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Spatial Statistics In Archaeological Texture Analysis

Mercè Adán¹, Juan A. Barceló¹, Jordi Pijoan-López¹, Raquel Piqué¹, Andrea Toselli²

¹Universitat Autònoma de Barcelona. Divisió de Prehistoria. Facultat de Lletres. 08193 Bellaterra. Spain
Merce.adan@uab.es, jbarcelo@seneca.uab.es, Jordi.Pijoan@uab.es, raquel.pique@uab.es

²Laboratori d'Arqueologia. Institució Milà i Fontanals (CSIC), c/ Egipcíacques 15. 08001 Barcelona (Spain)
atoselli@bicat.csic.es

Abstract. When analysing microscopic results, archaeologists use analogies to understand what they think they are seeing. When we move from description to explanation, we try to use the same subjective terms. A microscopic image is like a cartographic representation of homogenous luminance areas. Measuring how different luminance values are located in space, we can understand whether two images are similar or different. In this paper, we use real microscopic data from lithic use wear analysis, and charcoal analysis. In both cases, we want to compare different pictures, where their texture characteristics have been formed by different process.

Keywords. Texture, Image Processing, Statistics, Use-wear, Lithic tools, charcoal, wood.

1 Introduction. From Surface to Texture

What is a surface? Intuitively, it is that part of the object that we can see on top of it and all over its side, but more formally speaking it is the boundary of separation between two phases. A phase is a homogenous mass of substance, solid, liquid or gas, possessing a well-defined boundary. When we have two phases in mutual contact we have an interfacial boundary. This is called an interface. The surface of a solid, kept in atmosphere, is in fact an air-solid interface (Rao 1972, Lüth 1993).

The surface of solids plays a significant role in several interfacial phenomena. This study is usually called “tribology”: the science and technology of interacting surfaces in relative motion and the practices relate thereto” (Yamada 1993). Solids are rigid bodies and resist stress. When a force is applied a solid deforms; the deformation determines its shape to a large extent. As a result solid surfaces appear usually heterogeneous. The patterns can be the result of physical surface properties such as roughness or oriented strands which often have a tactile quality, or they could be the result of reflectance differences such as the colour on a surface.

Surfaces have two main properties: geometry and texture. Texture is the definition of surface attributes having either visual or actual variety, and defining the appearance of the surface. Any surface has variations in its local properties like albedo and color variations, uniformity, density, coarseness, roughness, regularity, linearity, directionality, direction, frequency, phase, hardness, brightness, bumpiness, specularity, reflectivity and transparency (Tuceryan and Jain 1993, Fleming 1999). All these perceived qualities or attributes of surfaces play an important role in describing the sources of irregularity and surface variation which are responsible of specific textures

Texture is the name we give to these variations, which seem to be usually caused as a result of the process that created that surface. If texture is a synonym for “surface variability” or “surface discontinuity”, then it can be described in terms of the peaks and valleys characterizing the surface micro-topography. Peaks-and-valleys patterns can be measured according to wavelength variations. In this case, we distinguish (using the Surface Metrology Guide, by Precision Devices, Inc. <http://www.predev.com/smg/index.html>):

Roughness includes the wavelength irregularities of a surface. It defines how that surfaces feels, how it looks, how it behaves when it comes in contact with another surface. For instance, in the case of use-wear, and according to the *size* of those wavelength irregularities, we can speak about the more widely spaced (longer wavelength) deviations (*waviness*), or the finest (shortest) wavelength deviations (*roughness*). The main parameter here is *spacing*, which refers to the distance between features on a profile in the x direction, parallel to the nominal direction of the trace. The features that determine a spacing parameter usually relate to peaks and valleys or to average wavelengths, etc

Lay refers to the predominant direction of the surface texture. Ordinarily lay is determined by the particular production method and geometry used. Turning, milling, drilling, grinding, and other cutting processes usually produce a surface that has lay: striations or peaks and valleys in the direction that the tool was drawn across the surface. It is important to distinguish between the lay (or the lack thereof) of the raw material (stone, wood, bone, etc.), and the directionality of the wavelength irregularities which define roughness. This second source of directionality is related to the work movement made with the artefact. For instance, a smooth finish will look rough if it has a strong lay. A rougher surface will look more uniform if it has no lay (it will have more of a matte look).

