Image Quantification as Archaeological Description

Juan A. Barceló, Jordi Pijoan and Oriol Vicente

Universitat Autónoma de Barcelona, Quantitative Archaeology Lab, Dept. of Prehistory, Faculty of Letters

Building B, 08193 Bellaterra, Spain

e-mails: ilphd@blues.uab.es, jordi.pijoan@uab.es, oriolvicente@teleline.es

Abstract

This paper deals with the use of microscopic images as a way to define textures, and with the statistical analysis of quantitatively described textures. Digital image processing is a normal technique in archaeology. Archaeological images range from the microscopic to the macroscopic, and a diverse toolbox of computer techniques is available to process such archaeological data. However, the very nature of images as archaeological data has not been evaluated. Images are not primary data, but a transformation of empirical reality, translated into a language of luminance contrasts. Images are therefore the result of a goal-oriented modification. But how may this modification alter the reliability of the analysis? Very few studies have been published as regards this topic. Our goal in this paper is to integrate different archaeological applications of microscopy (use-wear in lithic tools, and pottery archaeometry) in order to define the observational category we are dealing with: texture. If the texture is the complex set of surface properties in an artefact, how can we describe it? What kind of archaeological, historical information do we obtain from the analysis of texture? A related problem is that of image sampling. Digital image techniques have been applied in disciplines where the assumption of surface homogeneity is valid. However, the modified surface of an archaeological artefact is always discontinuous. Different images can be obtained from the same artefact, and all of these images may be different. Statistical sampling is therefore a basic problem in archaeological image processing, and very few studies have been made. We explore the use of neural networks and related approaches to deal with this problem.

Key words: image processing, use-wear, archeometry, lithic analysis, pottery analysis, microscopy, neural networks

1. The concept of texture

Work modifies matter. As a result of human action, matter is exposed to changes and modifications, the result of which we call *artefacts*. David Clarke defined an *artefact* as anything modified as a result of human action: a tool is an artefact, in the same sense as a house, a pit, a burnt bone or a landscape (Clarke 1978). Social Sciences study how humans modify nature by creating artefacts, and these artefacts should be described in terms of human induced modifications on natural resources, and the sequence of changes across time.

Consider a lithic tool. It is made of stone, consequently, we should explain its *cause* as a human modification on a natural resource (flint), producing as an *effect* a *product*, an artefact whose properties are the result of the modification process or *production*. The same idea is valid for a vase. Here production can be described as: obtaining the resource (clay), obtaining other resources (temper, water, fuel), and processing them. In both cases, artefacts should be considered as nature modified by humans.

The goal of Archaeology (or one of its goals) should be the analysis of these processes, that is to say, the study of how humans modify natural resources in some specific historic circumstance. We study a *cause-effect* relationship, i.e. how social activity *causes* observable modifications in nature. Therefore, we should process a set of observable properties in order to be able to identify material effects of human work. Although the list can be very long, we consider that observable variability can be reduced to: shape, size, composition, texture and location.

Shape and size are the most commonly analysed properties of artefacts (see, for a theoretical introduction Small 1996), as it also holds true for location analysis. There is a lot of research on how to calculate the shape, size and location of lithic tools, pottery artefacts, metallic elements, etc. The shape of bones (human and animal), for instance, has been studied intensively in order to obtain taxonomic information. Composition is also a rather standard domain, especially in recent years: archaeologists are able to decompose any artefact into its compositional elements, both at a formal level (a house is composed of walls, a wall is composed of bricks), or on a physical-chemical level (archaeometry). But not many studies were performed on how human work modifies the surface properties of artefacts.

Artefacts have surface properties because of the way they have been made, or the way they have been used. In this paper, we analyse *archaeological textures*, that is surface properties, in pottery and lithic artefacts. In the first case, texture is a result of manufacture: different ways of producing and using a vase give a thin-section with a characteristic texture. In the second case, use changes the physical characteristics of the flint surface, producing a distinctive texture wear for each use. We explain how texture can be defined using different attributes, such as coarseness, contrast, directionality, line-likeness, regularity and roughness.

2. Observing textures: the creation of images

Observation is a process by which the human brain transforms light intensities into "visual" models. What we usually call *data* are not primary inputs, but a transformation of sensory information into an explanatory model of it. Observation is a 3 stage process: Perception, Recognition, Description (Bunge 1981, Hacking 1983), in which "perception" is only the first. Only once our brain recognises sensory information according to prior experience, we begin "seeing" reality around us. *Data* is the result of the final stage: description – that is, translation of recognised sensory inputs into a specific language.

Observation is a mode of knowledge acquisition, and it is used as a test mechanism for evaluating the reliability of already acquired knowledge. That is, observation is always an intentional act, guided by specific goals. As an intentional act, observation, even the so called "scientific" observation is always affected by available knowledge and can be direct or indirect, precise or wrong, misguided or even fraudulent. This fact leads some authors to reject the scientific method because without "objective" observation, there is no "objective" knowledge. However, given that observation is an "intentional" act, we can build observation in order to be objective. To do that we need is that observation results (data) be made public or collective, and not limited to a single observer.

"Objective" observation is produced by externalising perception, and by formalising recognition and description. We should impose control on:

- the object of observation,
- the observer and his/her/its perceptions,
- the circumstances of observation,
- the means of observation (senses, auxiliary instruments and procedures),
- a knowledge base relating to all above elements.

