithm to detect the ridge. However, the feature does not possess the required ridge points with slope greater than the boundary class to be extracted. The restrictions for ridge point identification were



(a) (b)

Figure 2. Manually derived boundaries (white) and automatically classified mounts (gray) for Gettysburg, Pennsylvania, DEM. (a) All mounts. (b) Well-defined mounts only.



(a) (b)

Figure 3. Manually derived boundaries (white) and automatically classified mounts (gray) for Huntsville, Alabama, DEM. (a) All mounts. (b) Well-defined mounts only.

TABLE 2. STATISTICS FOR SELECTED TRAINING SITES

Location	Relief(m)	Percent Mounts Well-Defined	Ca_T^a	Ca_W^b
Verona, Wisconsin	93	91	0.65	0.65
Gettysburg, Pennsylvania	117	16	0.26	0.58
Huntsville, Alabama	346	97	0.81	0.87
Mustang Mts., Arizona	641	79	0.74	0.83
Paradise Range, California	800	91	0.81	0.82

[a]Ca_T = coefficient of areal correspondence for all mounts.
[b]Ca_W = coefficient of areal correspondence for well-defined mounts.

lessened by including diagonal neighbors as well; however, this resulted in too many identified points and was determined undesirable.

Huntsville, with a local relief less than that of Mustang Mountains and Paradise Range, produced the highest correspondence for well-defined mounts. This suggests that local relief does not affect the results of the classification algorithm as much as the percentage of well-defined mounts in the area. Ninety-seven percent of the total area of mounts classified automatically for Huntsville were considered to be well-defined, which is the highest rating of any of the training sites (Figure 3).

Test Sites

The four subjects generally agree on which areas in the DEMs are mounts. The correspondence is greatest where the mounts are well-defined or "prototypical." However, when the mounts are poorly defined and less obvious, the determination of their location and extent varies considerably from subject to subject.

Results for the test sites substantiate those obtained with the training sites. Visually there appears to be a high correspondence with the well-defined mounts and a much lower correspondence with the poorly defined mounts, especially in the high-relief areas. However, the classification algorithm still tends to merge mounts and produce more mounts than are manually identified.

The coefficient of areal correspondence further supports the findings of the visual comparison. As can be seen in Table 3, overall correspondences are better in high relief areas than in areas of low local relief. Correspondences of the well-defined mounts are fairly consistent for the three low-relief sites: Oregon, Post Oak Mountains, and Madison. The well-defined correspondences are much greater for the two higher relief areas of Farley and West of Drinkwater Lake.

The Post Oak Mountains site shows the lowest overall correspondences and the lowest correspondences of well-defined mounts. In addition to its low relief, another factor that contributes to the low correspondences is the inability of the algorithms to deal with the large flat-topped range in the south-east quadrant of the site. The problem lies in filling in the flat-top using the automated method. This is an issue that requires further investigation.

Relatively high correspondences, both for all mounts and well-defined mounts only, were obtained from the Farley site. This largely results from the fact that most of the mounts extracted manually are considered to be well-de-

TABLE 3. STATISTICS FOR SELECTED TEST SITES

Location	Subject 1	Subject 2	Subject 3	Subject 4
Oregon, Wisconsin				
Ca_T[a]	0.38	0.40	0.52	0.41
Ca_W[b]	0.45	0.55	0.57	0.47
Post Oak Mts., Texas				
Ca_T	0.38	0.38	0.37	0.37
Ca_W	0.38	0.43	0.37	0.45
Madison, Alabama				
Ca_T	0.18	0.19	0.36	0.38
Ca_W	0.63	0.56	0.63	0.56
Farley, Alabama				
Ca_T	0.70	0.63	0.75	0.72
Ca_W	0.80	0.77	0.82	0.82
West of Drinkwater Lake, California				
Ca_T	0.44	0.58	0.66	0.71
Ca_W	0.82	0.81	0.84	0.79

[a]Ca_T = coefficient of areal correspondence for all mounts.
[b]Ca_W = coefficient of areal correspondence for well-defined mounts.

fined. Like Post Oak Mountains, this site has a large, relatively flat-topped range along its eastern side. However, because the flat area on the top was not as extensive as that in Post Oak Mountains and the slope was not quite as low, the automatic procedure was able to identify most of the area as mount.

