

Robust Measurements

John C. Russ¹, J. Christian Russ², F. Brent Neal³

¹ North Carolina State University, Raleigh, NC ² Reindeer Graphics, Asheville, NC

³ Akzo Nobel N.V., Greensboro, NC

Abstract

Among the plethora of measurements offered by standard software programs that are applied to digitised images of objects, some are more meaningful and robust than others. The various measures provided for position, orientation, size, and shape include some that are poorly or inconsistently defined, or have implementations with limited accuracy. Perimeter, for example, is a particular problem, since it is highly dependent on image resolution and the choice of a measurement algorithm. This paper describes the measures that are most robust in performance and meaning, and best capture the information about the objects in a way consistent with human visual expectations. Examples provide comparisons of various measurement approaches and algorithms.

Introduction

The authors have previously presented methods (Russ, 2017) for describing ways that shapes may depart from circularity, and have pointed out (Russ et al., 2018) that measuring the perimeter of an object in a digitised image is a dubious procedure, since the resolved boundary of an object is frequently a function of magnification and resolution, and the measurement algorithms for perimeter in digitised images are inconsistent both in what they measure and in their results, especially as object orientation on the pixel grid may vary. This leads to the obvious question: "What should be measured that will give robust and meaningful results?" This paper is an effort to complete the trilogy by providing some suggestions. Many, but not all, of these measurements are supported in various available standard software packages.

The purpose for measuring position, orientation, size and shape is often to investigate relationships between them, such as angle vs. position or length (Figure 1a), or size vs. shape (Figure 1b). Data may also be needed to study variation with some other property or behavior of the objects, such as size or shape vs. flowability and compaction of powders (Figure 1c) or flight characteristics of insect wings as a function of shape, size and angle (Figure 1d).

This paper is concerned with how to best measure various descriptors for position, orientation, size, and shape. Statistical correlations with properties are application-dependent and not considered here except to note that the intended purpose(s) should be considered before starting the process. Collecting a pile of data from every measurement offered in a software package, and hoping that a statistical analysis program can locate some potentially meaningful relationship, is not a recommended approach in spite of Lord Kelvin's statement that "The grandest discoveries of science have been but the rewards of accurate measurement and patient long-continued labour in the minute sifting of numerical results." Of course, he also said "When you can measure what you are speaking about, and express it in numbers, you know something about it; but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind; it may be the beginning of knowledge, but you have scarcely, in your thoughts, advanced to the stage of science, whatever the matter may be."

The many possible problems of appropriate image acquisition and subsequent processing, both of

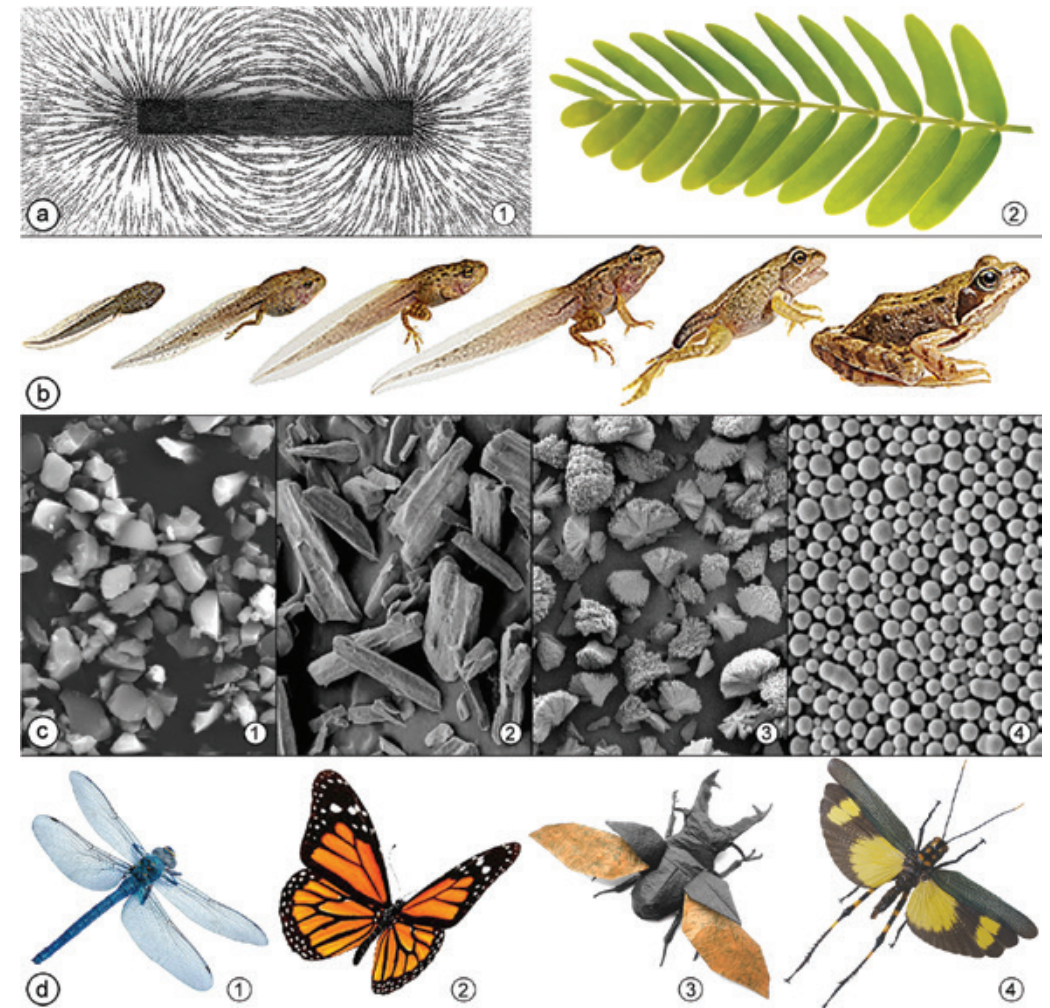


Figure 1. Examples of images for measurement and correlation: (a) angle vs. position (filings in a magnetic field, leaf angle varying along a stem); (b) shape vs. size (growth of a tadpole into a frog); (c) size and shape vs. history (crushed glass, ibuprofen, sand, catalyst); (d) shape vs. flight performance (wings of dragonfly, butterfly, beetle, grasshopper).

the original color or grayscale image and the thresholded or segmented representation, and the thresholding process itself, are not considered here, although they may certainly affect the quality and reliability of subsequent measurements. The starting point for this discussion is a segmented image with pixel values that distinguish the objects of interest from the surrounding background. The brightness values of pixels along boundaries in the original image may make it possible to obtain better measurements in some cases, for instance for area and length (Sladoje et al., 2005), but most standard programmes do not use

them. It is important to remember, however, that the true purpose of the measurement procedure is the original object, which the digitised, thresholded, processed image represents imperfectly and with finite, limited resolution. The discussion and examples are concerned with 2D images, but the same ideas extend naturally and directly to 3D voxel arrays.