The concept of texture is useful in a variety of applications and has been the subject of intense study by many researchers. One immediate application of archaeological textures is the recognition of artefacts. For example, based on textural properties, we can identify a variety of materials such as lithic tools, stripped bones, wood, leather, pottery, etc. Texture patterns may vary according to the physical properties of raw material.

In the case of wood, for instance, all species have specific anatomy features which determine different degrees of roughness. We can distinguish between different woods, because of their specific anatomic patterns. However, in this case, environmental conditions also alter surface features: trees grow each year, and the growing cycle depends on environmental conditions, which in turn determine the specific characteristic of growing rings, and hence, the texture of wood.

Anatomical plans of wood can be prepared for observation through microscope, variations in the surface of these planes are related to distribution of anatomical features, according to the taxa which they come from (Pique and Pique 1992).

In the case of tools, given that use and production make important alterations in surface features, we can use texture information to understand how the object was made and/or used (human work). Texture variations due to human work are evident, and vary according to the following causal factors:

- Movement: longitudinal (cut), transversal (scrape),...
- Surface of Friction: the effects of worked material (wood, bone, shell, fur, etc.)

2 Texture patterns as images

Light waves are reflected when they encounter a solid interface (surface), and this reflection is irregular depending on the heterogeneity of the surface, that is, depending not only on its geometry, but specifically on its texture. Consequently, texture should be seen as a consequence of anisotropic reflection, and thus, it can be defined as the modulation of diffuse reflectance coefficients.

Modelling this physical process is very difficult, so texture is usually characterized by the bi-dimensional variations in the intensities present in an *image* of the object we want analyse. We describe textures in terms of the particular dispersion of luminance values in a surface, because we accept the fact that light is reflected according to surface attributes. We are not seeing low and high areas, but we see dark and bright which coincide with high and low energy regions on the surface, that is regions which have lost material (low energy), and prominent points which produce modifications on another contacting surface when friction takes place (high energy).

Image texture then, may be defined as the local variation of brightness from one pixel to the next or within a small region, where the brightness of a point is a function of the brightness and location of the light source combined with the orientation and nature of the surface being viewed (Russ 1995). If the brightness is interpreted as elevation in a representation of the image as a surface, then the texture is a measure of the surface roughness.

Therefore when we examine surface features by looking through (naked-) eye or using any vision enhancement device (microscope), what we are seeing are irregularities in luminance distribution. In fact, we are not observing texture patterns directly. In this case, an image texture is an attribute representing the solid texture. An image is an object, and as such it has its own texture, defined as a function of the spatial variation in pixel intensities (grey values). But image texture is not the same as the object texture. The image is an effect of the instrument (the microscope, the eye), and consequently it shows features of the object being analysed, the context of observation and the mechanical characteristics of the observation instrument. There are always shadows and reflections which are not the result of original irregularities at the surface, but generated by the light source, the instrument or other objects in the scene. That means that an image texture not only contains the object surface irregularity data, but additional information which in the best case is just random noise, and in many other cases makes difficult to distinguish between the data that belongs to the object and information from the observation process.

Consequently, texture features are perceived as a combined effect of Light, Shadow, Topography and Edge, and computed based on tonal features such as mean, variance, skewness and kurtosis of grey levels along with texture features computed from grey level co-occurrence matrices (Tuceryan and Jain 1993).

We can use *heightmaps* as a 3D representation of textures. A Heightmap or 3D surface map is a painted map that represents a heightfield. It is a set of numbers arranged to form a two-dimensional grid, like a bitmap, except each number represents a surface elevation instead of a color or grey level..