The large variability in overall correspondences for West of Drinkwater Lake results from the high- and low-relief features in the same area (Figure 4). When only the well-defined mounts are considered, the correspondences are high, ranging from 0.79 to 0.84 (Figure 5).

Analysis

Mounts that are considered to be well-defined or "prototypical," *i.e.*, isolated, elevated masses with distinguishable boundaries and summits or peaks, are the most easily extracted by the developed method and most closely match the manual classification.

Local relief also plays an important role in the success of the method. In general, higher local relief produces a higher overall correspondence. The results are poorer in low-relief areas where the mounts have indistinct boundaries, extensive low-slope summits, and/or do not possess the required ridge point characteristics. The variability among the subjects for the test sites suggests that manual classification of poorly defined mounts is also more difficult than the classification of well-defined mounts, using elevation data alone.

Success of the mount/non-mount classification may be limited by the method used in this study. Limitations of the method include its uniform, global approach to each DEM; reliance on 3 by 3 local neighborhood operators; and the search for "critical values" such as a unique relationship between local relief and the boundary between mount and non-mount (Graff, 1992).

Incorporation of knowledge-based procedures may help constrain and simplify the classification problem, thereby reducing the limitations of the current approach. These procedures can include regional knowledge about the area such as the physiographic region and climate, or local knowledge such as vegetation and landuse.

The results of this research suggest a relationship between the physiographic region sampled by the DEM and the success of the method. The method was successful in the three sites located in the Basin and Range province. Similar results could be expected in other high-relief physiographic regions such as the Rocky, Blue Ridge, and Appalachian Mountains.

Poor results may be expected, however, in low-relief regions such as the Great Plains, Interior Low Plateaus, and Coastal Plain. This type of knowledge can be used to suggest features that might be expected in the area, thus tailoring the applied method to the specific region.

Additional limitations of using digital elevation data to classify terrain may be imposed by the resolution and quality of the data source (Lee *et al.*, 1992). Better data may produce more accurate slope values (Chang and Tsai, 1991), resulting in more well-defined boundaries. Information such as gully shape and drainage patterns, commonly used in manual terrain classification, may also be extracted. This information could aid in the automated classification process, especially in areas with a high percentage of poorly defined mounts.

Conclusions

A method was developed to automatically classify certain generic terrain features from digital elevation data. The two-class system differentiates mounts and non-mounts. Mounts are considered to be elevated features, such as hills and mountains. All remaining terrain features are considered to be "non-mounts."

Initial results suggest that the classification algorithm used in this divide-and-conquer approach to terrain classification is useful in some areas but not in others. The method is most successful in moderate- or high-relief areas where the mounts are well-defined and have definable ridge points. The classification is less successful in low-relief areas or where the mount has a broad relatively flat summit, or a narrow linear shape.

Although automated terrain classification systems that accurately identify specific geomorphologic landforms have yet to be developed, this work presents a first step toward that goal. By simplifying the classification problem and first attempting to identify generic terrain features such as mounts, basins, and plains, additional processing of these features may lead to the identification of more specific landforms.