Position

The most widely used set of coordinates for the position of an object is the centroid or centre-of-mass location. This is obtained by summing the x, y coordinates of the pixels making up the

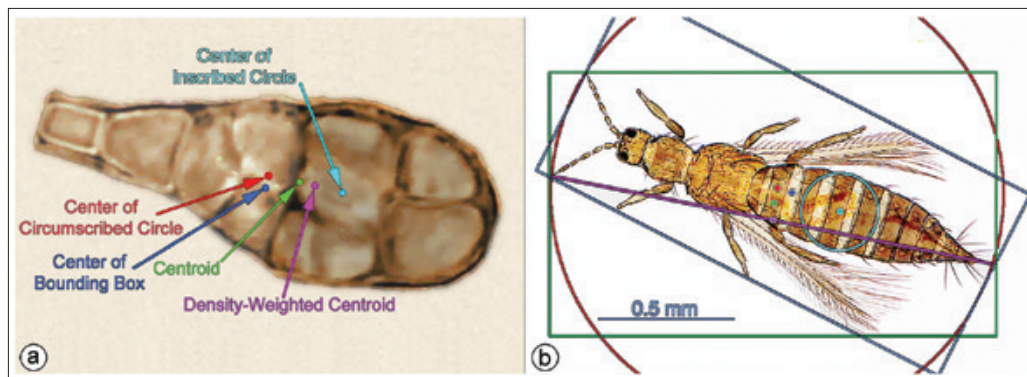


Figure 2. Microscope images of a mold spore and an insect: (a) points that may be used for location: centroid based on area, centroid using the pixel density values, centres of the inscribed and circumscribed circles, and centre of the minimum bounding box; (b) constructions used in determining location as well as size: the x-y oriented bounding box (green), the minimum bounding box (blue), the minimum bounding circle (red), the maximum inscribed circle (cyan), and the maximum caliper dimension (magenta), all with centres marked.

representation (Equation 1). If the pixel values v have meaning (e.g. density) they can be included, for instance to find the centre-of-mass balance point (Figure 2a)

$$x_c = \frac{\sum v_i x_i}{\sum v_i}; \quad y_c = \frac{\sum v_i y_i}{\sum v_i} \quad (1)$$

The centre of a bounding box (Figure 2b) is generally not a good choice, and may not even lie within the object's borders (for example, the shape of the letter C). If just the horizontally oriented bounding box is used, based on the extreme x and y coordinates, the calculation is trivial, but may not be meaningful depending on the object's orientation. Finding the

minimum bounding box, also shown in the figure, is a computationally more demanding procedure (Chan & Tan, 2001; Barequest & Har-Peled, 2001; Chaudhuri & Sama, 2007; Huebner et al., 2008). But the centre of that box is a poor choice for location, especially for objects that are not symmetric about a principal axis.

Other possibilities for location include the midpoint of the maximum caliper or projected dimension (the distance between the two points farthest apart on the boundary), or the centre of the largest inscribed or of the smallest circumscribed circle. At least the circles are insensitive to orientation, and for the inscribed circle the centre is guaranteed to lie inside the object's bounds. It is determined as the location

of the maximum value in the Euclidean distance map of the object. Rokne (1991) gives a concise algorithm for finding the minimum circumscribed circle. The various constructions shown in the figure are used also in the size measurements discussed below. The distance between the various "centre" coordinates of a shape may be used as a measure of asymmetry, for instance the distance between the inscribed and circumscribed circle centres as a fraction of the radius of the circumscribed circle. Other shape measurements are discussed below.

In many cases the absolute coordinates (x , y coordinates in the image, or converted to world coordinates such as position on a microscope slide or latitude and longitude on a map) are less meaningful than distances to nearest neighbours. The statistics of clustering are based on the neighbour distances for a Poisson random distribution. Equation 2 calculates the mean nearest neighbour distance based on the number of objects N within an area. This can then be compared to the actual mean value determined for the image, omitting any observed nearest neighbour distance that is greater than the distance to the image border (since there might be an unseen nearer neighbour outside the image bounds). Neighbour distances are usually calculated based on centre-to-centre distances but for some purposes may instead use the minimum boundary-to-boundary distance, which can be determined from minima along the medial axis transform of the background.

$$\text{Mean Distance} = 0.5 \cdot \sqrt{\frac{\text{Image Area}}{N}} \quad (2)$$

As shown for the examples in Figure 3, the ratio of the measured mean distance to that calculated for a random distribution determines whether the objects are clustered or self-avoiding. Clustering indicates some attractive property or relationship for the individual objects (much as humans cluster in cities), while self-avoidance can result from depletion of the surrounding region in the

process of precipitate formation, or competition for resources (as for cacti in the desert). It is also important in flocks of birds and schools of fish, which move individually while constantly adjusting and maintaining their distances from near neighbours.

Orientation

The angle of the line connecting the two points on the object boundary that are farthest apart, shown in Figure 2b above, is sometimes used as a measure of orientation, but is a poor choice for two reasons. First, the maximum projected or caliper dimension that is reported as the "length" of an object is conveniently determined by calculating the difference between maximum and minimum coordinates in a series of rotated coordinate systems. This is adequate for the purpose of determining the projected dimension since the maximum error is the cosine of one-half the angle of the steps used for the rotated coordinates. For example, a step angle of 10 degrees, which requires only a precalculated table of sines and cosines for 18 angles, has a worst-case misalignment of 5 degrees, whose cosine is 0.996. Consequently, an object with an actual length of 250 pixels would be reported as 249 pixels. Variations in the placement of the object's image on the pixel grid can produce a similar error so this is a minor concern. But the angle of the length vector determined in this way is approximated to the nearest 10-degree step.