The means of observation, together with the related knowledge base are *the instruments of observation*. When we "externalise" observation in order to produce objective knowledge of the world, we mechanise the perceptual phase. That is we substitute human senses with a microscope, for instance. Nevertheless, this is not really a substitution. Instruments are necessary for perception, but not sufficient for observation, because nothing can be detected without an observer. The world is not data, but a set of perceptual information waiting for an observer to impose order by recognising an object and by describing it. What we are doing when we use the microscope is trying to avoid perceptual misinformation: a microscope allows two different observers to agree on the perceptual basis of information, but they can disagree on the recognised objects and how to describe the recognised world. Therefore, a fact can be observed if an agent *a* (the observer) is able to record some perceptual information *p* using an instrument *r*, under some circumstances *y*. The instrument is as important as the circumstances of observation, which includes the goals - the knowledge to be tested.

Images are not something to be captured, because they are not a part of reality. They are data, that is formal descriptions of something that exists. Light and colour are properties that really exist in the world, and they can be captured using special devices which transform light into electric or chemical signals, which should be manipulated in order to create a representation (an image).

Data, which is the result of the observational process, is only a model, a representation of some aspect of reality. Given that images are a kind of data, they are not a manipulation of reality, but a guided and intentional explanatory representation of some regularities existing in that real world. They are "real" only in the sense that they are true, that is, they coincide with the real world. Consequently, shape, size, texture, etc. are properties of a perceptual model of reality. Any "visual model" is only a spatial pattern of luminance contrasts that explains how the light is reflected, and it is composed of visual bindings which can be divided into sets of marks (points, lines, areas, volumes) that express position or shape, and retinal properties (colour, shadow, texture) that enhance the marks and may also carry additional information (Foley and Ribarsky 1994, Astheimer et al. 1994). Points and areas connected by the same plane or surface have not the same values. This variation is called *texture*, and it is used to understand those geometric properties that are based on local features. Each surface appearance should depend on the types of light sources illuminating it, its physical properties, and its position and orientation with respect to the light sources, viewer and other surfaces.

A microscope is not a device producing data, but it is used as a perceptual mechanism, whose output is the input of our model. A picture is not primary data, but a visual model of some real world properties, among them also *texture*. Thus (see Marr 1982, Watt 1988, Gershon 1994, Wadnell 1995, Barceló 2000):

- a pattern of changes in light wavelength and surface-reflectance, should be translated into a model of *colour,*
- a pattern of changes in edge orientation (Curvature), where an edge is an abrupt change on luminance values, should be translated into a model of *shape*,
- a pattern of changes in luminance variations in a scene with non uniform reflectance, should be translated into a model of *texture,*
- a pattern of discrimination between edges at different spatial positions, should be translated into a model of *topology,*
- a pattern of discrimination between edges at different spatial-temporal positions should be translated into a model of *motion.*

Although humans readily recognise a wide variety of textures, they often have difficulty describing the exact features that they use in the recognition and description processes. In this paper, our goal is to explain how to create a visual model of texture, using geometry as the formal language for recognition and description of microscopic visual inputs.

3. Describing texture: measuring images

An image is not a surrogate for reality, it is a directed and intentional transformation of reality in order to extract some relevant information. The microscope is not a device for observing some aspect of reality, but for capturing some initial input (luminance perception), which should be translated into observed data by a human agent using a visual model. What we are looking for in that image is the patterning of luminance values across all pixels. This is not the texture of the image, but we should *recognise* texture patterns in it, and build a geometric model of it. This can only be done with the help of prior knowledge as regards the concept to be modelled. The way of obtaining that knowledge is relatively simple: by comparing different images observed in experimental conditions.

Our main assumption is that different artefacts have different textures because they have been altered by different work activities. Consequently, the geometrical model of luminance patterning in each microscopic image should be different, if the activity performed by that artefact was different. We should create a *prototype* model of texture produced by a specific activity, quantifying also different sources of variability within that model, and maximising the variability between models for different activities.

The texture of different images should allow us to discriminate between image groups with some characteristic pattern of luminance variation. Nevertheless, the problem of luminance pattern variation is a complex one. When we see a picture, we *recognise* some differential features (striations, polished areas, scars, particles, undifferentiated background). These features are then a consequence of our prior knowledge, although in some way, they exist in the image. *Recognition* is a subjective procedure if we follow our individual criteria. However, this stage can be formalised, using an algorithmic approach: if we can reduce the amount of irrelevant variation in luminance patterns, the result is a formal representation of relevant features. Of course, what is relevant or irrelevant must be strictly defined. That is, we should distinguish two kinds of texture, one of them is inherent to the artefact surface, and the other one is the result of modifications on the surface generated by work activities. Furthermore, we should also distinguish luminance variations produced during the perceptual stage as a consequence of microscope functioning. Given that generated texture modifies inherent texture, a formal procedure of deleting random variation should allow the extraction of "dominant" or relevant features. We should not look for "meaningful" features, but we should describe formally (quantify) relevant variation measured in a experimentally controlled situation in order to define variation patterns regularly associated with each experiment.

Once relevant features have been extracted ("recognised"), the construction of a geometrical model of their relationships is a fairly straightforward task.

Consequently, analysing archaeological textures is not a single comparison of images, but a comparison of geometric models. Each model is a generalisation of surface properties "observed" through a microscope.

3.1. Quantifying texture

We should take into account that properties of any visual model are expressed as intensity values of colour variation, light and reflectance over surface (Sonka et al. 1994, Ebert et al. 1994). Therefore, a digital image of texture properties is a two dimensional mapping of points (p_i, q_i) with a specific luminance value (r_i). The resulting function is then $p_x q_x r$.

