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FUNCTIONAL ANALYSIS FROM VISUAL AND NON-VISUAL DATA. AN ARTIFICIAL INTELLIGENCE APPROACH

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ABSTRACT

Why archaeological artefacts are the way they are? In this paper we try to solve such a question by investigating the relationship between form and function. We propose new ways of studying the way behaviour in the past can be asserted on the examination of archaeological observables in the present. In any case, we take into account that there are also non-visual features characterizing ancient objects and materials (i.e., compositional information based on mass spectrometry data, chronological information based on radioactive decay measurements, etc.). Information that should make us aware of many functional properties of objects is multidimensional in nature: size, which makes reference to height, length, depth, weight and mass; shape and form, which make reference to the geometry of contours and volumes; texture, which refers to the microtopography (roughness, waviness, and lay) and visual appearance (colour variations, brightness, reflectivity and transparency) of surfaces; and finally material, meaning the combining of distinct compositional elements and properties to form a whole. With the exception of material data, the other relevant aspects for functional reasoning have been traditionally described in rather ambiguous terms, without taking into account the advantages of quantitative measurements of shape/form, and texture. Reasoning about the functionality of archaeological objects recovered at the archaeological site requires a cross-disciplinary investigation, which may also range from recognition techniques used in computer vision and robotics to reasoning, representation, and learning methods in artificial intelligence. The approach we adopt here is to follow current computational theories of object perception to ameliorate the way archaeology can deal with the explanation of human behaviour in the past (function) from the analysis of visual and non-visual data, taking into account that visual appearances and even compositional characteristics only constrain the way an object may be used, but never fully determine it.

KEYWORDS: Function, Shape, Form, Texture, Material, Artificial Intelligence

1. INTRODUCTION: ARCHAEOLOGICAL THEORY, TECHNIQUES AND TECHNOLOGY

Computational (or "Artificial") intelligence is not just about robots. It is about understanding the nature of intelligent thought and action using computers as experimental devices. It also deals with the nature of inferential mechanisms and how computer programs allow us to discover how we produce inferences. In this paper we would like to introduce some of the key points in Computational Intelligence in Archaeology, exploring the implications in our discipline, both theoretically and methodologically of Machine Learning tools and techniques. Theoretical and practical aspects of computer programs which able to reproduce the same tasks archaeologists do are reviewed in this paper. The question of whether it is possible to automate the archaeological knowledge production is of both great theoretical interest and increasing practical importance, because knowledge and information are being generated much faster than they can be effectively analyzed.

This paper is not only about techniques and technologies. It is also a theoretical proposal on archaeological explanation. Our stating point is the assumption that archaeological artefacts have specific physical properties because they were produced so that they had those characteristics and not some other. In some sense, it is the same has been suggested by M. Schiffer on the idea of "Technological choice" (Schiffer, 2003).

It has been suggested that there is a direct constraining relationship – sometimes even deterministic – between how a prehistoric artefact looks like in the present and its past functionality. That means that artefacts we see today at the archaeological site were produced in a specific way, at least partially, because those things were intended for some particular uses: they were tools, or consumed waste material, or buildings, or containers, or fuel, etc. Therefore, archaeological items have different shapes, sizes, and materials. They also have different textures, and appear at different places and in different moments. That is to say, the changes and modifications in the form, size, texture, material, and location that nature experiences as the result of human action (work) are determined somehow by these actions (production, use, distribution) having provoked its existence.

In that sense, the scientific question we intend to solve can be expressed in the following terms:

Why the observed material entities have specific values of size, shape, texture, material, and why do they appear at some specific spatial and temporal location?

The main assumption is that some percept (*archaeological description*) should be related to a causal affirmation about the causal event (social event, work activity) having produced the perceived evidence (*archaeological explanation*). Artificial Intelligence computational procedures will allow us to predict the cause or formation process of some archaeological entity given some perceived evidence of the effect of this causal process. In its most basic sense, then, the task may be reduced to the problem of detecting localized key perceptual stimuli or features, which are unambiguous cues to appropriate causal events. For instance, a distinctive use wear texture on the surface of a lithic tool, and not on others, predicts that these tools have been used to process fresh wood, and we infer that at some moment a group of people was cutting trees or gathering firewood. Alternatively, we can consider that the shape of some pottery vases predicts their past use as containers for wine, and then we have evidence of wine production and trade; the composition of some graves predicts the social personality of the individual buried there and hence the existence of social classes. Here the output is not the object (trees or firewood, wine, social elite), but a causal affirmation: cutting trees or gathering firewood, wine production and trade, social power and coercion.

In the paper we will discuss how archaeological explanation occurs when a perceptual input matches a perceptual memory containing a description of each causal event the system is expected to recognize or identify (Figure 1).

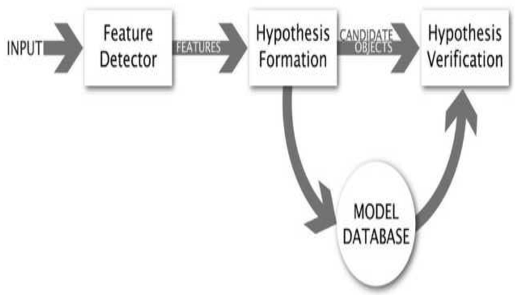


Figure 1 A model for an archaeological recognition system. The model database contains all the models known to the system. The information in the model database depends on the approach used for the recognition. It can vary from a qualitative or functional description, to precise parametric equations. The feature detector applies operators to the input, and identifies locations of features that help in forming causal event hypotheses. Using the detected features in the input, the hypothesizer assigns likelihoods to those events that may have produced the observed evidence. The knowledge base is organized using some type of indexing scheme, to facilitate elimination of unlikely causal events candidates from possible consideration. The verifier then uses causal theories to verify the hypotheses and refines the likelihood of explanations. The system then selects the causal event with the highest likelihood, based on all the evidence, as the correct event.

2. WHY ARCHAEOLOGICAL ARTEFACTS ARE THE WAY THEY ARE?

A possible answer to this question would be: because objects have a distinctive *appearance* for the sake of their proper *functioning*. The meaning of functioning is always related with the idea of using. An object's use can be defined as the exertion of control over a freely manipulable external object with the specific intention of: (1) altering the physical properties of another object, substance, surface or medium (the target, which may be the object user or another organism) via a dynamic mechanical interaction, or (2) mediating the flow of information between the tool user and the environment or other organisms in the environment (St. Amant and Horton 2008; see also Beck's 1980, McGrew 1993, Amant 2002, Bicici and Amant 2003).

According to Daniel Dennett (1987), the "function" of a certain item is (or should be) what it is best able to do (or be), given its physical constitution and its context. In accordance with Bonnet (1992), a function is taken as an activity, which can be performed by an object. Therefore, we can consider that the object's activity is in fact its operating mode or behaviour specification. Balachandran and Gero (1990) prefer to distinguish between *function, structure, and behaviour* as three classes of properties of a design object: function properties would dictate the object's intended purpose and requirements; structure properties would represent the description of the whole and its constituents; while the behaviour properties would spell out how the structure of the object achieves its function. For example, considering the main physical features of a cup, we can assign different functions to each part: the flat bottom is for standing the cup on a surface; the handle is for grasping the cup when lifting; the inside is for containing the liquid; the rim is for supporting the cup against the lips when drinking. The assignment of *causal interactions* to features *defines* the object as a cup (Leyton 1992, p. 163). We may argue, then, that the function of a cup is specified in terms of the actions applied to it, e.g., standing up, lifting, etc., and in terms of the

resulting actions that the cup applies back to the environment, e.g., conveying the liquid upward. All that means that we are describing the cup in terms of five components:
(1) INPUTS: e.g., standing up, lifting, etc.
(2) OUTPUTS: e.g., conveying liquid
(3) STATES: physical characteristics of the cup, e.g., its shape
(4) FIRST CAUSAL RELATIONSHIP:
e.g., lifting (input) acts on shape (state) → conveying liquid (output)
(5) SECOND CAUSAL RELATIONSHIP:
e.g., lifting (input) acts on shape (state) → shape does not change (dynamics: next state).

The above definition of function would seem correct only in the case of objects like huts or hats, or any other tool-like things, which have been made according to a clearly defined purpose (Wright, 1973, Millikan, 1999; Neander, 1991). Such definition would be also effective when dealing with objects with symbolic use, given that even "style" has a "function" (Wobst 1977).