A heightmap is not a metric representations of a surface micro-topography. It is the most efficient way to describe the numerous tiny undulations of a typical texture. But heightfields have their limits: they are only a representation of elevation differences, and there are many light undesired effects within them. Observed image texture depends on factors such as scene geometry and illumination conditions. Certain properties of surfaces have effects on the appearance of texture. Because grey values depend on shadows, and shadows depend on the position of light sources, if we do not take care, the same object surface may have totally different height maps associated. We should control light sources, and the influence of the image acquisition device to be able to understand observed patterns. Even for relatively flat scenes in which precedence is not a problem and the light source is well controlled, the combination of effects of surface orientation, color, geometry and other variables make it difficult to quantitatively interpret these parameters independently (Russ 1995). Most of the stress over heightfields comes from confusing them with bitmaps (microscopic images, for instance). In fact it is a mistake to consider that any photograph of an artefact surface is a model of its texture. We use a bitmap to store heightfields, only for practical reasons. Not always the brighter pixel in a photograph corresponds to the higher energy (most prominent) point of the object's surface. In Figure 3, for instance, there is a fuzzy region at the upper part of the photography which looks brighter than expected. That means that the heightmap is only valid for a restricted region of the original photography. In our experiments, we have solved this problem by selecting only the non-fuzzy and well framed areas of the original microscopic image, reducing the sampled area, and increasing the number of images, what has allowed a relevant decrease in the risk of confusing luminance effects with the original textures.

3 Texture Analysis

Luminance values vary from one location to another, and some times this variation has some appearance of continuity. What we are looking for is whether light reflection in one location is related with luminance values in neighbouring locations. The analysis then proceeds to examine whether characteristics in one location have anything to do with characteristics in a neighbouring location, through the definition of a general model of spatial dependencies.

Consequently, texture structure is simply analysed using the repetitive patterns in which elements or primitives are arranged according to a placement rule (Tamura et al. 1978). This placement rule can be studied taking into account that any texture model should be based on

- *spatial structure (pattern)*
- *contrast (amount of texture).*

The three principal approaches used to describe texture models are statistical, structural and spectral. Statistical techniques characterise texture by the statistical properties of the grey levels of the points comprising a surface. Structural techniques characterise texture as being composed of simple primitives called "texels" (texture elements), that are regularly arranged on a surface according to some rules.

3.1 Statistical Analysis

First-order statistics measure the likelihood of observing a grey value at a randomly-chosen location in the image. One of the simplest (but least versatile) of the texture operators is simply the range or difference between maximum and minimum brightness values in the neighbourhood. For a flat or uniform region, the range is small. Larger values of the range correspond to surfaces with a larger roughness. The size of the neighbourhood region must be large enough to include dark and light pixels, which generally means being larger than any small uniform details that may be present.

First order statistics can be computed from the histogram of pixel intensities in the image. These depend only on individual pixel values and not on the interaction or co-occurrence of neighbouring pixel values. The average intensity in an image is an example of the first order statistic (Julesz 1981). A number of other texture parameters and functions may also be calculated, based on the amplitude density function of pixels (Duran et al. 2001):

- INERTIA: Image contrast (difference moment), a measure of local variation
- CORRELATION: A measure of linear grey tone dependence
- HOMOGENEITY: A measure of monotonicity
- ENTROPY: A measure of the average uncertainty of grey tone co-occurrence
- ENERGY: Angular second moment, a measure of the average certainty of grey tone co-occurrence
- VARIANCE: A measure of grey tone variance within the window (second-order moment about the mean)
- SKEWNESS: Third order moment about the mean; the departure from symmetry about the mean grey level
- KURTOSIS: Fourth order moment about the mean; a measure of the spread of grey tones about the mean

