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Encyclopaedia of Environmetrics: Image analysis

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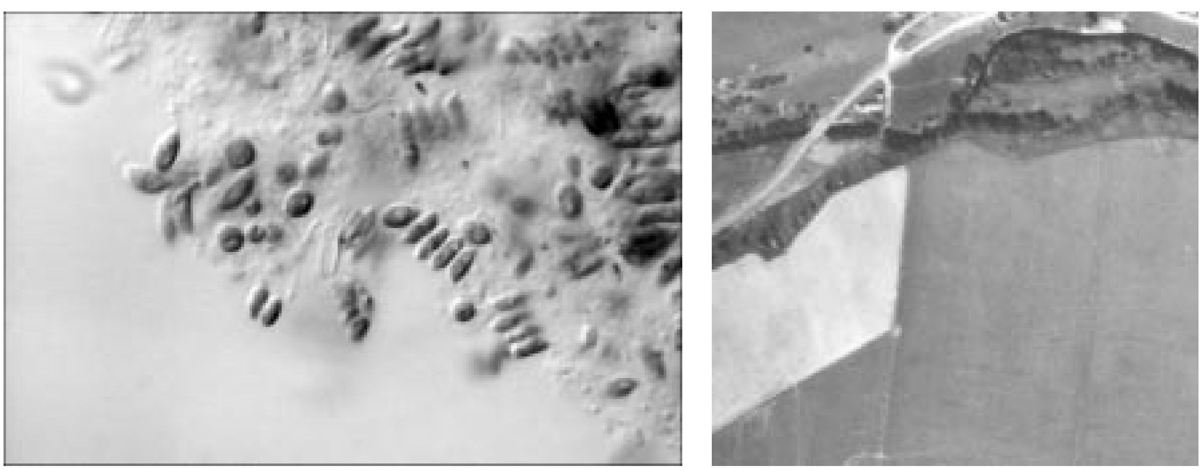
The extraction of information from images is a task that we humans do most of our waking lives; usually with little apparent effort. It is what you are doing in reading these words! The term 'image analysis' has come to mean the use of computers to interpret digital versions of images. Such methods are of increasing relevance in all sciences, including environmetrics. For example, Fig 1(a) shows a light microscope image of a sample of algae, ontained to identify, count and measure cells. At a totally different physical scale, Fig 1(b) is an aerial photograph 0.5km in size of Glassie, near Elgin, Scotland, in June 1988, showing fields and natural vegetation. Such photographs are an efficient means of mapping changes over time in land use and the distribution of semi-natural vegetation. The human vision system is a 'hard act to follow', but computers offer the possibility to relieve scientists of much tedious work in extracting quantitative information, and can sometimes transform images in ways that were not previously possible.



(a) (b)

Figure 1: Examples of images: **(a)** A sample of algae imaged using a differential interference contrast light-microscope, **(b)** an aerial photograph of Glassie, Scotland.

Image analysis is a broad, interdisciplinary field with many challenging problems to which statistical methods are applicable (see, for example, Serra, 1982; Jain, 1989; Glasbey and Horgan, 1995). A digital image usually consists of a rectangular array of pixels, each of which measures the brightness of a part of the original scene, where 'brightness' may denote reflected light but could equally represent any other variate that has been measured on a 2D grid. Methods of analysis range from low-level processing of individual pixels or small neighbourhoods, such as the use of filters to enhance images, through segmentation, the spatial clustering of pixels into segments that represent regions or objects, to high-level processing, where the information in whole images is summarised.

Segmentation is frequently the most challenging stage in image analysis to automate. It is needed before measurements can be made on images, such as counts or size distributions of algal cells, or areas of land in aerial photograph. There are four classes of approach to segmentation: thresholding, edge-, region- and model-based (for a review, see Haralick and Shapiro, 1992, chapter 10). In thresholding, pixels are allocated to categories according to the range of values in which a pixel lies. In edge-based segmentation, an edge filter is applied to the image, pixels are classified as edge or non-edge depending on the filter output, and pixels which are not separated by an edge are allocated to the same category. Region-based segmentation algorithms operate iteratively by grouping together pixels which are neighbours and have similar values, and splitting groups of pixels which are dissimilar in value. Finally, model-based methods include the use of Bayesian inference and stochastic templates (Grenander, 1996). To illustrate, we consider images such as those in Fig 1.

Young et al. (1998) developed a method for constructing templates of cells in differential interference contrast (DIC) microscopy, taking into account DIC optics. Fig 2(a) shows the template for a cell at a particular orientation, and Fig 2(b) shows the result of automatically segmenting an image containing several *Candida* yeast cells.