The problem is that, although functional behaviours (symbolic or nonsymbolic) seem to be *goal-directed activities*, sometimes desirable ends are achieved through the incidental or even accidental use of an object, and consequently the use of archaeological artefacts can also be *opportunistic*. Objects can be used for purposes not intended by their designers and/or manufacturers (St. Amant 2002, Bicici and St. Amant 2003). In this way, someone may insist in the apparent difference between things that people did of their own free will, from the things they did because they had to (Sackett, 1985). A presumably nonfunctional behaviour, "stylistic" in Sackett's terms – a wrong term for a correct concept in our view – would denote an action that does not have detectable intended purpose. The closer an action is un-intended, the less likely it is to be functional, i.e., patterned by rational choice. Binford (1989, 52-53) has considered this functional/ nonfunctional dichotomy as an opposition between conscious, explicitly-rational, problem-solving behaviour, on the one hand, and unconscious, rote-learned motor habits, and socially or symbolically-motivated behaviour, on the other. The distinction between "functional" and "nonfunctional" seems to be established between material consequences that are subject to causal intentional explanation, and material consequences that are not (Dunnell, 1978).

To avoid the apparent many functions of the very word function, we prefer to insist in the idea of *functional analysis* – as the analysis of the object's disposition to contribute causally to the output capacity of a complex containing system of social actions (Cummins 1975, 2000, 2002) –, rather than in a single substantive with a single meaning. This includes the use of objects used in a direct way with a material purpose (instruments), and objects used in a metaphorical way with an ideological intention (symbols). The only we would need to take into account is then the object's role in a human goal-directed activity.

We suggest that we should attribute *functions* to archaeological objects *because and only because* it can be proved that they may exhibit certain behaviours under the appropriate conditions: two objects will be functionally equivalent (or analogous) if they do the same (or similar) things in the same (or similar) systems in the same (or similar) environment. The key is in the emphasis on the word "do". No other features of the archaeological materials are relevant, other than the fact that they do the same things under certain conditions, which is to say that it is their behaviour that is important. What we, archaeologists, characteristically perceive are objects and changes in objects, and behaviours are reifications of these. Thus, an archaeological entity should be explained by the particular causal structure in which it is supposed to participate. The knowledge of the function of some perceived material element should reflect the causal interactions that someone has, or can potentially have, with needs, goals, and products in the course of using such elements.

According to such assumptions, if one wants to produce a specific tool that will be used in a specific way, designers/manufacturers cannot violate the laws of physics, which might prevent using the object in such way, or facilitate its use in another way. We should consider how physical properties (size, shape, texture, visual appearance, raw material, etc.) will affect what the object did in the past; its overall form (for holding or halting); the edge angle where cutting, scraping, or holding was important; the duration of its use, how specialized the working parts needed to be; whether it was at all desirable to combine two or more functions in the same tool; how reliable the tool needed to be; and how easily repaired or resharpened it needed to be (Hayden 1998). Furthermore, one also has to determine the history of social actions having used that tool for different purposes at different circumstances (Nagel 1961, Boorse 1976, 2002, Adams 1979, Cummins 1975, 2000, 2002).

According to Nagel (1961), a thing or event has to be explained in terms of the function it performs in some larger whole, or the role it plays in bringing something about. Functional explanation focuses attention on the culminations and end products of specific processes. Our approach equates function with causal links or goal-directedness, rather than logical purpose. What underlies this idea of function is essentially historical in character. Humans possess a large amount of functionally relevant knowledge for any material category, which includes:

a) The object's design history;

b) The object's physical structure and the physical settings in which it is found;

c) The events that arise during the object's use, such as agent's actions, object's behaviours, and outcomes.

Consequently, an object's function emerges from a relational system that links its physical structure (i.e., non-visual and visual data, which include shape, texture and material) with its use, background settings, and design history (Kitamura and Mizogouchi, 1999; Chaigneau et al., 2004).

FUNCTIONALITY FROM SHAPE

Archaeology has been traditionally considered as a quintessentially visual discipline (Shelley 1996). Among all features that describe archaeological evidences, some of them, the most important for the recognition and/or the discovery of the way an item was produced and or used in the past, have something to do with what we have been trained to "see" in the archaeological record. Unfortunately, there is no universal method of searching for informative visual marks. They can be extracted from any archaeological record almost *ad infinitum*, but one usually fails to formalize the significant criterion for what is intrinsically "visual". An additional difficulty is that different visual features will almost definitely be of importance for different explanations.

The insufficiency and lack of a clear consensus on the traditional methods of visual description – mostly based on spoken language, descriptive, ambiguous, subjective and qualitative – have invariably led to rhetoric, ambiguous and subjective interpretations of its functions. It is thus strongly advisable to systematize, formalize and standardize methods and procedures more objective, precise, mathematical and quantitative, and whenever possible automated (Barceló, 2009; Moitinho and Barceló, 2011). If visual features – which include shape description – of archaeological observables are not formalized, then possibilities of discovering the function the artefact had in the past is compromised.

Traditionally, archaeologists have referred to diameters and heights when they spoke about shape. The conventional method for capturing artefact's morphology has been to take linear measurements with calipers at fixed loci along an arbitrary line of maximum bilateral symmetry, generally defined as *length*. Such linear measurements, however, are absolute quantities reflecting only size. No geometric information is provided on the relative position of the various breadth and thickness measurements. Accordingly, the variables sampled constitute an abstract collection of relative size measurements. There is no assurance that two archaeological artefacts with identical size values at different parts of their extension will have similar *shapes*. The shape of every square, for example, is the same whether it is a large square or a small square.

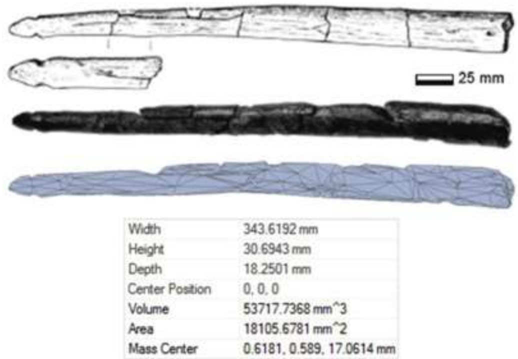
The attempts at formally defining the term *shape* are often based on the idea of any "single", "distinct", "whole" or "united" visual entity. In other words, it is the structure of a localized field constructed "around" an object (Koenderink, 1990; Small 1996; Costa and Cesar, 2001; Leymarie, 2011). Therefore, the shape of an object located in some space could be expressed in terms of the geometrical description of the part of that space occupied by the object, as determined by its external boundary – abstracting from location and orientation in space, size, and other properties such as colour, content, and material composition (Johansson, 2008, 2011; Rovetto, 2011). Consequently, the idea of shape should be understood as a process by which our mind "builds" a definition of some observable input (Barceló, 2010a; Leymarie, 2011). Within this paradigm, the shape of things appears to be a physical representation of the content of information associated with each thing. The word "information" itself comes from the Latin "in forma" meaning "in shape" and implies that "information" is what you need to know in order to put things into a proper shape (Gammaitoni 2011).

To completely characterize the shape of an object means to be able to re-create the whole geometry of the same object, using only the measurements made over its interfacial boundaries. However, even though in some cases a set of measurements may satisfy the archival property, it may as well fall in a redundant set of measures (Read 2007).

In the revealling new foundations to generative geometry proposed by Michael Leyton (1992, 2005), "shape" is defined by the sequence of operations needed to create the object's boundary. One should recover from that shape, the history of embryological development and subsequent growth, which the body underwent. The shape is full of the object's history. For instance, the shape of a tree gives us information about how it grew. A scar on a person's face tells us that, in the past, the surface of the skin was cut. A crack in a vase informs us that, in the past, the vase underwent some impact; i.e., this information is retrievable from the crack. In the same way, the vertical height of the vase is information about the past process that pushed the clay upwards; and the outline of the vase, curving in and out, is information of the past changing pressure that occurred in the potter's hands. Therefore, the crack is a memory store of hitting which sits on the vase which is a memory store of clay-manipulation. According to the Leyton's foundations for geometry, every feature of the world is a memory store. The recovery of such a memory can be carried out by simple procedure of partitioning the presented situation into its asymmetries and symmetries and following some inference rules to understand why an originally symmetric formation ended in asymmetry.