Texture is then described as the relationships of luminance values in one pixel with luminance values in neighbouring pixels. These values can be modelled as forming a set of regions, consisting of many small sub-regions, each with a rather uniform set of luminance values. In our case, these values are defined as grey levels. A group of related pixels can be considered as a texture minimal unit, sometimes called *texel* - texture element - (Sonka et al. 1994). Texture patterning in an image should be described as associations between *texels*.

A two-dimensional measure of texture is based on co-occurrence matrices, which show how often each grey level or luminance value occurs at a pixel located at a fixed geometric position relative to another pixel. For instance, an (3. 17) entry in a co-occurrence matrix means the frequency (or probability) of finding grey level 17 immediately to the right of a pixel with grey level 3. Each entry in a co-occurrence matrix could be used directly as a feature for classifying the texture of the region that produced it. Each different relative position between the two pixels to be compared creates a different co-occurrence matrix (Gose et al. 1996).

The first task in texture description is the *segmentation* of zones with the maximum contrast of luminance (texels). This task can be approached by calculating the *texture gradient* in the image - that is, the direction of maximum rate of change of the perceived size of the texture elements, and a *scalar measurement of this rate* (Sonka et al. 1994). This texture gradient describes the modification of the density and the size of texture elements and so regularity patterns in luminance variation can be determined. A *convolution filter* can be designed so that each pixel in the original image is transformed according to the following function:

$$g(x,y) = \mathrm{G}\left[\, f\,(x,y)\right] = \left|\frac{\delta f / \delta x}{\delta f / \delta y}\right|$$

that is to say, each pixel (with *x, y* co-ordinates) is transformed according to the median of the derivative of its pixel neighbours. This is called a *gradient operator.* Its magnitude is defined by the following expression:

$$mag\left[\mathrm{G}\left[\, f\,(x,y)\right]\right] = \left[\left(\delta f / \delta x\right)^2 + \left(\delta f / \delta y\right)^2\right]$$

This operator increases luminance values in areas with sharp luminance and brightness contrasts, and decreases the values in areas with soft luminance and brightness contrasts. As a result, isolated areas are segmented whose shape, size, texture, composition and position may be measured (Pijoan et al. 1999).

3.2. Real image, segmented image and "texel map"

Once texels have been extracted, we should calculate their formal and relational properties, using their variables of shape, size, composition, texture and position. Among others we should measure:

- Area measurements (number of pixels *within* a texel).
- Perimeter measurements (number of pixels around the edge of a texel).
- Perimeter shape. Measured as a pattern of changes in edge orientation.
- Convex Hull: the smallest region which contains the texel, such that any two points of the region can be connected by a straight line.
- Euler-Poincaré characteristic: difference between the number of regions (texels) and the number of holes within them.
- The Frequency and Entropy of Brightness within a texel (histogram of grey levels).
- The Frequency and Entropy of Contrast: local change in brightness (ratio between average brightness within the texel and the background brightness – neighbouring texels).
- Topology of Texture. A pattern of discrimination between the edges at different spatial positions, distance and adjacency relationships between different texels. Among them:

    Degree of Coarseness: edge density is a measure of coarseness. The finer the texture, the higher the number of edges are present in the image,

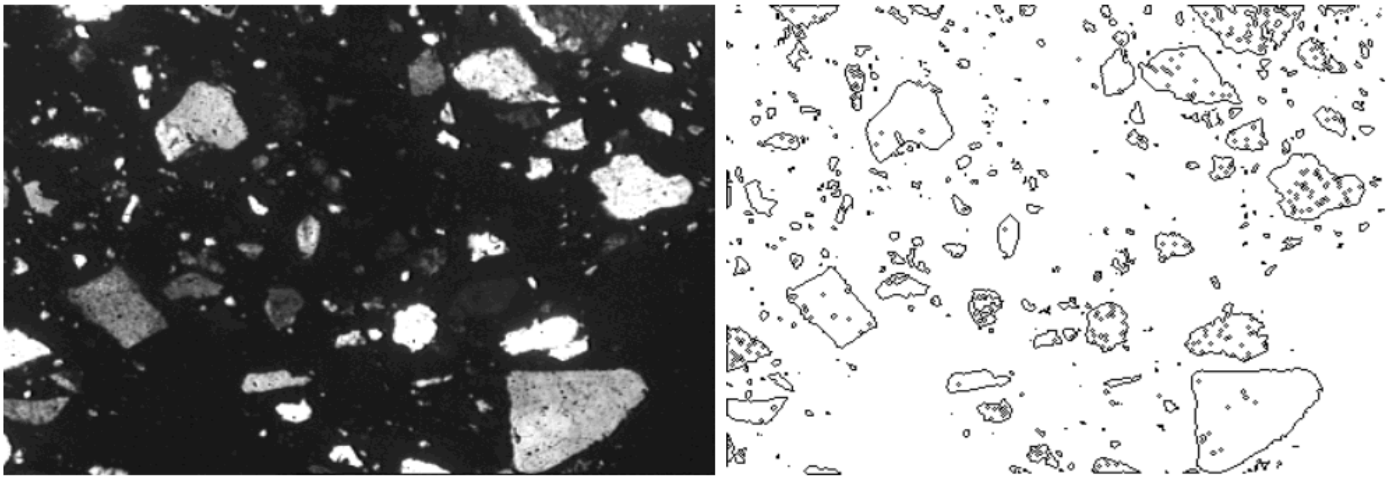


Figure 1: Describing mineral particles in a pottery thin-section by means of texel extraction.