The second problem is that the longest dimension of the object is not a very robust characterisation of the overall orientation unless the object has mirror symmetry about that line. This same concern applies to the long axis of the minimum bounding box, also shown in Figure 2b, which in addition to its computational requirements is not well related to the visual impression of overall orientation for most object shapes. The angle of the moment ellipse, described below, is a much more robust measure, and rather than being sensitive only to the boundary pixels, which are most affected by image processing and thresholding, it is able to incorporate actual

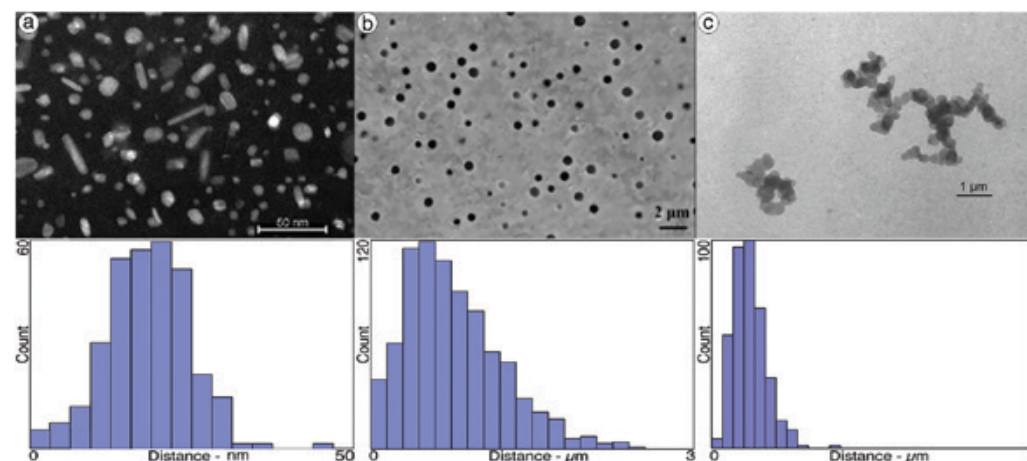


Figure 3. Distributions of nearest neighbour distances: (a) self-avoiding for precipitate particles in a metal (ratio = 1.327); (b) random for dust particles captured on an air filter (ratio = 1.004); (c) clustered for soot particles (ratio = 0.389).

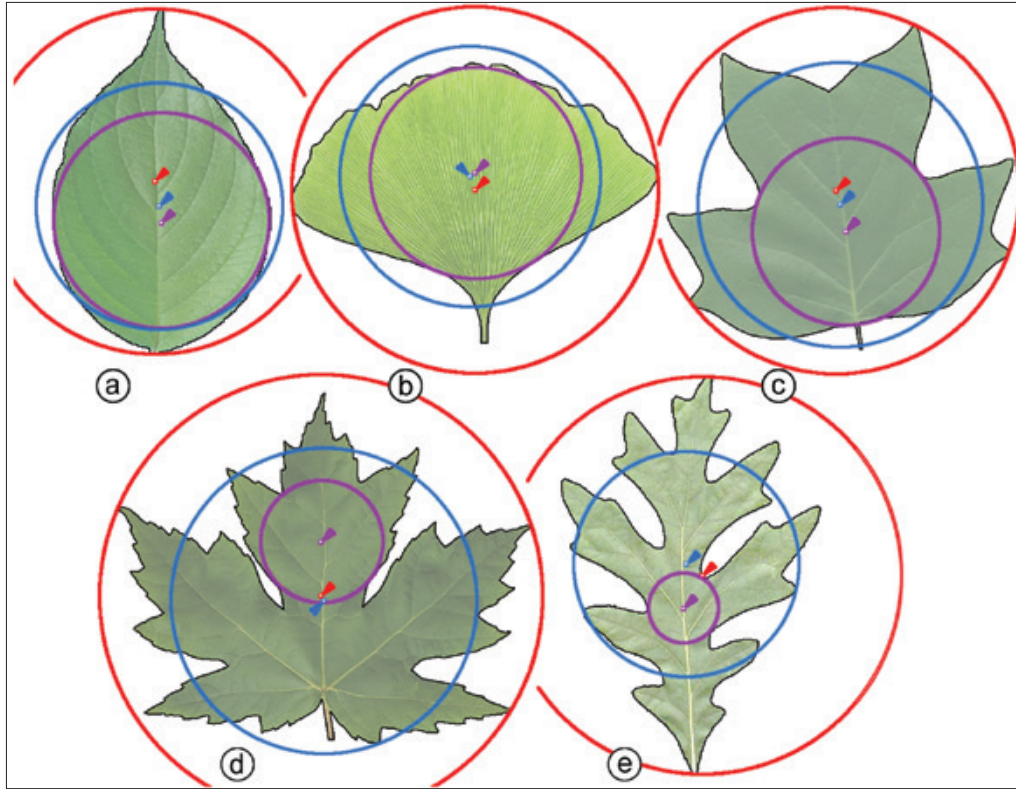


Figure 4. Several leaves from the author's yard (dogwood, ginkgo, tulip poplar, silver maple, white oak) with the smallest circumscribed (red), largest inscribed (magenta) and equivalent area (blue) circles and circle centres marked.

pixel values (e.g., density), and deal with internal holes or disconnected parts.

Size

The most obvious measure of size is the area covered by the object, and the most commonly used method for determining it is simply counting the pixels that are included, multiplied by the pixel spacing. This is unfortunately inconsistent with most other measurements performed on the image which use the pixel centre coordinates. For a straight edge, half of each border pixel lies outside the boundary. For a shape with corners or indentations, the area calculated by treating the border pixels as vertices of a polygon is a better choice. Equation 3 calculates the area based on the x, y coordinates of the pixels in the chain code boundary linking neighbours along the border, summing values starting at one point and following the boundary around to return to that point. The result is always smaller than the value that would be determined by simply counting

pixels but more meaningfully represents the size of the object portrayed in the digitised image, and is less sensitive to object orientation on the pixel grid. [Note that this procedure does not extrapolate to 3D voxel arrays, for which there is no complete closed path on the surface. The method of marching cubes (Cline & Lorensen, 1987; Lorensen & Cline, 1987) is efficient and often used to determine volumes in 3D.]

$$Area = \left| \sum_i \left(\frac{x_i + x_{i-1}}{2} \right) \cdot (y_i - y_{i-1}) \right| \quad (3)$$

Object area may be converted to the equivalent circular diameter $= 2 \cdot (Area / \pi)^{1/2}$ as a commonly used way to report size. The inscribed or circumscribed circles are also useful as size measures. Figure 4 illustrates these circles for several leaves, along with the locations of their centres. As noted above the distance between the centres