Most of the ways of representing shape in terms of the object physical boundaries have been developed in terms of extracted 2D contours or silhouettes (see Barceló 2010a for an overview of such methods). For some time, computer specialists thought that it would be very easy to adapt linear contour (Nelson and Selinger, 1998); landmark (Dryden and Mardia 1998; Adams et al. 2004; Slice. 2007; Elewa, 2010), or decompositional (Biederman, 1987, 1995; Edelman, 1994; Palmer, 1999; Edelman and Intrator, 2000, 2002; Binford and Levitt 2003; Jang et al. 2006; Cao et al. 2008) approaches of shape to the analysis of *form* (Ingram and Hudson, 1994), that is, 3D, but modern research has proved that we need much more than a mere adaptation. The third dimension is much more important than many archaeologists tend to think, it isn´t just a matter of realism in the representation of enhanced aesthetic qualities. In fact, it opens up new possibilities for incorporating movement and physic issues into a model, in the effort to understand the function of archaeological artefacts.

Fortunately for us, technology has produced a diversity of 3D scanner devices. Such "instrumental-observers" are able to capture the form of an archaeological object. The generated output data is composed by a point cloud with thousands of three-dimensional Cartesian coordinates – besides xyz coordinates, each point can also



Width	343.6192 mm
Height	30.6943 mm
Depth	18.2501 mm
Center Position	0, 0, 0
Volume	53717.7368 mm^3
Area	18105.6781 mm^2
Mass Center	0.6181, 0.589, 17.0614 mm

Figure 2 Fragmented wooden artefact (D05-KE90-7), from the Neolithic lakeside site of La Draga (Banyoles, Catalonia). It has been functionally analyzed as a bow. From top to bottom: Drawings and Photograph (Bosch 2006); 3D digital model, with original triangular mesh decimated; Basic geometric data of the original 3D digital model.

Figure 3 Detail of the 3D digital model of the archaeological artefact D05-KE90-7. To capture the point cloud, we used a non-contact close-range 3D structured light scanner (SmartSCAN3D Duo System, Breukmann), with a 150 mm FOV set of lenses (x,y resolution: 90 µm, according to the manufacturer). From left to right: 2D contour line (shape); 3D point cloud, 3D triangular mesh, 3D mesh with surface, 3D faceted surface (form).

have colour, normal vector, or image texture information –, which describe the overall scanned surfaces of an object. However, working with hundreds of thousands or even millions of points is difficult, because surfaces cannot be distinguished and the meaningful information that can be extracted may seem quite limited, and we have already suggested that shape/form is basically information. This leads us to digitally reconstruct the surface of the object from acquired coordinates, which can be done by converting the point cloud into a 3D polygonal mesh, and then to a 3D surface model (Figures 2 and 3) .

The resulting surface models are with no doubt quite impressive, and contain most relevant geometric information we will need to calculate the particular relationship between *form* and *function*. However, we should consider these surface models as an intermediate step in the process of quantifying form, because they cannot be used directly for explanatory purposes. The relevant information should be extracted before being used for inferring the object's function in the past.

It has been argued that neither *shape* nor *form* can be fully quantified (Johansson 2008, 2011); however, we consider that an approach towards the *statistical analysis of shapes and forms* is technically possible and even recommendable to archaeologists. In other words, even in the case the object's shape or form cannot be reduced to a single measure, shape-and-form variability can be effectively estimated and even explained in functional terms.

In this vein, we should extract a number of different shape/form descriptors from the automatically built 3D model. That means integrating some parameters related with the 3D geometry of the objects' interfacial boundaries in a set of relational coefficients. The fundamental role of such composite measures is that they allow evaluating archaeological observables from a population as similar or different.

This approach has some tradition in 2D shape analysis. Russ (2002) gives a list of some of them, namely:

1) *Elongation*. Perhaps the simplest shape index. It uses the ratio between length and width to measure the elongation of an object.

$$\frac{length}{width} \text{ or } \frac{MaximumDiameter}{MinimumDiameter} \quad (1)$$

2) *Roundness.* It measures the degree to which an object resembles a circle.

$$\frac{4Area}{\pi p^2} \quad (2)$$

In the equation, p is the perimeter, and *Area* is a measure of the surface of the object. The roundness calculation is constructed so that the value of a circle equals 1, while departures from a circle result in values less than 1. For instance, an isosceles triangle has a roundness value of approximately 0.492.

3) *Shape Factor* (or Formfactor). It is similar to *Roundness*, but emphasizes the configuration of the perimeter rather than the length relative to object area. It is based on the mathematical fact that a circle, compared to all other two-dimensional shapes (regular or irregular), has the smallest perimeter relative to its area. Since every object has a perimeter length and an area, this mathematical relationship can be used to quantify the degree to which an object's perimeter departs from that of a smooth circle, resulting in a value less than 1. Squares are approximately 0.78. A thin thread-like object would have the lowest shape factor approaching 0.

$$\frac{4\pi Area}{p^2} \quad (3)$$

In the equation, p is the perimeter, and Area is a measure of the surface of the object. Notice that shape factor varies with surface irregularities, but not with overall elongation.

4) *Quadrature*. The degree of quadrature of a shape, where 1 is a square and 0.8 an isosceles triangle. This index is expressed by:

$$\frac{p}{4\sqrt{Area}} \quad (4)$$

In the equation, p is the perimeter, and Area is a measure of the surface of the object.

These shape indices allow the integration of all parameters related with the 2D geometry of the objects' contour or silhouette into single measurements, in a way that a statistical comparison of such parameters allows a complete description of visual variability in a population of material evidences (Barceló 2010a). Accordingly, the form of the archaeological artefact is defined as an n-dimensional vector space (where n represents the number of shape coefficients), and whose axes represent global shape-and-form parameters, or further vector spaces denoting different domains of the same idea of "shape".

Unfortunately, many of the above coefficients cannot be directly generalized to 3D (Lian et al. 2010), and we have already argued the relevance of a proper 3D analysis. Up to now, just a few global form descriptors with direct meanings for 3D models have been proposed, where each of them describes 3D objects in a quite different manner, thereby providing new and independent information. A *compactness coefficient* for example, may describe:

1) The extent to which a 3D object is spherical (Wadell, 1935; Asahina, 2011). Sphericity (ψ) is expressed by the equation:

$$\Psi = \frac{\pi^{\frac{1}{3}}(6V_p)^{\frac{2}{3}}}{A_p} \quad (5)$$

Where V_p is volume of the archaeological object or building structure and Ap is its surface area. The sphericity of a sphere is 1 and, by the isoperimetric inequality, any form which is not a sphere will have sphericity less than 1.

2) The extent to which a 3D object is a cube (Martinez-Ortiz et al. 2009). The cubeness C_d (S) of an observed entity is the ratio of the surface area *A(S)* of a cube with the same volume as the given entity to the surface area of the entity:

$$C_d(S) = \frac{n(S) - A(S)/6}{n - (\sqrt[3]{n(S)})^2} \quad (6)$$

If the form is subdivided into faces, then *n(S)* represents the number of different faces. The cubeness of a cube is 1, thus any form which is not a cube will have cubeness less than 1.

Likewise, similar indices can be calculated for other forms (e.g., cylinders, ellipsoids).

Bribiesca (2000) has proposed a compactness measure which corresponds to the sum of the contact surface areas of the face-connected 3D form primitives. To measure rectilinearity, Lian et al. (2010) have used a genetic algorithm, which is an optimization technique. Kazhdan et al., (2003) have presented a 3D objects' reflective symmetry descriptor as a 2D function associating a measurement of reflective symmetry to every plane through the model's centroid. In addition, several other numerical methods to compute form descriptors have been proposed. Among them are: Volume-area ratio, Statistical moments, and Fourier transform coefficients (Zhang and Chen 2001a, 2001b), Bounding box (Paquet et al., 2000), Convex-hull based coefficients like hull crumbliness, hull packing, and hull compactness (Corney et al., 2002), 3D shape histograms, where the space in which the objects reside is decomposed, i.e., a complete and disjoint decomposition into cells which correspond to the bins of the histograms (Ankerst et al. 1999), a shape distribution sampled from a shape function measuring global geometric properties of the object (Osada et al. 2002), spherical harmonic descriptor (Kazhdan et al. 2003), skeleton based shape descriptor (Sundar et al. 2003), and other view-based methods used to extract 2D descriptors – e.g. 3D Zernike Moments (Novotni and R. Klein, 2003), Fourier coefficient, elevation descriptor, etc. – from the silhouettes or depth buffers captured around 3D models (Chen et al. 2003; Chaouch and Verroust-Blondet, 2006, 2007), 3D Spherical Harmonics (Jayanti, 2009), Ellipsoidal Harmonics (Mademlis et al. 2009), 3D-Shape Index (Marwan et al, 2004), Cone-Curvature descriptor (Adan et al, 2008), 3D Hough Transform, Canonical 3D Hough Transform Descriptor (C3DHTD) (Zaharia and Prêteux 2003), and 3D Shape Histogram-Solid Angle Histogram (Jayanti, 2009).