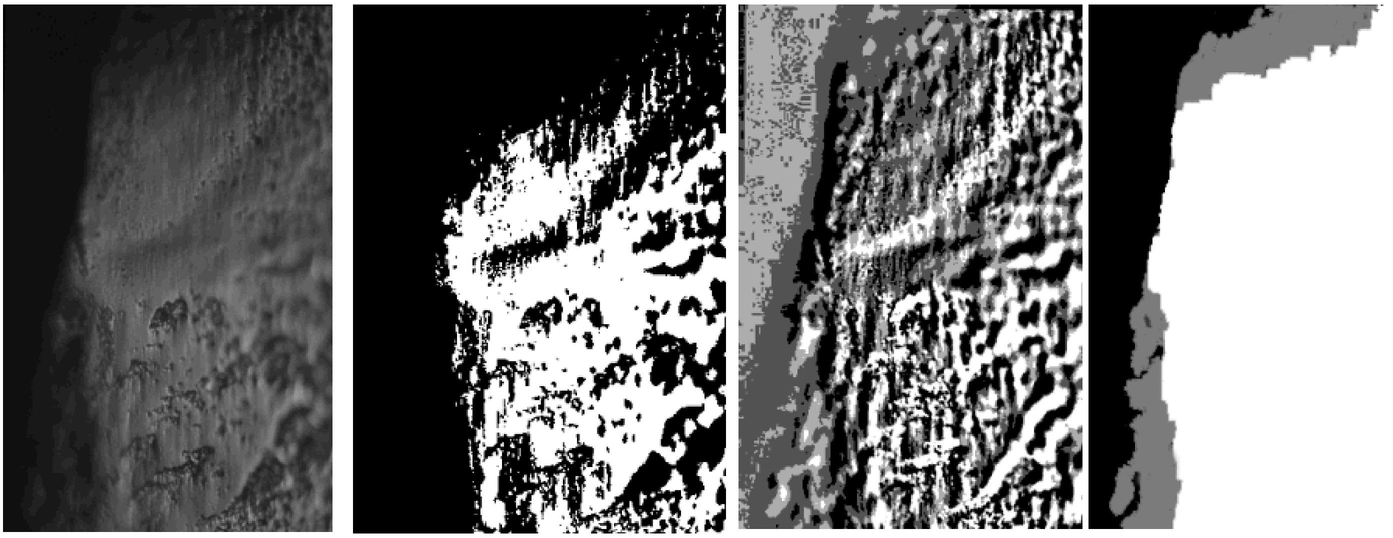


Figure 2: Extracting use-wear areas by means of texel extraction.

Contrast: high contrast textures are characterised by large edge magnitudes,

Randomness: may be measured as entropy of the edge magnitude histogram,

Directivity: entropy of the edge-direction histogram. Directional textures have an even number of significant peaks, direction-less textures have a uniform edge-direction histogram,

Linearity: is indicated by the co-occurrence of edge pairs with the same edge direction at constant distances,

Periodicity: texture periodicity can be measured by co-occurrences of edge pairs of the same direction at constant distances in directions perpendicular to the edge direction,

Size: texture size measures may be based on the co-occurrence of edge pairs with opposite edge-directions at a constant distance in a direction perpendicular to the edge directions.

In the long term, this approach should be directed to the generation or *synthesis* of texture from a program or model, rather than just a digitised or painted image (Musgrave 1994). We are looking for a "procedural" approach where the analysis of properties of observed textures is expressed as a statistical model which should be able to reproduce the textures from statistical data (Ebert et al. 1994).

3.3. Two case studies

The thin-section samples of pottery are utilised in petrography for the description of some petrographic attributes of the vessel fabric mineralogical composition. They are the results of a specific work process, where the productive agents modify the clay status of fabrics through a thermal alteration. These different petrographic attributes are the result of the natural formation of clays and the deliberated human alteration of them. We try to study thin-section samples in the most objective way. In this way we try to assign a series of numeric values to a thin-section microscopic image in order to quantitatively describe the sample. The purpose of this study is the description of mineral particles that compose the fabric of a vase. We represent each particle as texels defined against a general background (clay). In this way, mineral particles can be measured according to luminance intensity, shape, size, etc. The goal is to distinguish different vases (fabrics) from the different characteristics of particles contained in the fabric. These differences could be explained in terms of the manufacturing processes.

In lithic use-wear, we compare different images created as visual models of specific experiments. Each image is not a photograph of an artefact, but a model of the generated texture on a flint surface when an agent makes a longitudinal movement with that tool on a fresh wood material. Our goal is to distinguish between the visual model of that texture and the visual model of the generated texture on a flint surface when an agent makes a transversal movement with the same tool on a leather material. The extracted texels should be recognised as micropolish, microscarring and linear features. Each one should be considered a different kind of texel. We should distinguish these features produced by the movement of a lithic tool done on an specific matter, from the macro and microscopic traces characteristic of the lithic surface alone.

We have reduced the original complexity of microscopic images into grey scale pictures. In this way, it is easier to recognise texels. Once recognised, texels must be described. We use geometry to describe the shape, size, texture, composition and location of micropolished areas, scars and linear features detected on the lithic tool surface, or to describe the particles detected in the microscopic picture of a pottery vessel thin section. Shape is a property that can be used for the differentiation of texels, whereas size can also be used to differentiate between texels generated in different experimental conditions. Density measures give information about the texture (homogeneity within a particular texel) and the position. The following variables are those that the use-wear and thin section analysis techniques have used to describe the differences between cases, and to discriminate those between different groups:

Area measurements: The total number of pixels with the same luminance or range of luminance. The edge is defined by the proximity of a grey level. Normally a simple threshold operation is enough to define the area or areas of a discrete texel. In use-wear analysis we utilise the area measurements to extract the extension of micropolish, the size of microscars_and the striations length. Pottery thin-section analysis is used for measuring the size of each mineral particle in the fabric.