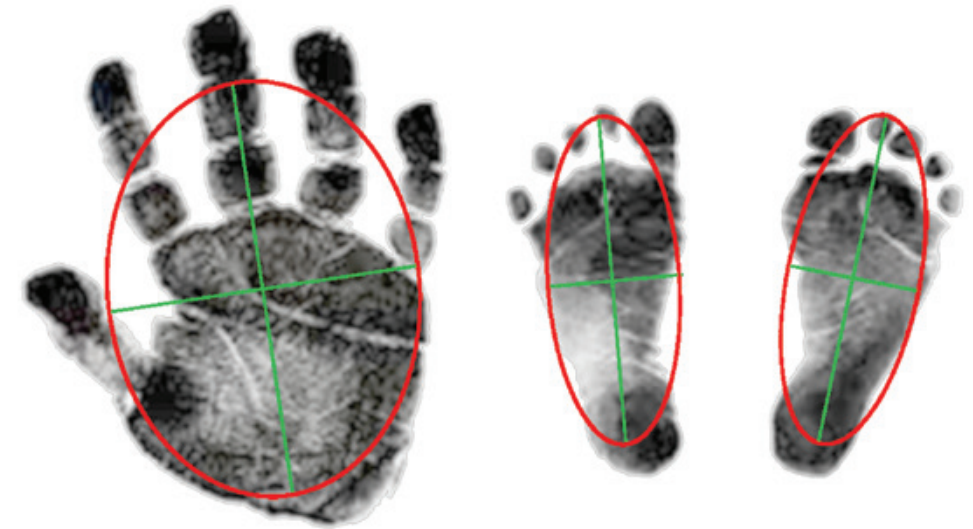


Figure 5. Baby hand and footprints with moment ellipses, including the separated toes.

may be used as a measure of asymmetry, and as discussed below the ratios of the circle diameters often provide a useful way to compare shapes.

Instead of expressing area as a circle, the second moments (Equation 4) can be used to determine the axial ratio (= length / breadth) of an ellipse (Equations 5, 6) as shown in Figure 5. The ellipse length, breadth, and area ($= \pi/4 \cdot \text{length} \cdot \text{breadth}$) can be used as measures of size. This is generally a better representation than a bounding box, since few objects have "box-like" shapes or symmetrically fill the box, and may include holes or disconnected

parts. The major axis also provides a good measure of orientation (Equation 7). The moments are summed as:

$$\mu_{pq} = \sum_i \sum_j v_{ij} (x_i - x_c)^p \cdot (y_i - y_c)^q \quad (4)$$

and the axial ratio is:

$$Aspect\ Ratio = \sqrt{\lambda_1 / \lambda_2} \quad (5)$$

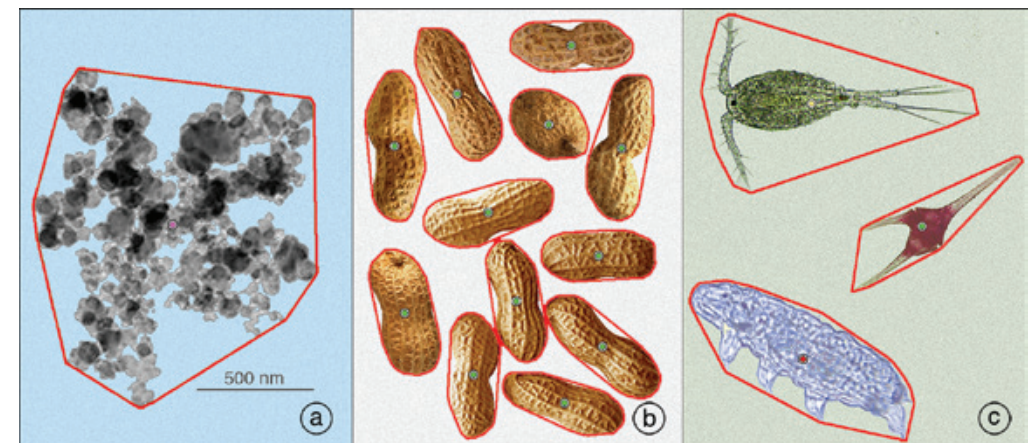


Figure 6. Convex hulls: (a) cluster of soot particles; (b) peanuts; (c) pond life. The centroids of each area inside the convex hulls are marked.

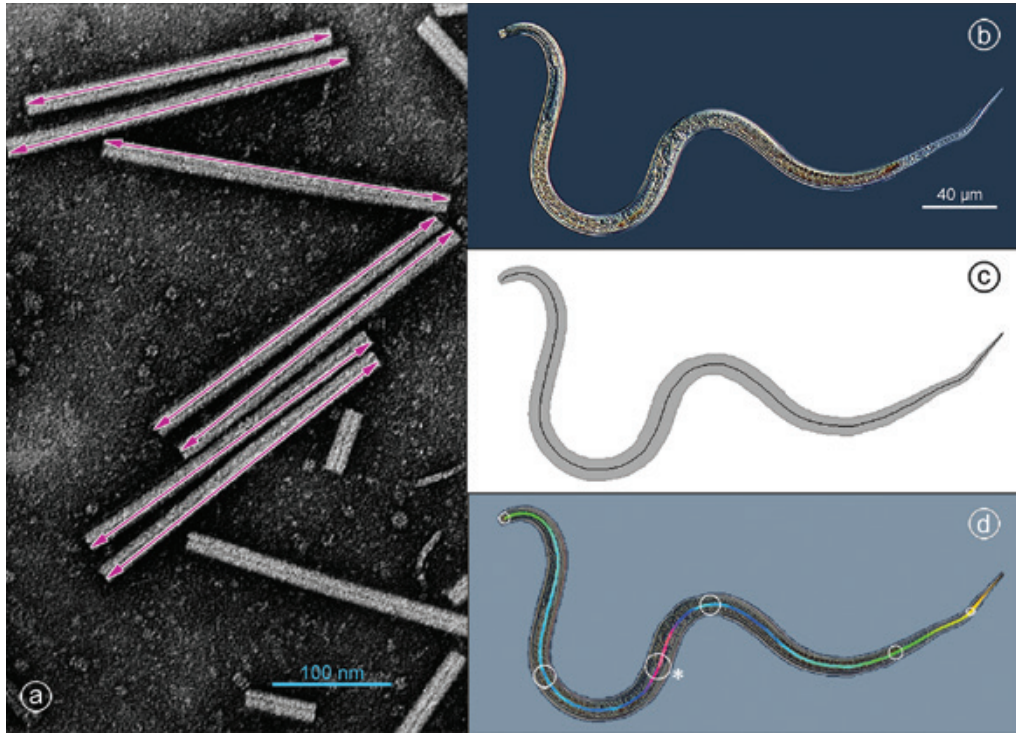


Figure 7. Measuring length: (a) tobacco mosaic virus with straight line measurements; (b) a nematode exhibits variable shape; (c) the skeleton length is 421.3 μm ; (d) based on the values of the medial axis transform, represented in color, the average width is 9.6 μm and the maximum width is 14.8 μm , which is the diameter of the maximum inscribed circle (marked *).