However, since no single descriptor outperforms others in all situations (Shilane et al. 2004), a well suited approach is to construct *composite form descriptors* (Vranić 2005; Ohbuchi and Hata, 2006; Laga et al. 2006; Gal et al. 2007; Ruggeri and Saupe 2008).

4. FUNCTIONALITY FROM TEXTURE

Texture is usually defined as those attributes of an object's surface having either visual or tactile variety, and defining the appearance of the surface (Tuceryan and Jain 1998, Fleming 1999, Mirmehdi, Xie and Suri 2008, Barceló 2009, Engler and Randle 2009). A *texture* perceived by humans is a visualization of complex patterns composed of spatially organized, repeated subpatterns, which have a characteristic, somewhat uniform appearance (Szczypinski et al. 2009). It is useful to distinguish between *visual appearance* (colour variations, brightness, reflectivity and transparency), from *tactile appearance*, which refers to microtopography (roughness, waviness, and lay).

Among visual irregularities, colour variations can be measured and described in an objective and precise way. By assigning a specific numeric value to each colour property, differences or distances between samples can be consistently compared (Wyszeki and Stiles 1982, Billmeyer and Saltzman 1981, MacAdam 1985, Hunter and Harold 1987, Hunt and Pointer 2011). Just to mention some of the most followed international standards are the ISO/CIE *(International Standard Organization/ Commission Internationale de l'Eclairage)* and the ASTM *(American Society for Testing and Materials)* E12.04 on Colour and Appearance Analysis, E12.06 on Image Based Colour Measurement, E12.07 on Colour Order Systems, E12.11 on Visual Methods, and E12.14 on Multidimensional Characterization of Appearance).

Colour measurement systems can be divided in:

- **Colorimeters**: measure tristimulus data, that is, lightness (value), chromaticity (saturation), and hue (rainbow or spectrum of colours) of a sample colour. The colour's numeric value is then visually determined using a specific three-dimensional colour model or three-valued system. Among the most widely used colour space graphs for defining and mathematically expressing colour attributes are the CIE's Yxy, established in 1931; the 1976 CIELAB, L*a*b* colour space; the 1994 L*C*h; and the CIEDE2000. Other three-dimensional colour spaces, such as CIELUV, Hunter Lab, and the Munsell colour notation system, also are in use. The disadvantage of the measured data is that they are fully dependent upon viewing conditions (viewer or image capture device, type of lighting, object´s microtopography/ finishing). These instruments provide measurements that correlate with human eye-brain perception (psychophysical), which can be a disadvantage in some archaeological analysis.

- **Spectrophotometers**: measure spectral data, that is to say, the amount of spectral reflectance, transmitting, and/or emitting properties of a sample colour at each wavelength on the visible spectrum continuum, without interpretation by a human. The measured data has the advantage of not being dependent upon light, object microtopography/finishing, and viewer. By gathering such complete colour information it provides the most accurate description of the actual coloured object. Furthermore, it is able to indirectly calculate colorimetric information.

Briefly speaking, *tactile variation* can be understood as the irregularities that emerge when considering coarseness, roughness, waviness, lay, smoothness, polish, burnish, and bumpiness. At some level, this microvariation may be an intrinsic feature of an individualized surface, its *topography*. In a 3D approach, we basically perceive surface geometric irregularities in terms of planes variations or *curvature variability* (angle and distribution) (Figure 4).

In the same way as when using shape-and-form cues to infer functionality, texture data can be also used to recognize function. This is usually called a *texture classification problem,* whose goal involves deciding to which functional category a geometric model of the observed texture variation belongs. In order to accomplish this, we need to have prior knowledge of the functions to be recognized, to delete all texture features observed in the object that were not related with labour induced variations. In fact this is a popular approach in archaeology. When a surface interacts with another surface, higher points may have more intense effects (higher energy) than lower areas. When a surface is plane and uniform, all surface points have the same interfacial contribution, that is, all points have the same potential to induce changes on a contacting surface (energy). Major types of wear include abrasion,

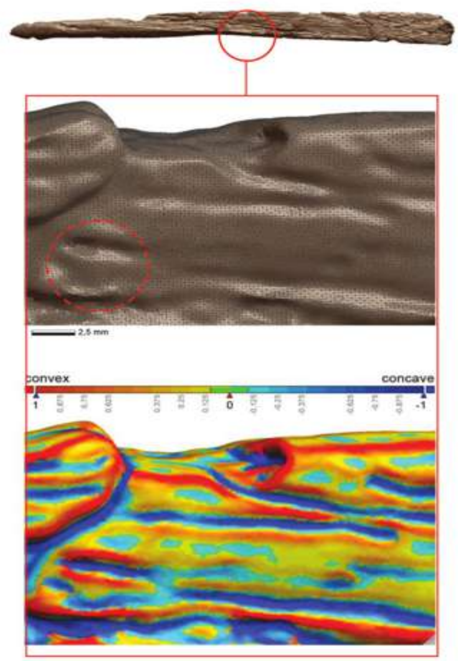


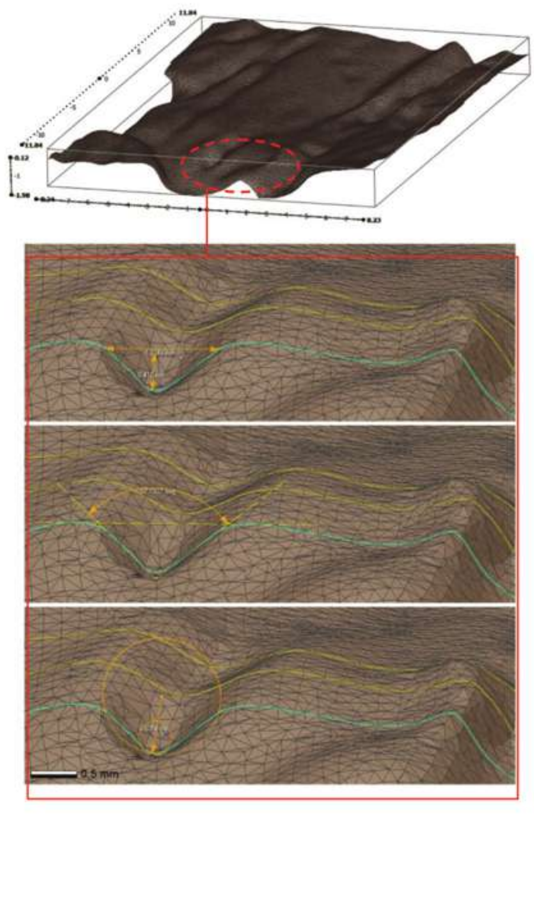
Figure 4 From top to bottom: 3D digital surface model of the archaeological artefact D05-KE90-7; Detail of the 3D digital surfaces' topography (detail of red dashed circle area in Fig. 5); Analysis of the 3D digital surfaces' curvatures.

friction (adhesion and cohesion), erosion, and corrosion. By replicating lithic tools and performing some activity (e.g., cutting green wood) for a certain period of time, we will be able to test the relationship between kinematics, worked material and observed use-wear on the surface of the tool (Semenov, 1964; Hayden ,1979; Anderson, 1981; Grace, 1989; Clemente et al, 2002; González and Ibáñez, 2003; Longo et al., 2009).

In archaeology, texture has been traditionally measured in terms of transforming grey-level image information into a map of bumps within a surface. *Texture analysis* was then essentially the operation of detecting significant local changes among *luminance values* in a visually perceived scene and its translation into a geometric language. Such an approach has produced good results in archaeology (Pijoan-Lopez, 2008; Barceló

2009), but it is no more tenable because it is still based on the probably wrong assumption that digital pictures (coded in pixels) are surrogates of real objects.