Texels perimeter: We took the information as regards the size of a mineral particle or the length of the striation. This variable is used for calculating different ratios of the variables related with the perimeter shape.

The *Euler-Poincaré* characteristic is used for measuring the ratio in the microtopography and the micropolish spread. This variable is not necessary in the thin-section analysis.

The *frequency* and *entropy of brightness* within a texel is calculated using the histogram of grey levels.

The *frequency and entropy of contrast*: local change in brightness (ratio between average brightness within the texel and the neighbouring texels) is used as an intermediate calculus to describe coarseness.

Perimeter shape and *orientation*: To introduce the category of shape we use the natural geometric shapes as indicators, in order to define the pattern of the geometric model of the sample.

Circularity: the degree of circularity of a texel. I.e. how similar is this texel to a circle. Where 1 is a perfect circle and 0.492 is an isosceles triangle. This shape is expressed by:

$$\frac{4\pi s}{p^2}$$

s: texel area
p: texel perimeter

Quadrature: the degree of quadrature of a texel, where 1 is a square and 0.800 an isosceles triangle. This shape is expressed by:

$$\frac{p}{4\sqrt{s}}$$

Irregularity: measurement of the irregularity of a texel, calculated as the relationship between its perimeter and the perimeter of the surrounding circle. The minimum irregularity is a circle, corresponding to the value 1. A square is the maximum irregularity with a value of 1.402. This shape is expressed by:

$$\frac{p_c}{p}$$

Elongation: the degree of ellipticity of a texel. A circle and a square are the less elliptic shapes. This shape is expressed by:

$$\frac{D}{d}$$

D: maximum diameter within a texel
d: minimum diameter perpendicular at D

All shape measurements are used in use-wear and thin-section for the study of tendencies in the geometric pattern, both for describing the orientation and shapes of the micropolish and the striations in the use-wear analysis, and mineral particles in thin-section pottery analysis.

Orientation: the orientation given by the angle of the detected linear features with the tool's edge is used in use-wear analysis to define the direction of the movement *made* with the tool.

Topology of texture: these measures are measured from relationships and associations between texels (and not at each texel).

Randomness: entropy of the number of texels within a modified surface. It can be used in use-wear for distinguishing the area of the micropolish from the background.

Linearity: linear features can be represented using linear equations: y = a + bx, where *y* and *x* are co-ordinates, and *a* and *b* linear coefficients. We use both coefficients as quantitative variables in our study. We can also include some other numerical attributes such as the quantity of lines, and their longitude. The width of linear features can be measured on a three-dimensional representation, and included in the image quantification.

Directivity: entropy of the edge-direction histogram. Directional textures have an even number of significant peaks, direction-less textures have a uniform edge-direction histogram. This can be used in the description of striation orientation.

Size: number of pixels corresponding to each contour in the image. It allows the study of micropolish topography.

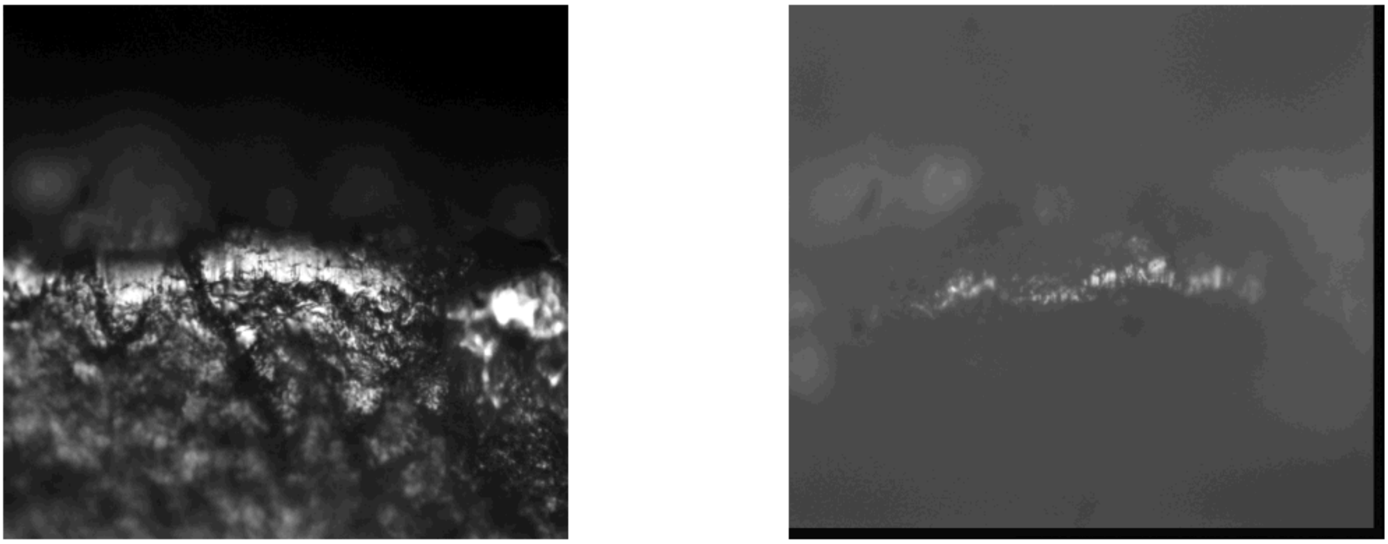
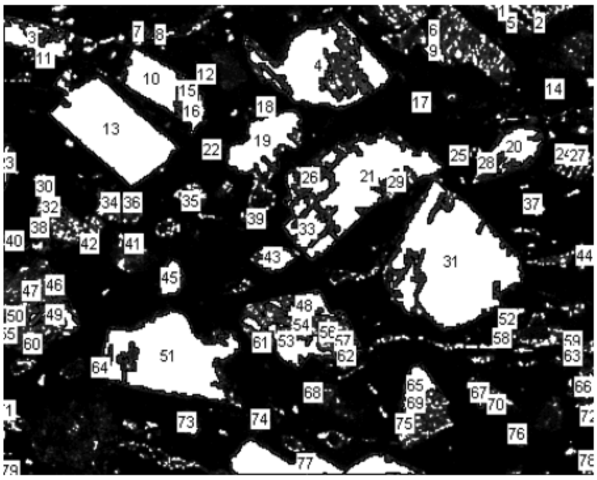


Figure 3: Variations in texture due to focus adjustment. Only the edge of the tool is visible.