A first experiment consisted of comparing stone tools made of the same type of raw material (flint from the same source) and then use them for different activities: cutting and scrapping animal fur, fresh wood and shells (Pijoan et al. 2002). Preliminary results show that the standard deviation of luminance patterns is statistically different (using a student *t* Test) when we analyse lithic tools used for "cutting" and lithic tools used for "scrapping". That means that on the surface of lithic tools, human work generated different textures, which can be differentiated using first order statistics. In this case (Fig. 1), the standard deviation of luminance patterns is statistically different (using a student *t* Test) when we analyse lithic tools used for "cutting" and lithic tools used for "scrapping". We can prove that lithic tools used for "cutting" (longitudinal textures) have a greater diversity of luminance (in our experiment: mean of SD=6.31), than tools used for "scrapping" (transversal textures), with less important luminance variation (in our experiment: mean of SD=5.42).

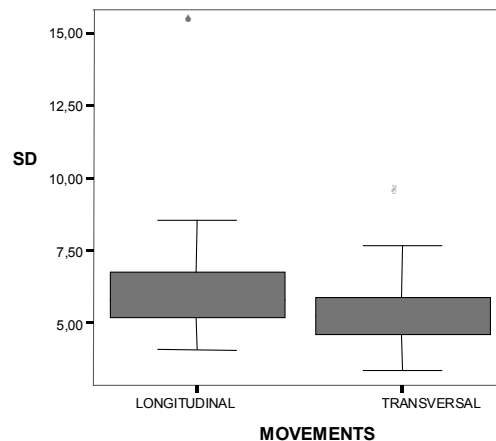


Fig. 1. Differences on the Standard Deviation of luminance values (Y axis) between longitudinal and transversal textures, that is, textures generated when "cutting" and textures generated when "scrapping".

Coarseness is related to the dispersion of luminance values in the image, (S_D),

$$COARSENESS = 1 - 1/(1 + S_D)$$

Consequently, as a result of cutting, coarser textures are generated (coefficient= 0.864) on the cutting edge of the tool, than when we scrap (coefficient=0.847).

In a second experiment (Toselli et al. 2002), we have tried to distinguish between different stone textures. In this case we have processed three varieties of andesite and one kind of obsidian. Luminance values do not seem statistically different among the materials, however, the strong difference among variances are interesting. In the obsidian case, there is a far greater diversity of luminance, than in the case of andesites, with a much more recurrent pattern. However, there is not any relevant difference between use wear generated by the same movement and worked material between different raw materials.

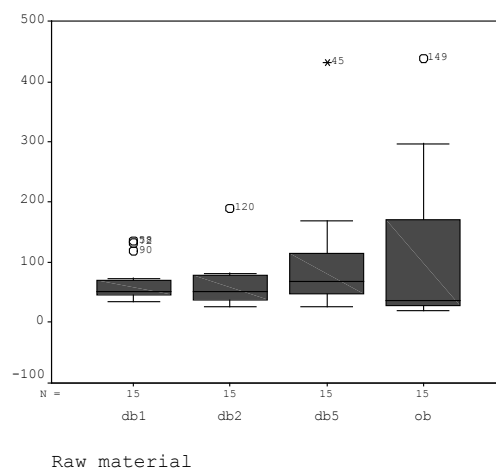


Fig. 2. Differences on the mean luminance values (Y axis) among different stone tools made of different materials (db1, db2, db5: three types of andesite; ob: obsidian).

In another experiment with the same data (Toselli et al. 2002), the luminance mean value among all pixels in an image was used to define differences among tools submitted to

different friction surfaces: fur, wood and shell. Again, we find differences in the mean luminance value of the different textures, indicating that light reflects differently on surfaces modified by different use actions.

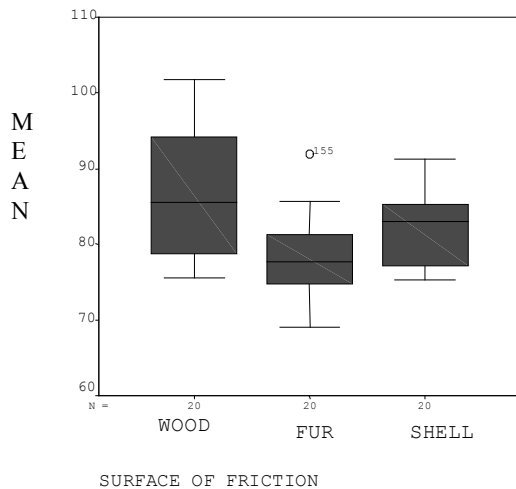


Fig. 3. Differences on the mean of luminance values between results generated after scraping wood and fur, and cutting shell.