Nowadays, the high resolution precision of many modern 3D scanners allows accurate measurements of tiny details of complex microstructures. Some non-contact close-range 3D scanners can capture surface data points with less than 50 microns (0,05 mm) between adjacent points. In addition, confocal optical microscopy, interferometric microscope, optical focus sensing, Nomarski differential profiler, scanning electron microscope (SEM) stereoscopy, just to name some other non-contact instruments, can produce 3D representations of surface irregularities with even higher detail, and thus allowing finer measurements. In this way, instead of using grey-level values measured at pixel resolution, we have proper measurements of depth and height at well localized points within the surface (Stytz and Parrott, 1993, Swan and Garraty, 1995; Lark 1996, van der Sanden and Hoekman, 2005) (Fig. 5).



As in shape and form, we do not have enough with a simple spatial invariant measurement of heights and depths at the micro-level of a single surface. Since texture should be regarded as a similarity grouping in the visual and tactile constituents of a surface, the idea would be to decompose the analyzed surface into regions which differ in the statistical variability of their constitutive features.

The textural character of the surface usually depends on the spatial size of *texture primitives*, in such a way that coarse texture can be decomposed in large areas, while small areas give fine texture surfaces. Leung and Malik (2001) have developed further this decomposition approach by building a small, finite vocabulary of microstructures, which they call 3D *textons*. Once a universal vocabulary of 3D primitive components of texture is defined, the surface of any material such as marble, concrete, leather, or rug can be represented as a spatial arrangement (perhaps stochastic) of symbols from this vocabulary (Cula and Dana 2004; Varma and Zisserman 2005; Dong and Chantler, 2005). For an archaeological application, see Beyries et al. (1988).

The same way shape/form information can be coded into specific indices, the

Figure 5 From top to bottom: Detail of the 3D digital surface topography of the archaeological artefact D05-KE90-7; Surface section (blue line) basic measurements: width and height, angle, minimum and maximum radius.

Table 1. 3D Areal and 2D Profile parameters, for measuring the microtopography of a surface (Whitehouse 2002, Varadi et al. 2004, Masad et al. 2007, ASME 2010). (1) Functional - Index family and Volume family: for Bearing and Fluid Retention Properties. (2) Nonmandatory Appendix D, from International Standards and Parameters.

SURFACE TEXTURE: MICROTOPOGRAPHY		3D AREAL PARAMETER	2D PROFILE PARAMETER
Sa: average roughness	Arithmetic average deviation of the surface (the absolute values of the measured height deviations from the mean surface taken within the evaluation area).		
Sq: root mean square (rms) roughness	Root mean square average deviation of the surface (the measured height deviations from the mean surface taken within the evaluation area).		Height
Sz: 10 point height of the surface (8 nearest neighbor)	2D approximate: *Height function, Z(x,y); and Maximum area peak height, Sp.*	Amplitude	
Ssk: skewness	Measure of the asymmetry of surface heights about the mean surface		Shape
Sku: kurtosis	Measure of the peakness of the surface heights about the mean surface.		
Sds: density of summits	2D approximate: *C number of peaks.*		Area Spacing
Sal: fastest decay autocorrelation length	(Only to be interpreted in 3D.)		-
Str: texture aspect ratio	Measure of the spatial isotropy or directionality of the surface texture.	Spatial	
Std: texture direction of surface	Determined by the APSD (*Angular Power Spectral Density Function*) and is a measure of the angular direction of the dominant lay comprising a surface.		
SΔq: area root mean square surface slope, (Sdq)	Root mean square sum of the x and *y* derivatives of the measured topography over the evaluation area.		other parameters
SΔq (θ): area root mean square directional slope, (Sdq θ)	Root mean square average of the derivative of the measured topography along a selected direction, (θ), calculated over the sampling area.	Hybrid	
Ssc: mean summit curvature	Evaluated for each summit and then averaged over the area. Based on a summit.		-
Sdr: developed surface area ratio	Developed Interfacial Area Ratio. 2D approximate: *Lr.*		
Sci: core fluid retention index	Geometrically speaking, is the value of empty volume pertaining to a sampling surface unit of the core zone, as referred to *Sq*. 2D approximates: *Rk parameters.*	Functional – Index family (1)	
Svi: valley fluid retention index	Similar to *Sci*. It represents the value of empty volume pertaining to a sampling surface unit of the valley zone, as referred to *Sq*.		
Sm: surface material volume	Volume from top to 10% bearing area.		
Sc: core void volume	Volume enclosed 10%-80% bearing area.	Functional – Volume family (1)	
Sv: valley void volume	Volume from 80% to 100% bearing area.		
Area power spectral density function, APSD	The square of the amplitude of the Fourier transform of the measured topography. This 3D function is used to identify the nature of periodic features of the measured topography. 2D: Single profiles through the function can be used to evaluate lay characteristics.		
Area autocovariance function, AACV	This 3D function is used to determine the lateral scale of the dominant surface features present on the measured topography. 2D: Measure of similarity between two identical but laterally shifted profiles. Single profiles through the function can be used to evaluate lay characteristics.		other parameters
Surface bearing area ratio	Ratio of the area of intersection of the measured topography with a selected surface parallel to the mean surface to the evaluation area.		
Area waviness height, SWt	Area peak-to-valley height of the filtered topography from which roughness and part form have been removed.		Waviness
Average peak-to-valley roughness R and others	Is intended to include those parameters that evaluate the profile height by a method that averages the individual peak-to-valley roughness heights, each of which occur within a defined sampling length.		
Average spacing of roughness peaks AR	Average distance between peaks measured in the direction of the mean line and within the sampling length.		additional parameters for surface characterization (2)
Swedish height of irregularities (profiljup), R or H	Distance between two lines parallel and equal in length to the mean line and located such that 5% of the upper line and 90% of the lower line are contained within the material side of the roughness profile.		

texture of an archaeological artefact can be defined as an n-dimensional vector space, whose axes represent global microtopographic and/or visual parameters. Several works have been performed in particle analysis, and there are not relevant archaeological applications, in spite of the interest of the approach.

In this vein, we propose the following 3D areal and 2D profile parameters to measure the texture of archaeological objects (Table 1) (for details on technical procedures see Whitehouse 2002; Varadi et al. 2004; Masad et al. 2007; ASME 2010).

FUNCTIONALITY FROM MATERIAL

Visual features are not enough for an exhaustive documentation of archaeological material. Among non-visual data we can mention compositional data, which are most frequently understood as the enumeration of basic or fundamental elements and properties defining a material. Although in the historical beginnings of the discipline, the enumeration of the substances an archaeological object was made of was regarded as a visual inference based on the scholar previous experience (in terms of the "colour" or texture of different materials like "pottery", "stone", "bone"), nowadays, mineralogical and physico-chemical compositions are measured objectively using appropriate instruments: x-ray and ◎-Raman spectrometry, neutron activation analysis for elemental composition information, neutron scattering for revealing alloys and organic material; particle accelerator, Laser Induced Breakdown Spectroscopy (LIBS). Archaeometry provides an unquestionable valuable source of data for inferring possible functional behaviours of ancient and prehistoric artefacts. Nevertheless, we should take into account that the material components of any archaeological object can be defined and delimited at a variety of scales (e.g., atomic, molecular, cellular, macroscopically), what prevents taking compositions as magnitudes. Instead, we have different compositions at different analytical scales.

Archaeometric data have proved difficult to handle statistically, because of the awkward constraint that *compositions* are not mere lists of substances but multi-component vectors, where the addition of components is a constant in the population under study. Compositional vectors should fulfil two conditions:

A) The components should be "generic", in the sense that all objects can be described as different combinations of the same components. For instance, the chemical components of a knife can be decomposed in steel and wood; the components of a pottery vase can be decomposed into *Al, Mg, Fe , Ti, Mn, Cr, Ca, Na, Ni.*

B) The components should be expressed as a proportion of the total sum of components, which defines the composition of the entity. Compositions should be expressed as vectors of data, which sum up to a constant, usually proportions or percentages. To say that there is steel and wood in this object, is not a true decomposition of the knife. Instead, we have to say that 13% of the object consists in wood for the grip, and the remaining 87% is composed of steel. In this case the components sum a constant (100), and composition is measured against this total.