Nº	Area	Circularitat	Quadratura	Elong.	Irregula
1	13	1,05	0,87	1,09	1,07
2	25	0,38	1,44	2,87	1,04
3	36	0,76	1,02	1,82	1,26
4	77	0,28	1,68	2,61	0,85
5	28	0,77	1,01	2,13	1,28
6	13	0,96	0,91	1,79	1,31
7	19	0,75	1,03	1,90	1,19
8	11	1,02	0,88	1,37	1,18
9	46	0,73	1,04	2,17	1,26

Figure 4: Measuring texels.

4. The variability of textures: statistical sampling

A single microscopic image is not a good prototype to determine the artefact's texture properties. This assumption would be correct if all the artefact surfaces were modified in exactly the same way. In the case of use-wear in lithic tools this is clearly not the case, because modified texture related to the work activity appears only in some areas of the surface. Consequently, a geometric model of textures cannot be built as a generalisation of a single image. Sources of variability are too important, and should be taken into account.

Measurement error is the most obvious source of variability. Features we "observe" in a microscope image come from a 3D reality, but the picture is a 2D model. As a result, any image should be considered as a modification of perceptual reality, because it cannot maintain the same focus for the entire field of vision. It is impossible to give the same sharpness to the complete observed surface, because it is not on the same level. As a result, microscopic images are characterised by narrow observation plans, that can be wrongly considered as discrete texels. This is a case of measurement error, and the only way to deal with it is by not using primary images, but modified visual data. That is, texture data should be composite images made of microscope pictures taken with different focus levels. By merging all levels into one, and by posterising them, we obtain a visual model of a sharp-equalised image.

Colour and shadow are also some sources of measurement error. They are the consequence of light reflection across the artefact's surface, and, in a reflected light microscope – used in material sciences – this reflection depends on the angle between the light beam and the observed layer. In these circumstances, we can get a paradoxical situation where a polished texel (more light reflection) seems darker than an unpolished texel, which is less reflective, but light reflects at a perpendicular angle in respect to the source of light. Observing coarse areas (texels with a large number of minor variations of luminance contrasts) is then a matter of light orientation, and not only of surface parameters. To appreciate this, it is only necessary to consider a regularly patterned object viewed in 3D - two effects would be apparent; the angle at which the surface is seen would cause a perspective distortion of the texture element, and the relative size of those elements would vary according to the distance from the observer. The best way of dealing with this source of measurement error is by controlling all observation parameters, and maintaining all of them fixed during the entire procedure. Among these parameters, we can find the following: the distance from the observer slant, the angle at which the surface is sloping away from the viewer (the angle between the surface and the line of sight), and tilt, the direction in which the slant takes place (Sonka et al. 1994). The control of observation parameters is not an easy task, because there is not a single perceptual plan that is useful for all kind of observations. Some features are best seen with perpendicular beams of light, while other can be discovered only using fast horizontal beams.

These are some of the sources of error measurement, and there is a long tradition of dealing with them and reducing their effects. Less known are the sources of variation that prevent the simple generalisation of perceptual images. In our case, the main problem is that the microscope field of vision is too limited for our purposes (from a 4x4 cm. field in the easiest case, to 0.001x0.001 mm or less, if we use electronic microscopes). Without further investigation we cannot accept the assumption, that a reduced frame contains all the elements that characterise the complete surface. We need more than one single image to correctly represent all texture variation present in the surfaces of the artefact.

Consequently, sampling questions are of great importance. In this research we have used a series of images to investigate the variability of texture within an artefact, before using the resulting geometric model to explain differences between artefacts. The problem is to merge different files containing shape, size, composition, texture and position of individual texels identified in all images of different artefacts.

We have used the following approach:

4.1. *Within-artefact* description

We have considered the processing of all observed texels in different images of the same artefact. The number of images depends on the complexity of texture and the position of modified surface patterns. In our research we have selected three or four images for each artefact, in order to look for differences among all texels produced in the same experimental conditions in the same artefact. These texels are described using the variables defined above, and within-artefact variation is then analysed, using standard statistics.

The purpose is not only to describe variation, but also to define prototype values for relevant features. For instance, we have used mean and standard deviation of area and perimeter measures, as well as skewness and kurtosis measures. It is not the absolute value of these prototypes that interests us, but the range of variation each texel may adopt within an artefact.

4.2. *Between*-artefact description

Of course, central-tendency measures are relevant only if within-artefact variation is approximately normal, and this assumption should be tested in each case. However, even when within-artefact variability is not normal, measures of dispersion can be used to compare textures produced by different activities. In some cases, there is not any identifiable texture pattern associated with some specific activity, but a greater or lesser dispersion of values than others. For instance, micropolish in use-wear analysis should be understood not as a discrete texel, but as an area with a low degree of texture variation due to friction, and given as a result a specific luminance value due to light reflection on that homogeneous surface.