where $\lambda_{1,2}$ are the eigenvalues of the covariance matrix of second moments (normalized by μ_{00} , which is just the object area if the pixel values v are uniform):

$$C = \begin{bmatrix} \mu'_{20} & \mu'_{11} \\ \mu'_{11} & \mu'_{02} \end{bmatrix} \quad (6)$$

and the angle of the ellipse major axis is:

$$\theta = \frac{1}{2} \tan^{-1} \left(\frac{2\mu_{11}}{\mu_{02} - \mu_{20}} \right) \quad (7)$$

As described above, the maximum straight-line distance between extreme points (the maximum projected or caliper dimension) can be efficiently determined with acceptable accuracy by using a

relatively small number of rotated axes to calculate the difference between extreme coordinates. By connecting the extreme points for each of the rotations a convex hull or taut-string boundary can be formed, and the area of this n -sided polygon calculated. For some objects, such as the clustered soot particles and other objects shown in Figure 6, this size is related to the ability to pass through sieves, filters or the passageways in the lungs, or the number that will fill a container. The value may also be used in the shape ratios discussed below.

As discussed above, the straight-line distance between extreme points provides an adequate length measurement for straight objects (Figure 7a). For irregular, curved or branched objects, or ones such as the nematode shown in Figure 7b whose position and curvature in the image are accidental and unrelated to actual size and shape, a better approach uses the skeleton (Figure 7c). This is best determined as the central ridge of the medial axis transform (Blum, 1967). Measurement

of the length must deal with problems arising from the 45/90-degree orientation of the pixel links along the skeleton, which could overestimate the actual length by as much as 8% depending on the orientation with respect to pixel grid. Fitting of smooth curves by various methods can improve this. For broad objects, the skeleton length may be adjusted by adding the radii of the ends (the medial axis values at the end points).

Just as there are different definitions and measurement procedures for length, there are multiple possibilities for width, some more or less meaningful than others in particular cases. For example, the minimum caliper or projected dimension may be used, which is much more difficult to determine than the maximum length described above, since the error is related to the sine of the misalignment angle rather than the cosine. Other choices are the projected dimension perpendicular to the orientation of the length (longest dimension), or the width of a bounding box, and it is important to know which of these measures is being given the “width” label. Especially for narrow, branched or curved objects (e.g. fibers) the values of the medial axis along the skeleton are most useful. These are the radii of inscribed circles, as indicated in Figure 7d, and so measure the local width. The minimum, maximum or average of these values may be

reported. If the skeleton has branches, the lengths and widths can be measured for each of the parts, distinguishing those which are internal (extending from node to node) or terminal (from a node to an end point).

Shape

For the preceding categories of position, size and angle, there are multiple measurement possibilities but at least somewhat familiar concepts and words used to describe them. We may not agree on how to best measure length but the word is one that people use with familiarity and with a general understanding of the underlying meaning. Shape is more complicated. There are few words that apply, such as skinny, bent, pointy, etc., and their human interpretations shift according to situation, and are prone to miscommunication. Consequently, the need for meaningful and consistent numerical measurement becomes even more important.

Combinations of size measures that are formally dimensionless are easy to calculate but capture very little of the “shape” of a complex object as seen by a human. There are many commonly used combinations, unfortunately with no consistency in names. Examples include ratios of the various circle diameters (inscribed, circumscribed, equivalent area), or the ratio of area to that of the minimum

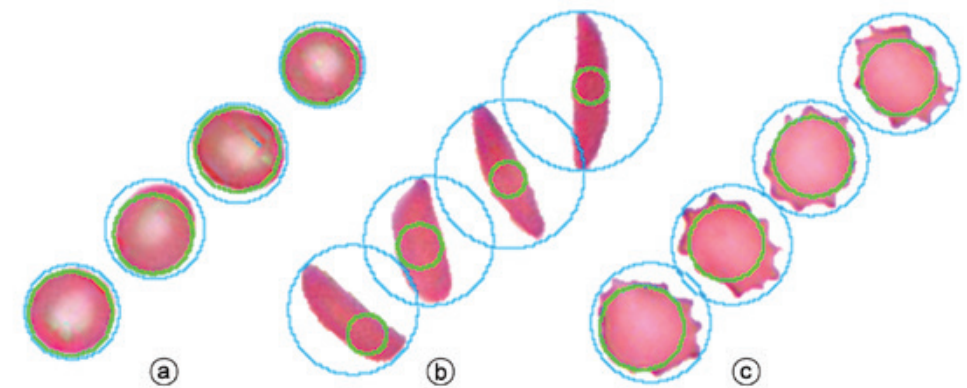


Figure 8. Circumscribed and inscribed circles with diameter ratios: (a) normal red blood cells (average ratio=1.108); (b) sickled cells (average ratio=3.147); (c) echinocytes (average ratio=1.421).