This special characteristic of compositional data means that the variables involved in the study occur in constrained space defined by the simplex, a restricted part of a mathematical space, what imply dangers that may befall the analyst who attempts to interpret correlations between ratios whose numerators and denominators contain common parts. It is important for archaeologists to be aware that the usual multivariate statistical techniques are not applicable to constrained data (Aitchison, 1986, 1994, 1997, Aitchison and Barceló-Vidal 2002, Barceló-Vidal et al. 2001, Billheimer et al. 1998).

In any case, what we seek it is not only an enumeration of the substances (at the atomic, molecular or composite level) the archaeological object is made of, but a specific combination of non-visual features – a "property profile" (Ashby 2005) – that allows to make inferences about the past function of the artefact. These additional properties make reference to the biological, chemical, physical, or mechanical constraints any substance may experiment (Markwardt 1930, 1935; Winandy 1994; Ashby 2005; FPL 2010; Siegismund and Snethlage 2011).

5.1 **Atomic properties** – are defined by the chemical and physical reaction of each substance at the atomic level. They determine how an object defined by a particular compositional vector will react in different circumstances. Environmental resistances, such as flammability and corrosion or oxidation, are examples of these.

5.2 **Molecular properties** – are defined by the chemical and physical reaction of each substance at the molecular level, that is to say, the consequences of molecular structure on the capabilities of the raw material. They also determine how an object defined by a particular compositional vector will react in different circumstances. Solubility can be among the properties at this level

5.3 **Mineralogical properties** – are defined by the chemical and physical reaction of each material beyond the molecular level. Some archaeological objects were made of different mineral components, or the production mechanism (cooking, alloying) generated new reactive minerals as a consequence of chemical and physical transformation. They also determine how an object defined by a particular compositional vector will react in different circumstances.

5.4 **Biological properties** – are also defined by the chemical and physical reaction of each material beyond the molecular level. Some archaeological objects were made of raw materials from the living world: bone, wood, vegetal fibre, leather, etc. For instance, in the case of prehistoric wooden artefacts, chemical constraints apply, but also those derived from the cellular or anatomical structure, which in their turn may determine mechanical properties and, thus, possible behaviours of artefacts.

5.5 **Physical properties** – are those properties characterizing static states and whose particular values can be determined without changing the identity of the substance, but are a consequence of constraints at lower levels. Among the physical properties, we can mention density (ratio of its mass per unit volume, kg/m3), moisture content (the ratio of the mass of water contained in a sample to the mass of the same sample dried, usually expressed as a percentage), *permeability* (the moisture-excluding effectveness), and *shrinkage* (meaning here the degree of reduction or downsizing. It can be affected by several variables, such as density, rate of drying, or even the size and form of the object). Physical constraints can be expressed in terms of thermal or electric properties of materials.

5.5a **Thermal properties** – they include *thermal conductivity* (e.g. heat exchange between the inner and outer environment of a structure), *thermal diffusivity, thermal expansion coefficient* (this can be highly important when analyzing wooden artefacts, in order to reason about drying processes, namely, swelling, shrinkage, and flexibility, leading to intentional form deformation, or hardening with heat), *thermal shock resistance, specific heat, melting point, creep resistance*. Many materials become weaker at high temperatures. Materials which retain their strength at high temperatures, called refractory materials are useful for many purposes. For example, glass-ceramics have become extremely useful for cooking, as they exhibit excellent mechanical properties and can sustain repeated and quick temperature changes up to 1000 °C.

5.5b **Electric Properties** – notably, *resistivity* and *conductivity*.

As a consequence of atomic, molecular, mineralogical, biological, and physical properties of their particular raw material, archaeological objects also have particular **mechanical properties.** Their values may vary as a result of differences in their compositional vectors but also of the chemical, physical, and biological constraints inherent to each substance, describing how the object will react to applied forces. The main properties are elastic, strength, and vibration.

5.6 **Elastic Properties** – materials that behave elastically generally do so when the applied stress is less than a yield value. When the applied stress is removed, all deformation strains are fully recoverable and the material returns to its undeformed state. The *Elastic modulus,* or *modulus of elasticity,* is the ratio of linear stress to linear strain. It measures the stiffness of a given material and is measured in units of pressure MPa or N/mm². It can be obtained by the *Young modulus, bulk modulus, and shear modulus.* The Poisson's ratio is the ratio of lateral strain to axial strain. When a material is compressed in one direction, it usually tends to expand in the other two directions perpendicular to the direction of compression.

Nevertheless, besides elasticity, an object can also respond to force by viscoelasticity, plasticity or fracture. *Yield strength* refers to the point on the stress-strain curve beyond which the solid starts to deform plastically and cannot be reversed upon removal of the loading, thus producing permanent plastic deformation, but still remaining in one piece. Prior to the yield point (MPa) the material will deform elastically and will return to its original shape when the applied stress is removed. When the stress is greater than the yield stress, the material behaves plastically and does not return to its previous state, and fracture can occur.

Non-linearities in mechanical properties can be due to non-linear material behaviour or be caused by changes in geometry. Material non-linearity is originated by non-linear relationships between properties arising from the kinetic and kinematic variability. A material is said to be linear if some specified influence (e.g., stress) produces a response (e.g., strain) proportional to the influence, as described by Hooke's law. In this case, a *linearly elastic material* deforms proportionally to the applied load, returning to its original shape and size upon removal of the load, as discussed above. For instance, glass is a linear material. Conversely, wood is definitely a non-linear material, since it does not comply with Hook's law. So are soils, and anisotropic metals, ceramics and stones (Reddy 2004, Ashby 2005).

5.7 **Strength Properties** – the material's mechanical strength properties refer to the ability to withstand an applied stress without failure, by measuring the extent of a material's elastic range, or elastic and plastic ranges together. Loading, which refers to the applied force to an object, can be by:

5.8 **Tension**: this involves pulling or elongating two sections of a material on either side of a plane. It can be quantified as *ultimate tensile strength,* which is the maximum amount of tensile stress a material can withstand while being stretched or pulled before failure. *Ductility* measures how much a material deforms under tensile load before breaking. It can be measured in percentage of elongation of a tensile sample after breaking. On the contrary, *brittleness* is the ability of a material to fracture with very little or no previous detectable deformation.

5.9 **Compression:** involves pressing the material together. In fact, it is the opposite of tensile loading. *Compressive strength:* is the maximum amount of *compressive stress* a material can withstand while being compressed before failure. *Hardness (and nanoindentation hardness)* is the ability to withstand surface indentation, e.g. *Brinell hardness number.* A measure for material hardness can also be the *degree of abrasion*, which is the resistance to grinding force.

5.10 **Bending**: involves applying a load that causes a material to curve, resulting in compressing the material on one side and stretching it on the other. It can be quantified as bending strength and flexural strength, in MPa.

5.11 **Shear**: involves applying a load parallel to a plane, causing the material on one of the sides of the plane to want to slide across the material on the other side. It can be quantified as Shear strength, which is the maximum amount of shear stress a material can withstand before failure. Shear strain: change in the angle between two perpendicular lines in a plane. Shear modulus (or modulus of rigidity, ratio of shear stress to shear strain) (MPa), measures the stiffness of materials indicating the resistance to deflection of a member caused by shear stresses. It is concerned with the deformation of a solid when it experiences a force parallel to one of its surfaces while its opposite face experiences an opposing force (such as friction).

5.12 **Torsion**: torsion strength indicates the applied force which causes twisting in a material.

5.13 **Fatigue**: fatigue limit refers to the maximum stress a material can withstand under cyclic loading. This resistance to failure under particular combinations of repeated loading conditions is measured in MPa.

5.14 **Friction properties** – they include the coefficients of static, kinetic, and rolling friction, which depend on the moisture content, the surface roughness, and the opposing surface's characteristics. Friction is expressed by the ratio of the magnitude of the friction force (or maximum friction force, when static friction) per the magnitude of the normal force, and is measured in Newtons (N). Although related with the visual appearance of texture, they should not be confounded.

5.15 **Vibration Properties** – speed of sound and internal friction are of most importance in structural materials, or even in the study of archaeological musical instruments. Speed of sound is a function of the modulus of elasticity and density. Internal friction is the term used for when solid material is strained and some mechanical energy is dissipated as heat, i.e., damping capacity.