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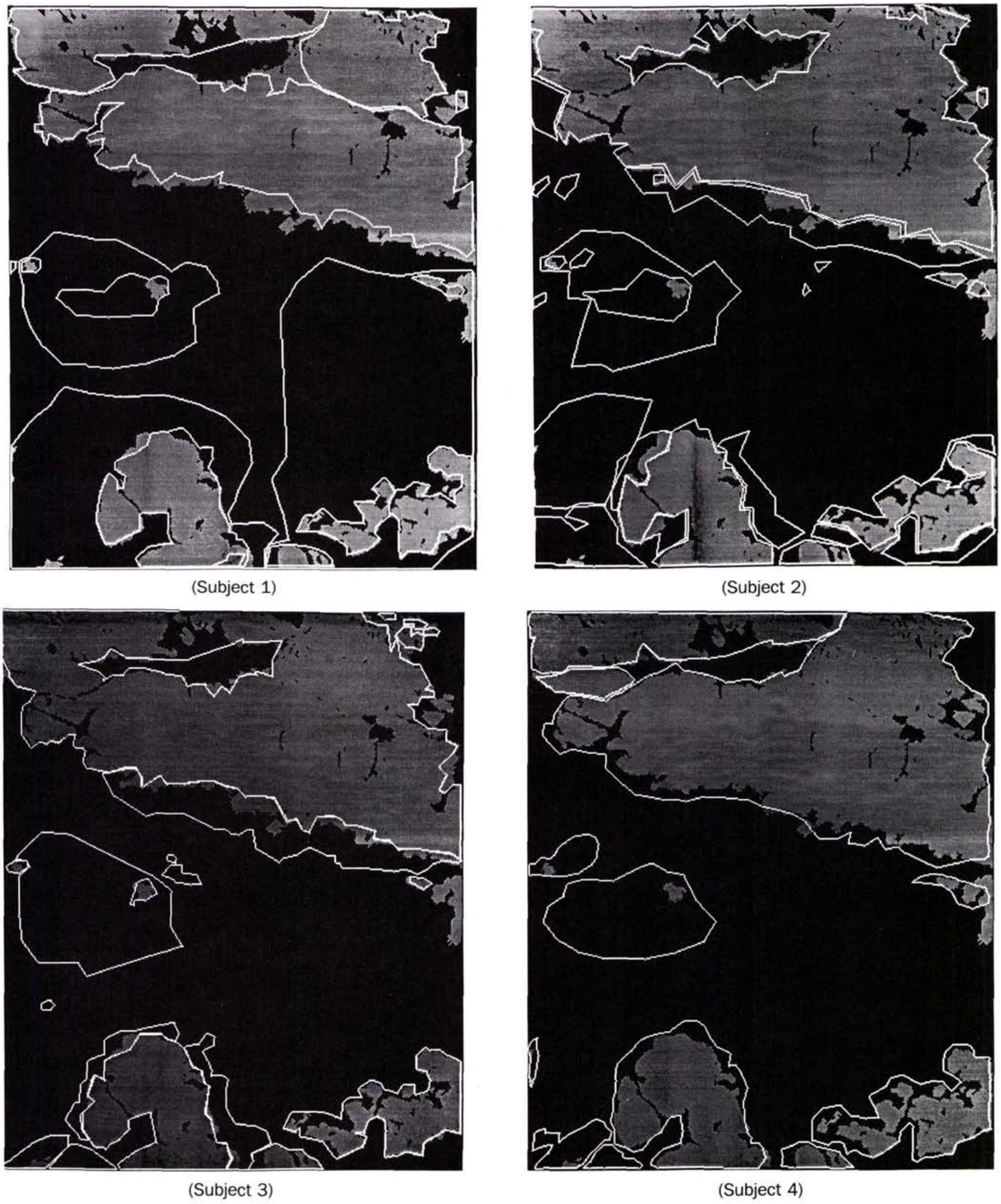

Figure 4. Manually derived boundaries (white) and automatically classified mounts (gray) for all mounts in West of Drinkwater Lake, California, DEM.