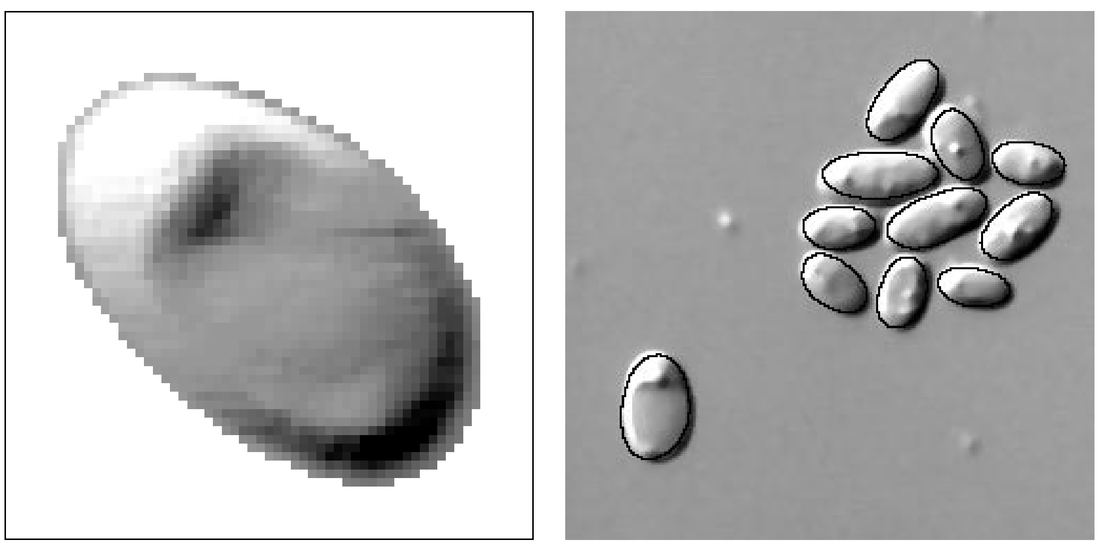
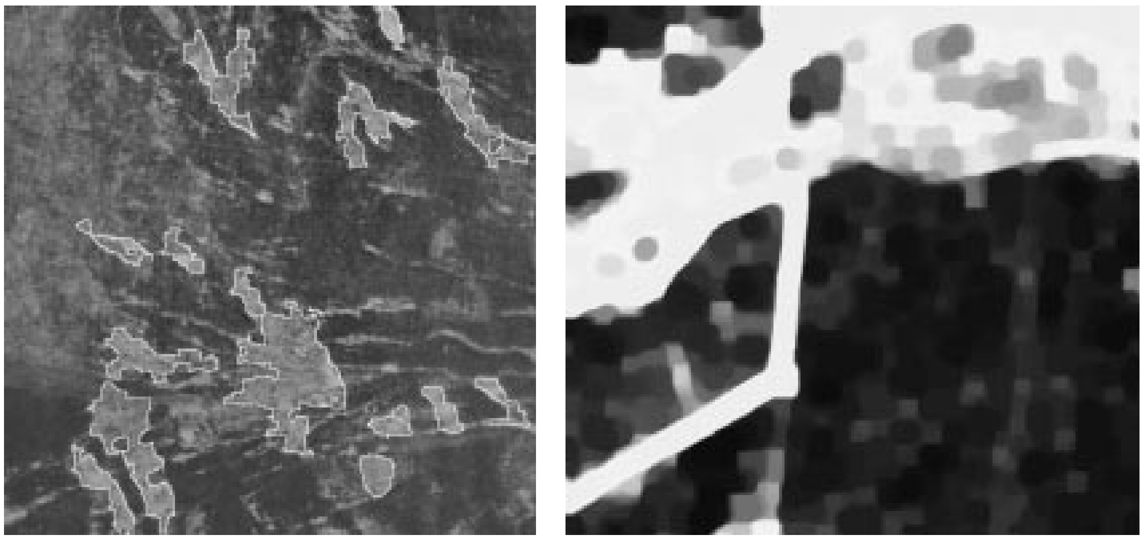


Figure 2: *Candida* yeast cells: **(a)** example of template for cell at orientation of 45°. **(b)** DIC microscope image with identified cell boundaries superimposed.

Fig 3(a) shows an aerial photograph of Glen Feshie, Scotland, with areas of muirburn identified, that is heather moorland which have been burnt as part of the management of a grouse shooting estate. These were identified automatically, by applying a spatial clustering algorithm to pixels with values in a prespecified range. Segmentations may also make use of texture, which describes regular or irregular patterns of intensity variation. For example, at a resolution of between 1 and 5 metres, an area of grassland may appear uniform, whereas a woodland will show some pattern of variation which will depend on the size, type and arrangement of the trees. See Reed and Dubuf (1993) for a review of texture measures. Fig 3(b) shows the effect of applying a moving variance filter followed by a morphological closing to Fig 1(b) (see, for example, Glasbey and Horgan, 1995). It clearly picks out the more heterogeneous ground cover in parts of the image, although it also responds to boundaries between land cover types.



(a) (b)

Figure 3: Land cover detection in aerial photographs: **(a)** Image from Glen Feshie, Scotland, with automatic detection of muirburn; **(a)** Texture measurement of Fig 1(b) by closure of moving variance. (Brighter intensities indicate greater local variability in land cover.)

Although fully-automatic image analysis is the ideal, semi-automatic methods are often the reality: a human-computer symbiosis. Consider boundary detection: a person can accurately locate objects in noisy images and roughly outline them, whereas computers provide smooth, accurate and detailed outlines much more quickly, but fail occasionally. Human and computer inputs can be combined by the computer refining a user-supplied outline to optimise a smoothness and edge-following criterion, or by the user modifying computer-generated boundaries. Most published research has focused on fully-automatic algorithms, even though semi-automatic methods are often more practicable: they avoid the need for an algorithm to be very precise or much effort to be expended to automate what people can do easily, if laboriously, by eye. Samadani and Han (1993) distinguished two types of semi-automatic algorithm: batch methods, where inputs from a user are subsequently refined by the computer, and interactive methods, which combine simultaneous user and computer inputs. Also, the nature and intensity of user input is important, and can take many forms. It may simply involve locating a few points on a boundary, between which the algorithm interpolates (Wu and Barba, 1995). Alternatively, a complete boundary may need to be input, or user intervention may just be an option within a system, to be utilised if and when necessary. Frey (1969); Ramesh et al. (1992); Ruiz and

Fairhurst (1995) discuss interactive computer systems.

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