Although nowadays there is a vast number of publications and digital material libraries available with the proper values for the different atomic, molecular, physical, and mechanical properties for different elements and materials, for less common materials in

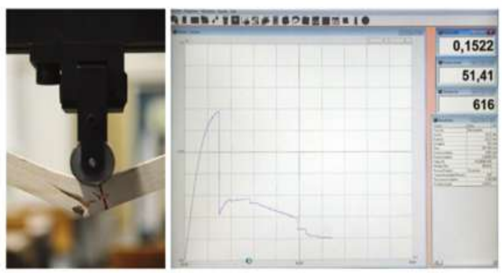


Figure 6 Universal Testing Machine (< 50 kN), using the UNE 56-537-79 standard: *Salix sp* yield strength test perpendicular to wood grain (left), graphic showing results of yield strength test (right) (Moitinho de Almeida and Barceló 2012a).

modern life, notably some of the most used in prehistory and ancient times, it can be hard, or even impossible, to measure how their chemical, physical, or biological structure constrained their mechanical properties. In those cases, it can be necessary to conduct real-world tests (Figure 6) in order to obtain the particular physical and mechanical values of a specific material that a given archaeological object is made of. Taking the example of wood, to measure such values with a Universal Testing Machine (UTM) implies the direct manipulation of real wood samples. Here, modern material specimens of the same family, type and/or taxon, need to be arranged, prepared, and tested in a controlled manner following the appropriate international standards, meaning that:

b) The tests can be replicated with reasonable accuracy;
c) Measures can be taken and used as the material´s properties reference values.

Because wood is a heterogeneous and anisotropic material, it may be necessary to perform tests not only parallel but also perpendicular to the wood's grain, in order to fully characterize its physical and mechanical properties.

It is surprising the lack of research on the physical and mechanical properties of materials in mainstream archaeological and archaeometric studies. Archaeologists insist in documenting ancient artefacts, but such documentation never takes into account these properties of ancient materials, when without such information any effort in functional analysis is impossible. It is undoubtedly reasonable the impossibility to "use" in the present, or even "to touch", prehistoric or other ancient objects in order to preserve its integrality, may be the cause for the delay in this area of investigation. Imagine the answer of a Museum director when we ask her/him to break a prehistoric object so we may measure its physical and mechanical properties.

6. ARTIFICIAL INTELLIGENCE TECHNIQUES AND TECHNOLOGIES FOR FUNCTIONAL EXPLANATION

Functional analysis in archaeology is a fast perfect example of an inverse problem. That is, the answer is known, but not the question. The problem we want to solve can always be represented in the motto: "Guessing how the object was used from the object's visual appearance and material composition". Here the past function is the unknown question we are looking for, and the form, texture, material properties are the raw data we have measured. The more precise and quantitative are such perceptual features, the more reliable the inferences about past behaviour.

Functional analysis can be carried out conjecturing unobservable mechanisms that link the input (observation) with the output (explanation). It can be defined as the recognition of observed patterns or the prediction to a larger set of circumstances of unobserved outcomes, by generalizing from a group of measurements for which the desired outcome is known. Since Aristotle, generalization has been the paradigmatic form of inductive inference. In our case, the task will be to find the common structure in a given perceptual sequence, under the assumption that: structure that is common across many individual instances of the same cause-effect relationship must be definitive of that group (Holland et al. 1986, Thagard 1989, Triantaphyllou and Felici 2006, Kowalski 2011, Flach 2012).

Consequently, certain characteristics or properties should be more probable than others when the object was manufactured to fulfil a specific "function". That means that the characteristic perceptual properties of a precise function will be more probable when the more characteristics be "frequent" in objects that performed such action, and the less characteristics be "infrequent" in the same set of objects. The propensity, inclination, or tendency of certain properties of form, texture and material to appear together is then, what we need to learn how perceptual data can be related with concrete functions. That is, we should learn a mapping from the hypothetical function to the measured values of form, size and material provided some instances of such a mapping are already known or can be provided by direct experience in the world. When subsequently asked to determine whether novel instances belong to the same function, those instances that are similar to instances characteristic of a single event of a single class of events will tend to be accepted.

This way of understanding functional analysis lead us directly to the concepts of Classification and Clustering, because we always can understand functional analysis as the partitioning of an observation set according to a similarity criterion and generating class descriptions from these partitions.

Clustering is the process of grouping input samples in similarity classes partitioning the input space, so that diversity may be explicitly recognized and encoded. The starting point is the formal description of each object as an ordered set of features. “Similar” objects are those that have nearly the same values for different features. Thus, one would like to group samples to minimize intra-cluster distances while maximizing inter-cluster distances, subject to the constraints on the number of clusters that can be formed. This approach is popular within statistics: Principal Component Analysis, Cluster Analysis, etc., are good examples. A more “artificial intelligence” approach to unsupervised learning, beyond classical statistical procedures is vector quantization methods, a general term used to describe the process of dividing up space into several connected regions, using spatial neighbourthood as an analogue of similarity (Kohonen, 2001; Barceló, 2009). Every point in the input space belongs to one of these regions, and it is mapped to the corresponding nearest vector. For example, the attributes for "object A" are mapped to a particular output unit or region, such that it yields the highest result value and is associated with that object, while the attributes for "object B" etc. are mapped to different regions (Engel and van der Broeck 2001). There are many applications of self-organization or unsupervised learning for functional analysis: Mayorga and Ludeman (1991, 1994), Jain and Karu (1996), Ruiz del Solar (1998), Kulkarni (2001), Acebrón-Linuesa et al. (2002), Chandraratne et al. (2003), Valiente-González (2001, Bhakar et al. (2004). Relevant examples of unsupervised analysis of functional analysis based on archaeological texture data have been published by Fulcher (1997), Bell and Croson (1998), López Molinero et al. (2000), Ma et al. (2000; Ma 2003), Novic et al. (2001), Petrelli et al. (2001, 2003), Chang et al. (2002), Grudzinski et al. (2003; Grudzinski and Karwowski 2005), Lletí et al. (2003), Fermo et al. (2004), Kadar et al. (2004), Beardah and Baxter (2005), Baxter (2006), Toyota et al. (2009).

Classification is a form of categorization where the task is to take the descriptive attributes of an observation (or set of observations), and from this to label or identify the observation within a different phenomenological domain. The descriptive attributes may themselves be drawn from different data domains, each domain effectively contributing an axis to a combined feature space of all possible object descriptions. Hence, the task of the classifier is somehow to partition this feature space into disjoint regions that each represents a particular class, cluster, or pattern. The goal in a classification problem is to develop an algorithm which will assign any artefact, represented by a vector x, to one of c classes (functional assighments). The problem is to find the best mapping from the input patterns (descriptive features) to the desired response (classes). Some finite or infinite set of patterns (binary or real valued vectors) are partitioned into classes, and a particular problem is specified by a set of selected training patterns, which are given together with their corresponding class names, and the goal is to classify all patterns as correctly as possible. The problem is of dividing the set of possible input vectors into two sets, one for which its output is positive, and the other for which its output is negative. The classes will be said to be linearly separable when the separation of different input-output patterns is better than if no decision rule was used, In the other case, when it seems there is no clear decision rule to separate examples from counterexamples, we say that classes are not separable.

Whereas Clustering equals self-organized or unsupervised learning, Classification tasks are a kind of supervised learning problem, on the grounds that the known instances of a cause-effect relationship are like information given by a teacher or supervisor. In this way, we learn to classify visual and non visual data as members of contrastive functional categories through trial and error with corrective feedback (the teacher). We can formalize this inferential task in terms of a kind of "automated learning":

Given:

- A description language LE for examples,
- A hypothesis language LH for possible hypotheses (i.e., possible learning results),
- A set of positive examples (instances of a certain concept)
- A set of negative examples (instances that do not belong to the concept),
- A predicate "covers", which indicates whether a given concept/hypothesis covers a given example,
- An acceptance criterion (measure) which evaluates hypotheses,

Find:

- An hypotheses in the language LH fulfilling the acceptance criterion. The partial order of LH can be used to prune the search.

In other words, the idea is to program a system able to look for common features between positive examples of the function to be predicted, and common differences between the negative examples. This task is exactly like an example of a truth-function learning problem:

1	1	0	1	1	→	1
1	0	0	0	0	→	0
0	1	1	1	0	→	1
1	1	0	0	1	→	0
0	0	0	0	0	→	?