A similar approach can be used to distinguish between different wood textures. Preliminary results show the relevance of statistical differences in luminance values in different regions of the image. In this case, the image is segmented using specific anatomic features of wood like vessels, rays, vegetal fibres, etc. (Piqué and Piqué 1992).

3.2. Structural Analysis

Texture patterning in an image should be described as associations between *image discontinuities*, which refers to basic texture elements called *texels* (Pijoan et al. 1999, Barceló et al. 2001). Identification of luminance discontinuities that correspond to surface texture elements is then a significant problem since the scale at which surface detail is captured varies continuously with the three-dimensional distance, and therefore across the image texture (Sklansky 1978).

Texels may exhibit a systematic variation in a priori unknown properties, e. g., size, density or contrast. For instance, the textural character of an image usually depends on the spatial size of texels, in such a way that coarse texture can be decomposed in large texels, while small texels give fine texture surfaces (Singh and Singh, n.d.). Our goal is to segment those texture elements, in order to be able to study their variability in shape and spatial location. Archaeological textures fast always are an irregular pattern of different texels, each one with different shape edges and different luminance means.

Structural analysis includes the study of texels directionality (anisotropy) or non-directionality, periodicity or irregularity and measures of structural complexity: (a) Texel placement rules. (b) Shape/size. (c) Intensity distribution. (d) Compound (placement rules and shape/orientation) (Chetverikov 1998).

In our experiments with lithic tools and wood and charcoal remains, we have observed that texels have different shapes when generated by different processes. In the case of wood, distribution of vessels, and other anatomic features explain texture variability, and can be determinant to identify the

pattern. The pattern of vessel distribution can be analysed as textures elements. In those cases, texel structural variability is related to the taxa, but also to the specific environmental conditions, that every year can be different, producing variations in this pattern: trees grow each year, and the growing cycle depends on environmental conditions, which in turn determine the specific characteristic of growing rings, and hence, the shape, size and location of texture elements (Schweingruber 1996).

In our experiments on lithic surfaces (Toselli et al. 2002), we have selected three luminance intervals on the image (Fig. 4), in a grey scale of 256 intensities from 0 –white– to 255 –black–:

- From 0 to 80
- From 0 to 120
- From 160 to 200

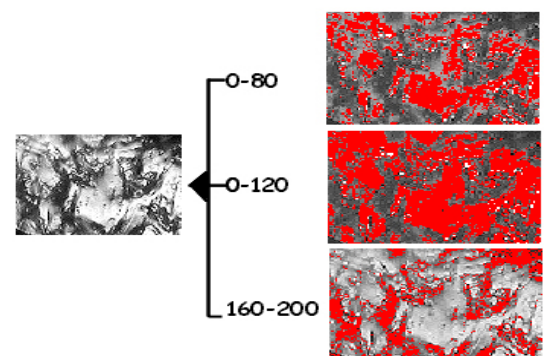


Fig. 4. Light intervals, and texel segmentation.

Through the intervals 0-80 and 0-120, we observe luminance discontinuities within the "bright zone" of the grey scale (brighter in the first case, include some medium dark areas in the second. That is, we select the highest points of the texture. Through the interval 160-200, we observe the irregularity of the "dark zone" of the grey scale, or the more depth areas.