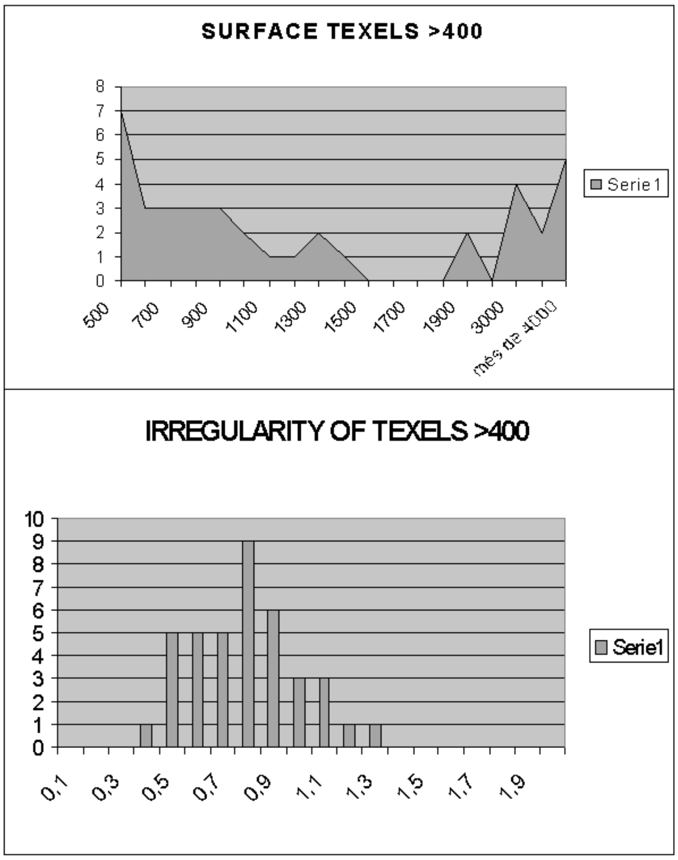


Figure 5: Statistical analysis of some properties (Surface, Irregularity) of the biggest particles (more than 400 pixels surface area) from all four microscopic pictures of the same object.

In such circumstances, specifically when normality is not assumed, between-artefact variability is very difficult to discriminate. In order to perform this task we have used a neural network approach (Barceló 1996, Barceló et al. 2000).

The system we want to build is a diagnosis machine that predicts the probability of any artefact (a lithic tool, a pottery vase) to be it used or produced in any way, given a set of inputs (a quantitative description of macro- and microscopic texels extracted from a number of different images of the same artefact). This prediction does not follow a rigid algorithm in producing an answer based on given inputs, but it is actually learned through training examples.

The network consists of many simple, but individual processing elements ("nodes") arranged in one or more layers and a system of connections. These connections transmit the signals, which the nodes manipulate. A transfer function contained in each node governs this manipulation. The nodes add weight adjusted inputs, and a bias value, and finally they pass the result through an activation function (also called a transfer or squashing function) to be used by other neurones or offered as an output. A learning process is usually performed in the network of connections. Although a network's transfer functions usually do not change, the connection strengths change during the learning process. These changes result from the network making predictions on training examples, which contain known outputs based on real inputs. In our case, training examples are pairs of archaeological experimentation results, that is, the descriptive features observed in those lithic tools that were used for some specific activity in the laboratory.

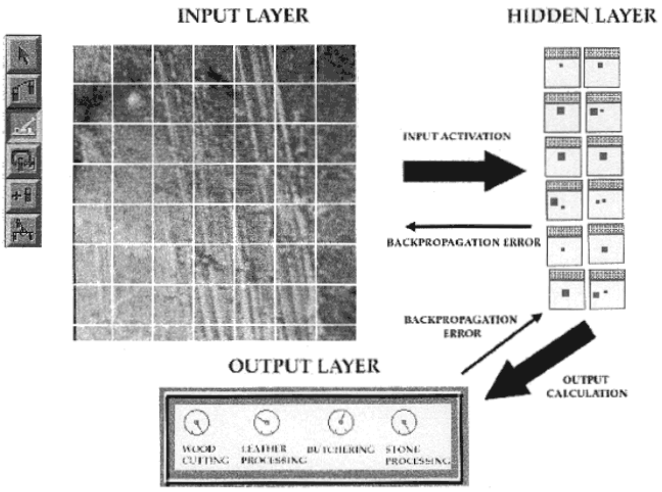


Figure 6: A Neural Network scheme for the analysis of use-wear microscopic pictures.

Observable information (image data) is the input to the first layer which then propagates through the structure of connections and nodes. When the input values finally reaches the output nodes in the final layer, these units produce an answer (a number reflecting the intensity of the function in each unit), which is the network's prediction of the output based on the given data input. The predicted output at every node in the final layer is then compared to the correct (known) output at every node. Errors are generated as the difference between the correct output and the network's predicted output. These errors propagate backwards through the network, modifying the connections' weights based on a mathematical equation that defines what is described as the learning rule. This process continues until the user is satisfied with the accuracy of the network's predictions.

Once the network is satisfactorily "trained", it is put into actual use. The network is fed only input data, preferably data it has never seen before. Feeding the network the exact same data that was used during training only tests the network's ability to "memorise" data. A useful network can accurately predict output to data it has never seen before.