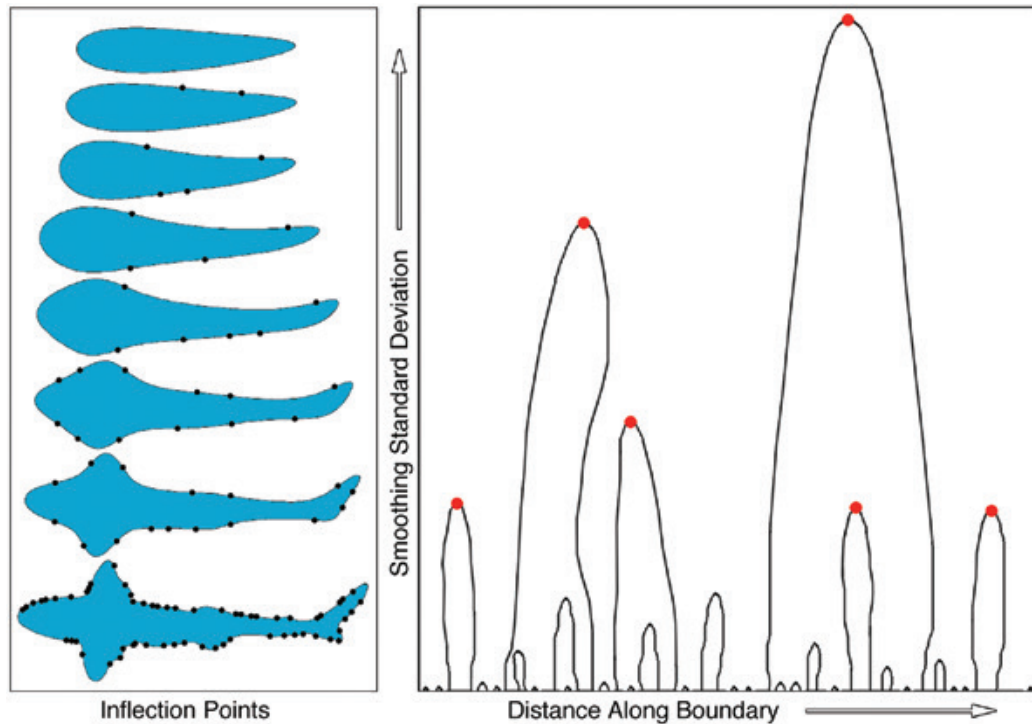


Figure 9. Curvature Scale Space applies progressive smoothing to the object boundary and finds locations where inflection points merge and cancel. The relative positions of the final few of these locations (red) and their relative heights are used for matching shapes.

bounding box or convex hull. Figure 8 shows an example using the ratio of circumscribed to inscribed circle diameters. Formulae such as $(4 \text{ Area} / \pi \text{ Length}^2)$, or $(4 \pi \text{ Area} / \text{Perimeter}^2)$, or $(\text{Perimeter} / \text{Convex Hull Perimeter})$, etc., with a variety of names such as formfactor, roundness, circularity, shape ratio, convexity, and others, are used in an attempt to describe the extent to which a shape differs from circular (Russ, 2017). Those that incorporate perimeter are also hampered by the inherent problems with that measurement.

The ratio of length to width is often called the aspect ratio, but in view of the various ways these may each be measured, the aspect ratio of the moment ellipse, shown above, is preferable as a measure of elongation. Another measure of aspect ratio is the amplitude of the second term in the Fourier harmonic series for the object's outline, but this does not take into account the interior details.

The complex terms in the Fourier harmonic series for the boundary fully represent an object's outline

(Ehrlich & Weinberg, 1970; Zahn & Roskies, 1972; Beddow *et al.*, 1977; Meloy, 1977) and can be analysed to obtain characterisations for some aspects of size and shape. The series may be calculated using the radius from the centroid as a function of angle (Equation 8), but this fails for reentrant boundaries and instead the series may use the change in angle vs. position along the boundary. This is somewhat computationally demanding but the principal objection is that it produces too many numbers, which tend to obscure rather than clarify the actual object shape. Statistical methods such as principal components analysis are often used to extract a few numbers deemed significant for some particular correlation, and which may (but frequently do not) correspond to human visual impression.

$$r(\theta) = \sum a_k \cdot \sin(2\pi k\theta + \delta_k) \quad (8)$$

This is likewise a problem for wavelet methods and for complete or invariant moments. Complex moments (Bigun & du Buf, 1994; Shen *et al.*, 1999;

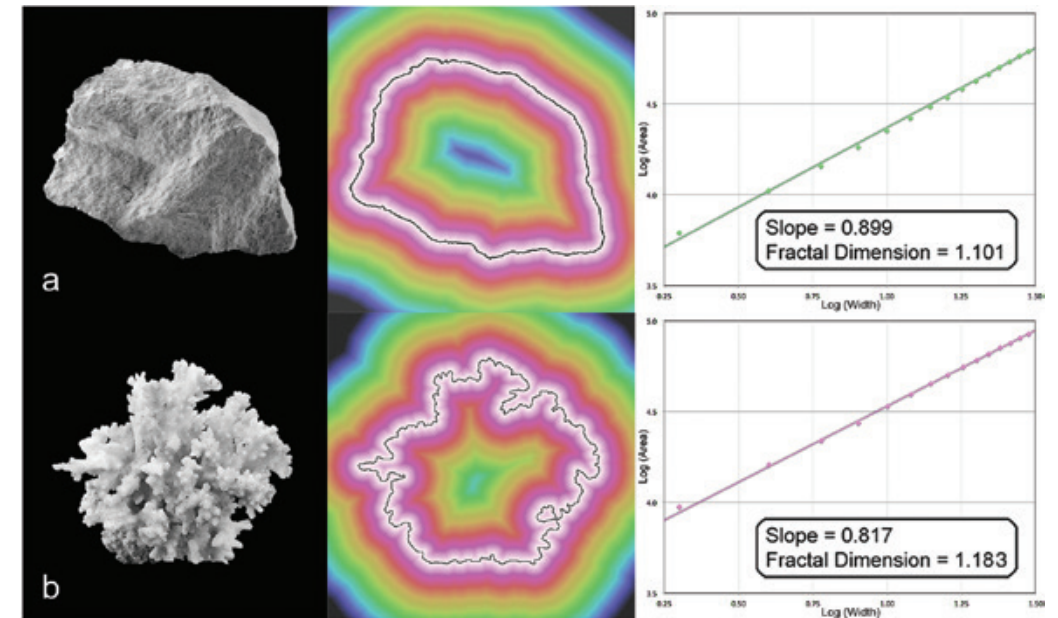


Figure 10. Comparison of the fractal dimension for particles of sand (a) and coral (b), determined using the Euclidean distance map, shown with colour coding of distance from the boundary.

Derrode & Ghorbel, 2004; Crespo & Aguiar, 2011) and Fourier coefficients are both able to identify some symmetries in shapes based on the presence of small amplitudes for some terms (Russ, 2018). These also require more intensive calculations and are not illustrated here.

Curvature Scale Space (Mokhtarian & Mackworth, 1986) represents a different approach to representing shape, but is not a “measurement” in the usual numeric sense. As indicated in Figure 9, applying Gaussian smoothing with increasing

radial standard deviation progressively removes the inflection points in the boundary curvature. The plot of the locations of these points along the boundary shows where each pair of inflections finally merge and disappear. The relative locations of the final mergings, and the relative heights of the peaks in the plot, provide a compact representation of the shape that is very efficient for searching a database to find similar or matching shapes.