These three luminance intervals have been selected based on our preliminary experiments (Toselli et al. 2002). For instance, the dark band of light spectrum (160-200) allows us to distinguish fur processing generated textures on stone tools, because those items have dark areas which are smaller and more frequent than bright ones. In our experiments, this phenomenon seems to be characteristic of flint surfaces, but not in other cases. Use wear is much more complex than we expected. This is the reason why we repeat the segmentation process on the three light intervals. Only one of the intervals gives us more understandable results.

In the case of the low zone of the luminance scale –values from white to median grey value: 0-120–, which means positive *bumps* or elevations in the texture model, preliminary results show that the number of positive bumps is greater (and their size smaller) when the lithic surface has been modified as a result of fur processing. When we process wood with the lithic tool, positive bumps are less frequent, but bigger, forming on the surface large plateaux which are usually called "micropolished areas".

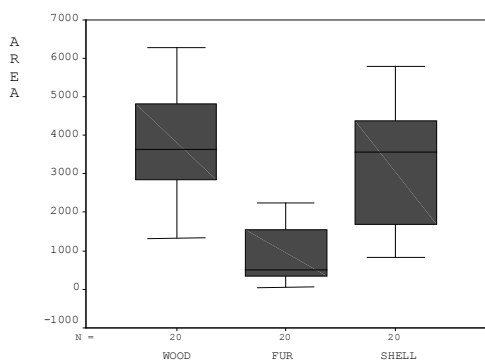


Fig. 5a. Number of segmented texels in the interval 0-120. Differences according to surface of friction.

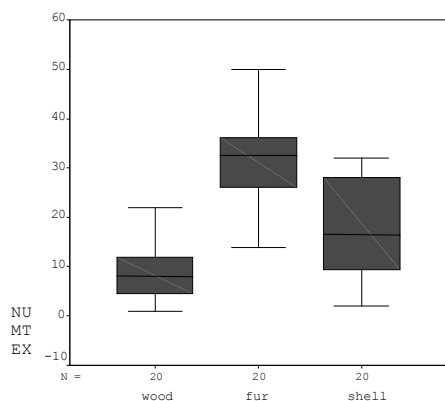


Fig. 5b. Size of texels in the Interval 0-120. Differences according to surface of friction

In the case of lithic use-wear, texels are different depending on the movement made with the tool (longitudinal or transversal), and according to the surface of friction (wood, shell and fur). For instance, surfaces of tools used for processing *fur* have more texels, but smaller than tools used for processing *wood*. The tendency to differentiate textures generated by friction over hard and soft worked materials has been confirmed through tests applied over the luminance interval 160/200. For instance, we have found that shell and wood processing generate similar texture, very different to that generated when processing dry fur. Specifically, the texels on fur-generated textures are more glossy than the texels associated with wood processing if we select the interval 0/120. In the interval 160/200 fur is less glossy. Generally, alterations by use related to fur processing are the darkest in the series. Results for shell processing are in the middle.

We can also study the shape of those texels which correspond to *bumps* or “large plateaux” seen on the lithic surface, and not only their frequency and size. For instance, to measure the differences between textures features associated to the kinematics (movement) of the working action, we should take into account other attributes: the angle of the major axis of the edge of the tool, and the shape of the texel, specifically its *elongation*, which is a “deformation” feature associated with kinematics (Barceló et al. 2001). In our experiments, not all texels were good indicators of the working movement, because not all texels were oriented to the direction of movement (transversal or longitudinal). We observed that the longest

texels were also the best oriented according to the working movement (along the edge of the tool when cutting, across the edge of the tool when scrapping). That means that surfaces of tools used with a longitudinal movement have texels parallel to the *x* axis in longitudinal working movement (cut) and to the *y* axis for transversal working movement. In the same way, the more elongated the texel’s shape, the more parallel to the major axis (Toselli et al. 2002).

In another experiment (Toselli et al. 2002) we have computed a Principal Component Analysis integrating first order statistics and structural information about texels. Variables in the analysis were: luminance mean, luminance mode, Area, Angle, shape -a circularity coefficient: $[(4*\pi*A)/(P^2)]$; A = AREA, P = LENGTH] (see Barceló et al. 2001, about those variables).