The real challenge in developing a useful neural network system is the training process. We are comparing different supervised learning algorithms where the "training" of the network is an iterative process based on large numbers of data samples representing the traffic flow within a certain region. Using standard connection weights, the network computes a set of outputs, and compares this set of outputs with the input values by calculating a root mean square difference (or global error) and modifies the connection weights to displace the outputs toward the expected values. If the training is successful, the global error is reduced. In over-simplified terms, gradient descent works to optimise a system by minimising a given function. In the case of backpropagation, network error is minimised by optimising the weights values of the connections among nodes. The total network error is minimised by following the gradient (actually followed down towards a *minimum*, hence descent).

Since many indicators appear to be relevant at first glance, we should perform sensitivity analysis with respect to the different inputs. This involves noting the percent change in the output caused by a specific percent change in one of the inputs, keeping all the other inputs the same. But we have also included the possibility of non-linear interactions, that is, changes to two or more inputs in tandem can have a different effect from that of changes to one input alone. Redundancy has not been deleted, because it was one of the goals in our analysis, that is, to evaluate if classificatory results are affected by redundancy. We have carried out only a preliminary sensitivity analysis, in order to drop features that do not produce enough information.

5. Conclusions

The way neural networks process redundancy and irrelevant variation is the reason we have selected this approach. It is important to realise, however, that an erroneous understanding of image processing has confused the fuzzy nature of image descriptions, even at a quantitative level. We think that redundancy, error measurement and within-artefact variability exists at the level of perceptual input, that is, they are inside the images we want to compare. Any experimental approach is nothing more than a "supervised-learning" framework, where it is assumed that between-artefact variation is greater than within-artefact variation, and its patterning can be distinguished. Most image analysis in archaeology and other disciplines neglect the sources of within-artefact variability and error measurement. In this paper we have proposed an approach to deal with this problem.

Acknowledgements

The authors would like to thank Assumpció Vila, Xavier Clop and Ignacio Clemente, for initiating the project and for their continued support during its development. We also express our gratitude to the Center for Computer Vision at the Universitat Autònoma de Barcelona for all analysis carried out using their facilities. This research has been made possible thanks to Project DGICYT PB97-1161 from the Spanish Ministry of Education and Culture. J. Pijoan is a bursary of The Universitat Autònoma de Barcelona, and he thanks this institution for his Grant. J. Pijoan and O.Vicente also received a special bursary from CAA2000. We would also like to thank the Ljubljana organisers for attending the conference. We acknowledge all the aforementioned financial supports.

References

ASTHEIMER, P., DAI, F., GÖBEL, M., KRUSE, R., MÜLLER, S., ZACHMANN, G., 1994. Realism in Virtual Reality. In Thalmann, N.M. and Thalmann, D. (eds.), *Artificial Life and Virtual Reality.* New York: John Wiley Publ.

BARCELÓ, J.A., 1996a. Arqueologia Automatica. Inteligencia Artificial en Arqueologia. Sabadell: Ed. Ausa, *Cuadernos de Arqueologia Mediterranea*, No. 2.

BARCELÓ, J.A., 2000. Visualizing what might be. An Introduction to Virtual Reality in Archaeology. In Barceló, J.A., Forte, M. and Sanders, D. (eds.), *Virtual Reality in Archaeology*. Oxford, ArcheoPress (BAR International Series).

BARCELÓ, J.A., VILA, A., GIBAJA, J., 2000. An application of Neural Networks to Use-Wear Analysis. Some preliminary Results. In Lockyear, K., Sly, T.J.T., Mihailescu-Birliba, V. (eds.), *CAA96. Computer Applications and Quantita-*

tive methods in Archaeology. Oxford, ArcheoPress (BAR International Series).

BUNGE, M., 1981. *La investigación Cientńifica.* Barcelona, Ed. Ariel.

CLARKE, D.L., 1978. *Analytical Archaeology* (2. edition) London, Methuen.

EBERT, D.S., MUSGRAVE, F.K., PEACHEY, D., PERLIN, K. and WORLEY, S., 1994. *Texturing and Modelling. A Procedural approach.* Boston: Academic Press Professional.

FOLEY, J., RIBARSKY, B., 1994. Next-generation data visualisation tools. In Rosenblum, L. et al. (eds.), *Scientific Visualisation. Advances and Challenges.* New York, Academic Press: 103-127.

GERSHON, N., 1994. From perception to visualisation. In Rosenblum, L. et al. (eds.), *Scientific Visualisation. Advances and Challenges.* New York, Academic Press, pp. 129-139.

GOSE, E., JOHNSONBAUGH, R., JOST, S., 1996. *Pattern Recognition and Image Analysis.* Prentice Hall. Upper Sadler River, NJ.

HACKING, I., 1983. *Representing and Intervening.* Cambridge University Press.

MARR, D., 1982. *Vision*, San Francisco: W.H. Freeman and Co.

MUSGRAVE, F.K., 1994b. Procedural Fractal Terrains. In Ebert, D.S., Musgrave, F.K., Peachey, D., Perlin, K. and Worley, S. (eds.), *Texturing and Modelling. A Procedural approach.* Boston: Academic Press Professional.

PIJOAN, J., BARCELÓ, J.A., BRIZ, I. and VILA, A., 1999. Image Quantification in use-wear analysis. *Computer Applications in Archaeology '99.* Dublin (in press).

SMALL, C.G., 1996. *The Statistical Theory of Shape.* New York-Berlin, Springer-Verlag.

SONKA, M., HLAVAC, V., BOYLE, R., 1994. *Image processing, Analysis and Machine Vision.* London: Chapman and Hall.

WANDELL, B.A., 1995. *Foundations of Vision.* Sunderland (MA): Sinauer Ass., Inc.

WATT, R., 1988. *Visual processing: Computational, Psychophysical and Cognitive Research*. Hillsdale (NJ): Lawrence Erlbaum Ass.