Many natural objects exhibit fractal geometry, in which similar amounts of detail are present over

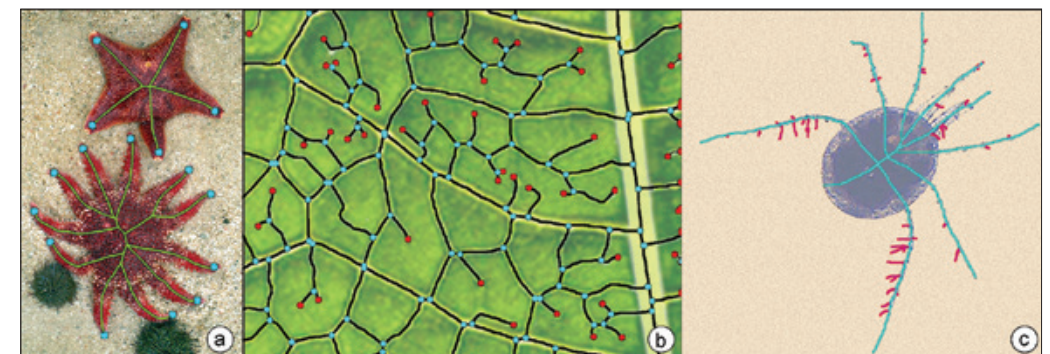


Figure 11. (a) Starfish with 5 and 11 arms; (b) veins in a leaf with the skeleton superimposed and the nodes and end points colour coded; (c) water mite with the skeleton superimposed, trimming the short terminal branches (red) leaves a more robust depiction of shape.

a wide range of dimensional scales (Mandelbrot, 1977). The classic method for determining the fractal dimension measures the perimeter using rulers of varying length and plotting the results on log-log axes (Richardson, 1961); the slope gives the fractal dimension (Fractal Dimension = $2 - |\text{Slope}|$). An alternate method (Flook, 1978; Clark, 1986; Russ, 1994) that is faster and has the advantage that it does not require perimeter measurement uses the area of a ribbon along the boundary, plotted as a function of the width of the ribbon. For a fractal boundary the rate of increase is less than that for a smooth shape. Using the Euclidean distance map to assign the value to each pixel inside and outside the boundary allows easy summation of the area of the ribbon as a function of its width, and a log-log plot has a slope that gives the fractal dimension (Fractal Dimension = $2 - \text{Slope}$), as shown in Figure 10.

Just as the various circles described above represent simplifications of size, skeletons simplify shape and isolate topological information (Russ & Neal, 2019). The numbers of ends, branches, nodes, and loops are readily determined from the skeleton. These are related to each other by the Euler formula (Equation 9). For example, the letters A B C D E can be

distinguished by the number of ends and loops (2 & 1; 0 & 2; 2 & 0; 0 & 1; 3 & 0 respectively). Counting ends determines the number of arms in the starfish in Figure 11a.

$$\# \text{ Loops} - \# \text{ Branches} + \# \text{ Ends} + \# \text{ Nodes} = 1 \quad (9)$$

For networks such as the one in Figure 11b, the number of ends and nodes per unit area is a useful measure of complexity. The ratio of the measured length of a skeleton, or the individual branches, to the distance between the end points is sometimes useful as a measure of irregularity or curvature (for the nematode in Figure 7c, the skeleton is 1.58 times as long as the end-to-end distance). The ratio measures the “tortuosity” of retinal blood vessels, which is an indicator of severity for several diseases including diabetes and hypertension (Hart *et al.*, 1999; Witt *et al.*, 2006; Sasongko *et al.*, 2011). For some skeletons, it may be appropriate to trim off short terminal branches (ones extending from a node to an end point) to obtain a more robust depiction of the shape and topology (Figure 11c). In the example of the letters A through E above, a serif font would generate short terminal branches requiring trimming.

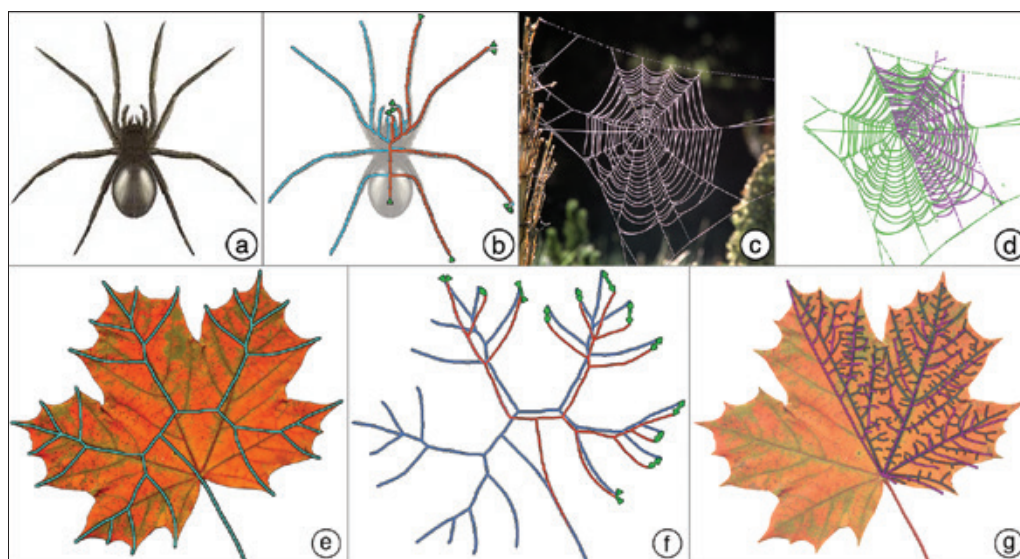


Figure 12. Evaluating mirror symmetry by folding the skeleton about the principal axis: (a, b) spider; (c, d) spider web; (e) maple leaf and skeleton; (f) result of folding one half of the skeleton over the other (green arrows indicate distances between ends); (g) performing the same operation with the actual vein structure does not produce useful matches