The first axis explains 33% of the variance, and it distinguishes textures characterised by small and dark texels with a rectangular shape (low values of the shape-circularity coefficient) from big texels with a high tendency towards circular shape. The second axis explains 30% of total variance, and it oppose big/non circular texels from big/circular ones. The third axis explains 15% of the variance, and it distinguishes transversal (vertical angles) from longitudinal texels (horizontal angles, parallel to the tool’s edge).

We have tested that the shape of texels is not relevant in this case, because when we delete the circularity coefficient from the analysis, Principal Component results are much easier to understand: only two axis explain 75% of total variance, and discrimination plans between the sources of texture variation are much more evident.

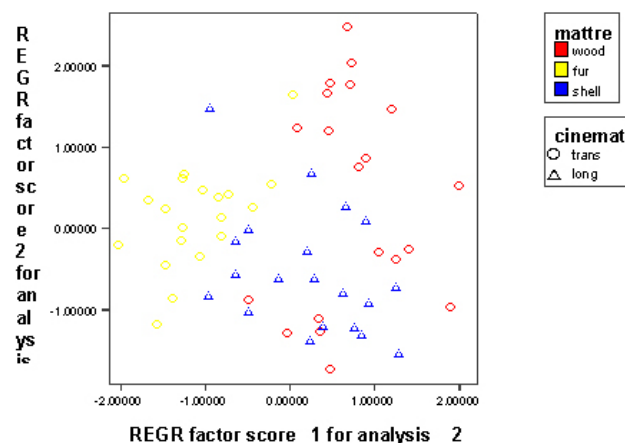


Fig. 6. Principal Components Analysis with a restricted set of variables

The results from the luminance interval 160/200 shown a less clear discrimination. We obtained a solution that explain the 83% of the variability through the attributes number of texels, mean of the mean of luminance, mean of the area size, mean of the angle of the major axis and mean of the elongation. However, this solution is not able to discriminate either working movement nor worked material.

Finally, we apply a factorial analysis (Fig. 6) for the longest texels from the luminance interval 0/80 through the attributes mean and mode of the brightness intensity, circularity, area and

angle. The 1st axis explains 33% of the variability, linking mean and mode of the brightness intensity, opposing it to circularity. The 2nd axis explains 30% of the variability, opposing area to circularity. The 3rd axis explains 15% of the variability, opposing angle to area.

We have until now statistical results that give us data about several attributes related to four parameters of the texture –size, shape, composition and location–. However, related to the parameter location, we have developed a statistical process about an attribute –angle– and we also want to apply statistical test through Cartesian coordinates (X,Y) of the texture elements in the canvas of the digital images.

In the case of wood, we are now doing experimental work to decide which luminance intervals are more convenient and provide more information about patterns of distribution of anatomical features (Pique and Pique 1992). Our working hypothesis is that texel differentiation depends on taxa. Shape, frequency and size of texels are the result of shape, frequency and size of vessels, that is, the plant vascular system. We also consider that orientation of texels and the spatial distribution of them can provide relevant information to distinguish between taxa. Work is now at a preliminary stage. Nevertheless, our goal has been to apply this methodology to archaeological material, and to be able to solve real archaeological problems.

Conclusions

Archaeological textures has usually been described in qualitative terms. When analysing microscopic results, archaeologists use analogies to understand what they think they are seeing. When we move from description to explanation, we try to use the same subjective terms. We say that two textures are similar, because both are “equally brilliant”, “equally glossy”, and the like.

In this paper we have presented a theory and a methodology of texture analysis based on the principle that a microscopic image of an object’s surface is like a cartographic representation of luminance areas. By studying shape and texture variability, and how different values are located in space, we can understand if two images are similar or different. Once we have described the minimum elements in an image (texels) according to their shape and luminance metrics, we can explain the results using spatial statistics. Spatial and multivariate statistics have been used to understand observable properties of archaeological materials.