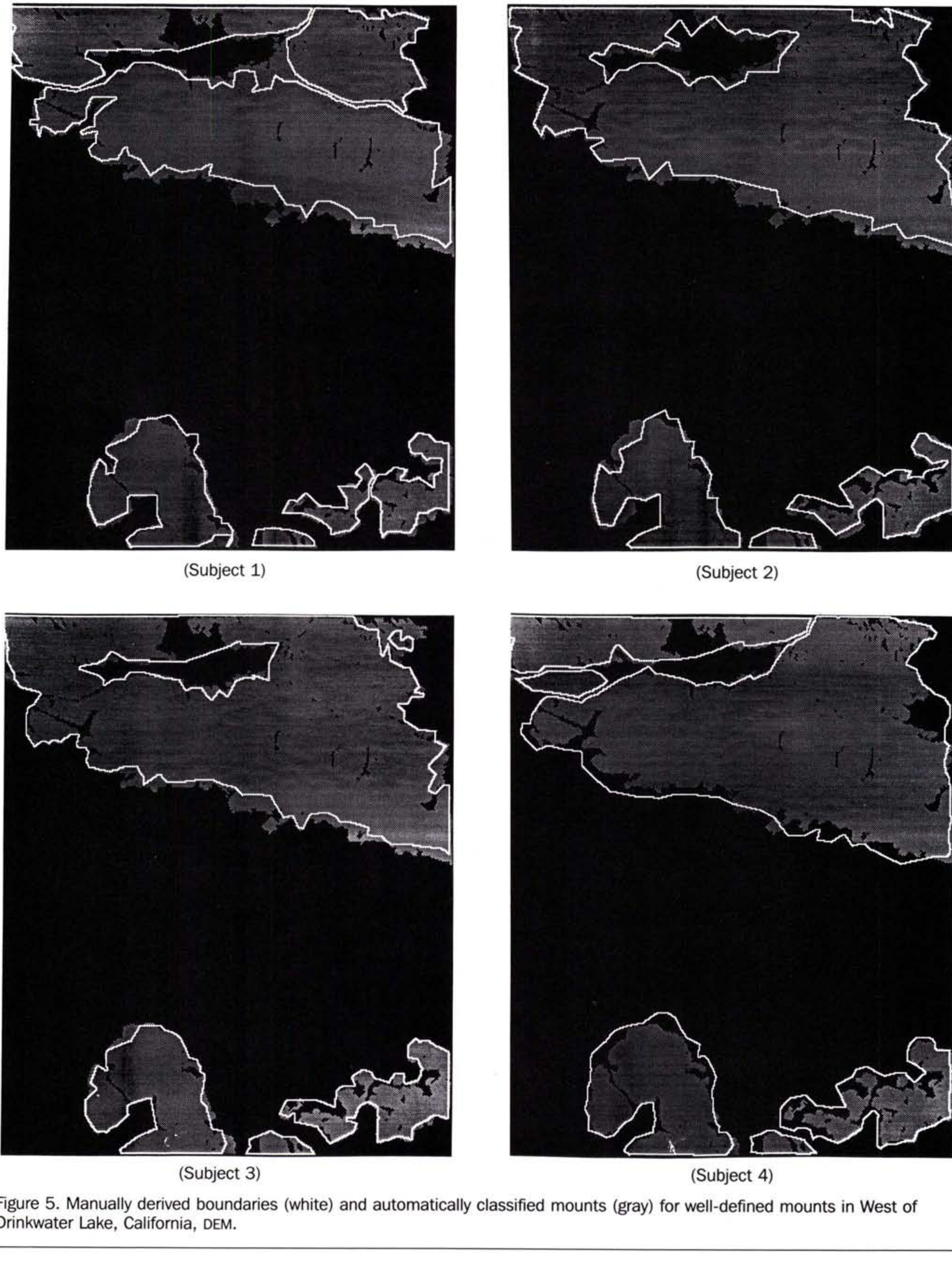

Figure 5. Manually derived boundaries (white) and automatically classified mounts (gray) for well-defined mounts in West of Drinkwater Lake, California, DEM.

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LIST OF "LOST" CERTIFIED PHOTOGRAMMETRISTS

We no longer have valid addresses for the following Certified Photogrammetrists. If you know the whereabouts of any of the persons on this list, please contact ASPRS headquarters so we can update their records and keep them informed of all the changes in the Certification Program. Thank you.

Jack R. Anthony
Dewayne Blackburn
Gerard Borsje
Albert Brown
Eugene Caudell
Robert Denny
Robert Fuoco
Franek Gajdeczka
George Glaser

William Grehn, Jr.
Louis T. Harrod
F.A. Hildebrand, Jr.
James Hogan
William Janssen
Lawrence Johnson
Spero Kapelas
Andre J. Langevin
Harry J. Miller

Marinus Moojen
Gene A. Pearl
Sherman Rosen
Lane Schultz
Keith Syrett
William Thomasset
Conrad Toledo
Robert Tracy
Lawrence Watson
Tad Wojenka