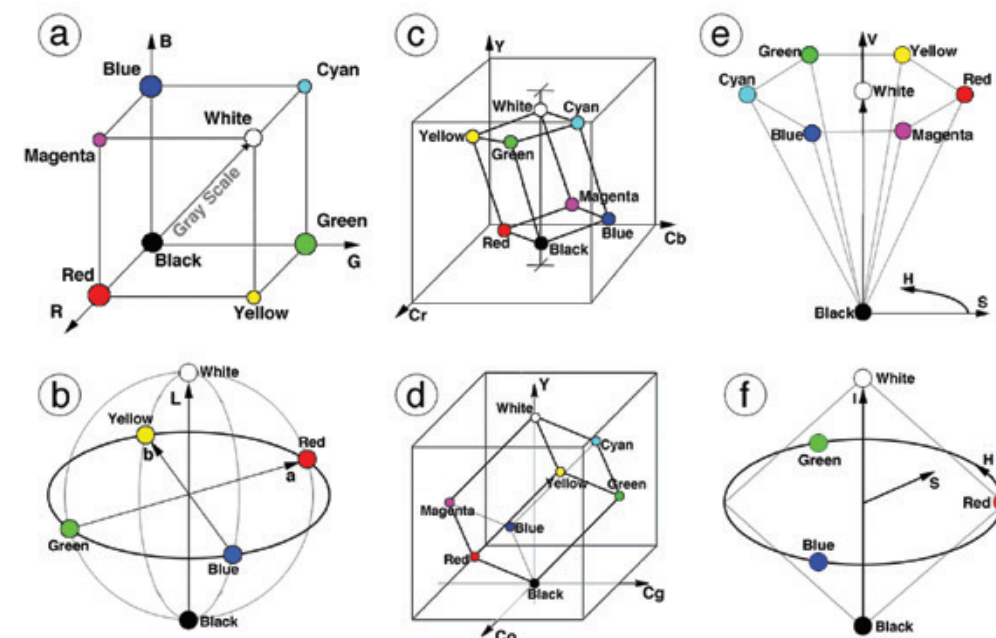


Figure 13. Several colour coordinate systems: (a) RGB; (b) Lab; (c) YCbCr (used in older JPEG); (d) YCoCg (used in newer JPEG); (e) HSV; (f) HSI. CMYK is not shown since the amount of substituted black varies. For all except RGB, the grey scale is vertical.

The use of distances between various centre locations is described above as one way to measure asymmetry. Skeletons can sometimes be used to measure symmetry. Like many animals, the spider in Figure 12a is symmetric about a central axis (mirror symmetry). The skeleton in Figure 12b represents the shape and folding one half over the other allows measuring the distances between corresponding end points (in some cases the distance between corresponding nodes may also be used). For the spider, the sum of distances between the end points is less than 1% of the total length of the skeleton. But for some other objects that visually appear to have partial symmetry, such as the spider web in Figure 12c, this method is not applicable because the folded halves of the skeleton do not match up (Figure 12d).

The skeleton is based on the object shape, but does not necessarily correspond to any actual structural components such as an animal's bones. In the example in Figure 12e, the skeleton of the leaf differs from the vein structure. However, measuring the distances between end points in the folded

halves (Figure 12f) provides a measurement of the degree of asymmetry. The sum of the distances is 8.7% of the total skeleton length. Folding the actual vein pattern (Figure 12g) does not produce matches in the number, length or positions of the branches, nodes or ends.

This does not exhaust the subject of shape (see, for example, da Fontoura Costa & Cesar, 2010; Neal & Russ, 2012; Dryden & Mardia, 2016; Laga *et al.*, 2019). Most of the measures shown here deal exclusively or primarily with the large-scale form of an object, but finer scale angularity (e.g., the inscribed radii of protrusions) and roughness (e.g., the variance of deviations from a smoothed boundary) may also be important, requiring more specialised methods and models.

Colour

Determining values that represent the original object's colour or brightness values, or information based on them, such as density of objects viewed in transmission, is fraught with many challenges. Variations in brightness from one location in the

image to another are common, partially due to the geometry of the lighting (off-axis) and specimen (curved surfaces or varying thickness), and partially to optics (vignetting). In addition, many lighting setups are not stable, with variations in line voltage or even air humidity producing significant changes in colour. Few cameras are perfectly linear or well calibrated, being generally intended to produce viewable images by applying nonlinear functions that vary with overall brightness. The image signal is often converted between different colour spaces before it finally becomes the familiar RGB values in computer memory (Figure 13). In principle the transformation from one colour space to another is lossless within round-off errors, but in practice the implementations may not be perfect. Compression reduces colour information significantly as well. Camera performance, such as variations in gain over time, may also be problematic.

Furthermore, most colour cameras use a single-chip detector with a colour filter array in front, and use various proprietary algorithms to “demosaic” the information to estimate the colour values for each pixel (Ramanath & Snyder, 2003; Li *et al.*, 2008). Not only does this produce less resolution in the image than the pixel count of the camera implies, it also means that colour interpolation typically varies with direction and with the presence of other nearby colours. Three-chip cameras avoid this problem but suffer from shading variations across the image width and height because of the prisms and filters used to separate the images for the detectors, which must also be maintained in perfect mechanical alignment.

Calibration of camera setups (including lighting and optics) can be performed (Menesatti *et al.*, 2012; Charrière *et al.*, 2013). Commercial software is available and colour charts exist that can be imaged and the recorded colours adjusted so that consistency is obtained, but the calibration is intended to match visual response, not to give accurate colour data. Fabricating such charts for

microscope use, even just neutral density steps to calibrate density measurements, is not easy. Furthermore, and most important, the purpose of colour matching (e.g., to make sure that computer displays and printed advertisements match the visual appearance of consumer products) is not the same as “measuring” colour for technical or scientific purposes. Colour cameras work by recording signals that cover three broad ranges of wavelengths (different for each manufacturer), and are not spectrometers. Many combinations of specific wavelengths and intensities will yield identical camera signals. If it is important to know the wavelength spectrum of light from particular object or location, then special apparatus is needed. RGB or Lab values, or the Hue, or some other derived colour-related value, may be useful in the process of image segmentation, but are not adequate, and in most cases not meaningful, as measurements.

Conclusions

There is no simple, universal recommendation for the “best” measurements of objects in a digitised image. Several possible choices exist for measurements of position, orientation, size and shape of objects in digitised images, and most of them are available in various image analysis programmes. The selection must be based on the type of object(s) being examined, and on what it is desired to learn. It is very important to understand what the measurements represent, to select ones that correspond to the intended utilisation of the data, and to test the algorithms and implementation used to determine them. Many programmes use different names for the same measurements (especially true for shape data), or apply the same name to different measurements. There are usually many additional possibilities offered, but the ones described here are those that are most capable of accurate determination and that have robust meaning. They have direct analogues for 3D objects imaged in voxel arrays, but the computations involved are more complex.

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About the author

John Russ is Emeritus Professor in the Department of Materials Science and Engineering, North Carolina State University. In his six-decade career as scientist and educator, Dr. Russ has used image processing and analysis as a principal tool for understanding and characterising the structure and function of materials. Much of his research work has been concerned with the microstructure, surface topography and composition of metals and ceramics. Images from a wide range of devices – including a variety of light and electron microscopes, x-ray and neutron

tomography, and more – required computer processing and measurement to extract the important data. Familiarity with the algorithms and instruments led to his expertise being extended to a much broader range of images, from astronomy, biomedical research, archaeology, food science and forensics. Now retired, he continues to write books and papers; this is the third part of a series for *infocus*. He and Helen enjoy travel (the picture shows them under sail near Malta). Dr. Russ has received the Ernst Abbe and August Köhler awards for contributions to the field of microscope image processing and analysis.



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