

## Chapter VI

# Shape Analysis

### WHY ARCHAEOLOGICAL EVIDENCE HAS “SHAPE”?

In order to be able to acquire visual information, our automated “observer” is equipped with *range* and *intensity* sensors. The former acquire range images, in which each pixel encodes the distance between the sensor and a point in the scene. The latter are the familiar TV cameras acquiring grey-level images. That is to say, what the automated archaeologist “sees” is just the pattern of structured light projected on the scene (Trucco, 1997). To understand such input data the spatial pattern of visual bindings should be differentiated into sets of marks (points, lines, areas, volumes) that express the position and geometry of perceived boundaries, and retinal properties (color, shadow, texture) that carry additional information necessary for categorizing the constituents of perception.

Currently, recognition of archaeological artifacts is performed manually by an expert. Generally, the expert attempts to find already recognized artifacts that are perceptually similar to the unclassified artifact. In order to recognize such artifacts, the human expert usually searches through a reference collection. A reference collection is a collection of reference artifacts, which is

usually published as a set of formalized descriptions together with line drawings of the artifacts. Manual comparison of excavated artifacts with artifacts from a reference collection is a highly intuitive and uncontrollable process. In order to overcome these drawbacks, an automated archaeologist will use a kind of content-based shape retrieval system to find geometrically similar artifacts. Here “shape” appears as the key aspect for the mechanization of visual perception.

The attempts at defining the term *shape* usually found in the related literature are often based on the concept of “object properties invariant to translation, rotation and scaling” (Dryden & Mardia, 1998; Palmer, 1999; Small, 1996). While such definitions manage to capture an important property of shapes as perceived by humans, namely what relates the different appearances of the same object seen from different perspectives, they do not clearly specify what a *shape* is. An alternative and less conventional definition of shape has been advanced by Costa and Cesar (2001, p. 266): a shape can be understood as any “single,” “distinct,” “whole” or “united” visual entity. Fortunately, these terms can be formalized using the mathematical concept of *connectivity*, which leads to the following definition:

*SHAPE is any connected set of points.*

Consequently, shape is not an intrinsic property of observed objects, but it arises in images in different contexts: linear separation between regions of relative light and dark within an image, discontinuity in the surface depth, discontinuity in surface orientation, markings on the surfaces, and so forth, usually called “interfacial boundaries:” surfaces and/or contours. In other words, “shape” is the characteristic that delimits distinct spatial areas which appear when visual appearances are “significantly different” from one area to the next.

Shape analysis is more a task of discovery than plain description. It is essentially the operation of detecting significant local changes among luminance values in a visual scene. The method for “finding” connected sets of points in the images that represent archaeological observables can be approached by calculating the *luminance gradient* in the data array, that is, the direction of maximum rate of change of luminance values, and a scalar measurement of this rate. Following an earlier algorithm by Marr and Hildreth (1980), the automated archaeologist can extract shape information in a data array by finding the position of maximum variation in the map of luminance (grey or RGB-color levels). First-order differential operators compute the variation levels of such intensity function, and the algorithm finds the connectivity by detecting the highest value in the first derivative of the intensity function. A more economical algorithm for finding edges would be to detect *zero-crossings of the second derivative* of the intensity function. The second derivative of a function is just the slope of its previously calculated first derivative. The second derivative thus computes “the slope of the slope” of the original luminance function. Notice that in this second derivative function, the position of the interfacial boundary corresponds to the zero value in between a highly positive and a highly negative value. In any case, these are not the only ways of finding interfacial boundaries. There is huge literature, indeed an industry, concerned

with “edge detection” algorithms (Costa & Cesar, 2001; Heideman, 2005; Martin et al., 2004; Palmer, 1999; Sonka et al., 1994).

Nevertheless, conventional shape analysis techniques, being sensitive to (image) noise and intensity variations, often *do not* give us the true boundaries of objects in images. It is now generally acknowledged that, without a higher-level information of the object itself (such as the geometry of the object), such techniques produce erroneous results. Consequently, it seems a good idea to build an optimal edge detector by training a neural network with a certain predefined network structure with examples of edge and non-edge patterns.

In any case, we are not interested in the mechanical procedure of extracting shape connectivity among visual input, but in explaining shape information. Consequently, we are considering a higher-order definition, in which “shape” refers to the visual individualization of objects. The fact that a machine be able to individualize what it sees carries important clues about the structure of what is visible, and therefore it is the prime carrier of information in computer vision.

## DIRECT SHAPE RECOGNITION

Let us consider the case, in which input neurons represent a matrix in which each row, and each column identify a point in the image and corresponding input neurons contain the intensity of light (grey or color level) at that point (pixel). In the case of bitmap images (black and white pictures), this is rather simple (Figure 6.1).

Díaz and Castro (2001) have used this approach to analyze the shape of rock-art symbols. The input data are real images (bitmaps), described in binary terms (1,0) (Figure. 6.2).

The neural network outputs the explanatory label of this visual input: abstract forms, zoomorphic and anthropomorphic motives. In this case, shape is appears as an a priori defined verbal category.

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