Experimental results show that luminance differences coincide with differences between texture components, and can be used to discriminate between archaeological objects based on their surface properties.

References

BARCELO, J.A., PIJOAN, J., VICENTE, O., 2001, “Image Quantification as Archaeological Description” In. *Computing Archaeology for Understanding the Past*. Edited by Z. Stancic and T. Veljanovski. BAR Int. Series S931., pp. 69-78.

CHETVERIKOV,D., 1998, Texture Analysis Using Feature Based Pairwise Interaction Maps, <http://visual.ipan.sztaki.hu/fbimweb/>

DURAN, M.L., CERNADAS, E., CARO, A., ANTEQUERA, M.T., 2001, “Clasificación de distintos tipos de jamón ibérico usando análisis de texturas”. *Revista Electrónica de Visión por Computador*. Num. 5 (Julio). <http://www.cvc.uab.es/revc/revista/05/>

FLEMING,b., 1999, *3d Modeling and surfacing*. Morgan Kaufmann Publishers, inc. San Francisco

JULESZ, B., 1981, “A theory of preattentive texture discrimination based on first-order statistics of textons”, *Biological Cybernetics*. 41, pp. 131-138.

LÜTH, H., 1993, *Surfaces and interfaces of solids*. Springer Verlag, Berlin.

PIJOAN,J., BARCELO,J.,A, VICENTE,O. 1999. “Image quantification in use wear analysis”, in *Computer Applications in Archaeology '99* Dublin (in press).

PIJOAN,J., BARCELO, J.A., CLEMENTE,I., VILA,A.,, 2002. “Variabilidad estadística en imágenes digitalizadas de rastros de uso: Resultados preliminares” in *Análisis Funcional: su aportación al estudio de Sociedades Prehistóricas 1er Congreso de Análisis Funcional de España y Portugal* British Archaeological Reports, Archeopress, Oxford.

PIQUE, R., PIQUE,J. 1992, ”Automatic Recognition and classification of archaeological charcoals”. In *Computing the Past*. Edited by J. Andressen, T. Madsen and I. Scollar. Aarhus University Press, pp. 85-90.

RAO, S.R., 1972, *surface phenomena*. Hutchinson Educational Ltd., London.

RUSS, J.C., 1995, *The Image Processing Handbook* CRC Press. Boca Raton. (2nd. Edition).

SINGH, M. S. SINGH., n.d., “Spatial Texture Analysis: A comparativeStudy” http://www.dcs.ex.ac.uk/research/pann/pdf/pann_SS_068.PDF.

SKLANSKY,H., 1978, Image Segmentation and feature extraction (*IEEE Trans Syst. Man cybern.*, 8, 237-247)

SCHWEINGRUBER, F.H., 1996: *Tree Rings and Environment. Dendroecology*. Birmensdorf, Swiss Federal Institute for Forest, Snow and Landscape Research. Berne, Stuttgart, Vienna, Haupt. 609 S.

TOSELLI.A. PIJOAN, J., BARCELO, J.A: 2002. “La descripción de las trazas de uso en materias primas no silíceas: resultados preliminares de un análisis estadístico descriptivo” In *Análisis Funcional: su aportación al estudio de Sociedades Prehistóricas 1er Congreso de Análisis Funcional de España y Portugal* British Archaeological Reports Archeopress, Oxford.

TUCERYAN, M., JAIN, A.K., 1993, “Texture Analysis”. In *Handbook of Pattern Recognition & Computer Vision*. Edited by C.H. Chen, L.F. Pau, P.S.P. Wang. World Scientific, Singapore, pp. 235-276.

TAMURA,H., S. MORI, Y. YAMAWAKI, 1978, “Textural features corresponding to visual perception”, *IEEE Trans. Syst. Man Cybern.*, (1978), pp. 460-473).

YAMADA, S., 1993, “The formation process of use-wear polishes”. In *Traces et fonction: Les gestes retrouvés*. Colloque International de Liege.. Editions ERAUL, vol. 50., pp. 433-445.