Concept learning problems have the same form, except that target outputs are either "yes" or "no"(or "true"=1 and "false"=0). Inputs that map onto "yes" are treated as positive examples of a particular concept. Inputs that map onto "no" are treated as negative examples (i.e., counterexamples). The process of finding a solution to such a problem is naturally viewed as the process of calculating the communalities among positive examples. As such, it is a variation of the philosophical theories seeing induction as a process involving the exploitation of similarity.

Differences with the classical statistical or clustering approach are obvious. In a clustering approach to functional analysis, a set of functional assignments will be modelleled by first describing a set of prototypes, then describing the objects using these prototypical descriptions. In such an unsupervised or self-organized task, the goal is to identify clusters of patterns that are similar, thus identifying potential generalizations. Functional assignments are based on the assumption there is a structure to the input space such that certain patterns occur more often than others, and it would look for what generally happens and what does not. The trouble is that with clustering approaches we are not discovering how to instantiate a specific function on the basis of some perceptual information. Whereas supervised learning involves learning some mapping between observed values of shape, texture and/or composition and their hypothesized functions, much unsupervised learning can be viewed as learning a mapping between observations and themselves. It is important to understand the difference between clustering and classification, and between learning and partitioning or clustering. A good functional classification should both impose structure and reveal the structure already present within the data. The outcome from a clustering of a set of archaeological objects may have little meaning since the resulting clusters are not associated (by design) with any functional assignment arising from the domain of study (although they may be as a consequence of inherent structure in the data). Automated explanation cannot be possible if the automated archaeologist cannot distinguish positive and negative instances of the explanation to be learnt. That is to say, if it has not any knowledge that will ensure that its causal predictions tend to be plausible and relevant to some predefined goals. Consequently, the acquisition of explanatory knowledge cannot be reduced to clustering, because such methods are limited by the natural grouping of the input data, and they are based on restricting knowledge production to finding regularities in the input. Such regularities are not generalizable out of the specific limits of the input data used.

On the other hand, a supervised classification approach to functional analysis will imply that instrumental functions as "cutting", "scraping", "containing", or symbolic functions like "visualizing the idea of violence", "representing the idea of dominance" or any other are to be learnt in an objective way, provided we have enough known instances for the underlying function, and a general background knowledge about how in this situation a human action has generated the observed modification of visual appearances. When subsequently asked to determine whether novel instances belong to the same function, those instances that are viusually (or non-visually) similar to instances characteristic of a single function or a single class of functions will tend to be accepted. For instance, we will understand what a house, a castle, a burial, a tool are when we learn how a prototypical house, a prototypical castle, a prototypical burial, a prototypical tool have been made, under which social and economic conditions they have existed.

The approach we are suggesting is a surrogate of experiment design. Experimental analysis is the process whereby the antecedents of a phenomenon are manipulated or controlled and their effects are measured. An obvious archaeological example is modern use wear analysis. By replicating lithic tools and using them a determined period of time performing some activity (e.g., cutting fresh wood) we will be able to test the relationship between kinematics, worked material, and observed use wear on the surface of the tool. When laboratory replication is not possible (i.e., not all social activities performed in the past can be replicated in the present), archaeologists are limited to mere observation. Ethnoarchaeological data can be also used to generalize observations and learn explanatory general principles.

Computer scientists are intensively exploring this subject and there are many new mechanisms and technologies for knowledge expansion through iterative and recursive revision. Artificial Intelligence offers us powerful methods and techniques to bring about this new task. Fuzzy logic, rough sets, genetic algorithms, neural networks and Bayesian networks are among the directions we have to explore. Although statistical reasoning is still giving its support to all these methods, it is not classical statistical inference. Artificial Intelligence paradigms differ from usual classification and clustering methods, in that they are (in comparison at least) robust in the presence of noise, flexible as to the statistical types that can be combined, able to work with feature (attribute) spaces of very high dimensionality, they can be based on non-linear and non monotonic assumptions, they require less training data, and make fewer prior assumptions about data distributions and model parameters. The huge number of learning algorithms and data mining tools make impossible that we can review the entire field in a single paper (Langley, 1996, Han and Kamber, 2001; Witten and Frank, 2005). Free computer programs like *Weka*[1] or *Tanagra*[2] can be explored to discover how to extract meaning and knowledge from archaeological data.

The most basic supervised learning algorithms are designed to find a conjunctive description for a single concept C that covers positive instances of C and that fails to cover negative instances. In this way, we can represent the solution to an inverse problem as a logical conjunction of Boolean features, values of nominal attributes, limits on the values of numeric attributes, or some combination of them. It is usual to refer to each component of such conjunction as a condition or a test. Alternatively, functional hierarchies provide a framework for knowledge organization, and a considerable amount of machine learning research has taken this approach. Such hierarchies can be represented as a decision tree consisting of nodes and branches. Each node represents a separate function, typically with its own associated intentional definitions. The links connecting a node to its children specify an "is-a" or subset relation, indicating that the parent's extension is a superset of each child's extension. Typically, a node covers all of the instances covered by the union of its descendents. In fact, such a decision tree can be seen as a collection of rules, with each terminal node corresponding to a specific decision rule.

Inductive decision trees are increasingly applied in archaeology. Modern applications range from sex determination of buried human bodies to the discrimination of geo-archaeological soil data. In any case, it is in archaeometry where these methods have found its greatest popularity in the recent years (Baxter 2006). More details on applications are given in Barceló (2009, 2010b).

Alternatively, we can use neural networks as a non-linear fitting mechanism to find regularities in a set of data. An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. It is composed of a large number of highly interconnected processing elements (neurons) working in unison accepting numeric inputs and sending numeric outputs. Neurons are organized in such a way that incoming vectors (descriptions) are sequentially transformed into output vectors (archaeological explanations) (Fig. 7).

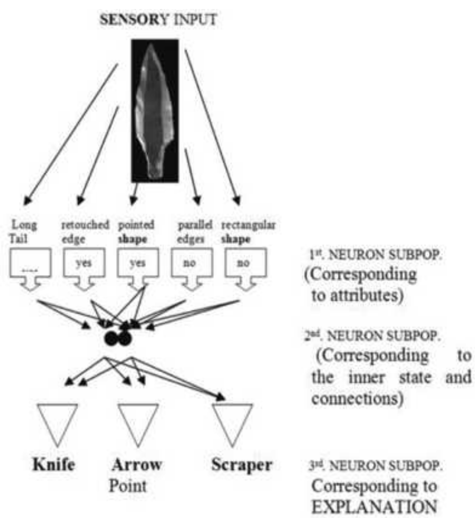


Figure 7 A Three-layer Neural Network topology, with a hidden layer (Barceló 2009).

1. http://www.cs.waikato.ac.nz/ml/weka/
2. http://eric.univlyon2.fr/~ricco/tanagra/en/tanagra.html

Different output neurons represent different “prototypical functions” along the continuum, and respond with graded signals reflecting how close the current exemplar is to their preferred value. Note that what is really being stored is the degree to which one neuron — representing a microfeature of the final concept or prototype — predicts another neuron or microfeature. Thus, whenever a certain configuration of input features is present, a certain other set of features is also present. This is important, because it means that the system does not fall into the trap of needing to decide which category to put a pattern in before knowing which prototype to average. The acquisition of the different prototypes proceeds without any sort of explicit categorization. If the patterns are sufficiently dissimilar, there is no interference among them at all.

ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well. In general, upon repeated presentation of various real examples and under the steady pressure of a learning rule or algorithm that makes small adjustments in the connections among artificial neurons, the network slowly but spontaneously generates a set of internal representations, one for each of the several features it is required to detect. The overall result is that after learning the network contains a number of processors chained together in such a way as to produce the appropriate outputs given a set of inputs. During learning, a network will typically develop a way of organizing its representations so that different inputs come to be represented as belonging to partitioned classes or groups (which may themselves be hierarchically ordered into various subgroups).

More than an analogy with a universal database, we are suggesting an *associative memory.* This is a device storing not only associations among individual perceptual representations, but organizing “conceptual” information not directly derived from the senses. Neural networks are used as associative memories. Pattern associators are constructed from the neurons and modifiable connections defined in the neural architecture. During a learning stage, the activation states of the input processing neurons are used to represent patterns to-be recalled. The connection weights are then modified to store the association between the two patterns. It is a distributed representation because this association is stored throughout all the connections in the network, and because one set of connections can store several different associations. During the recall stage, a cue pattern is presented to the network by activating the input units. This causes signals to be set through the connections in the network and to activate the output processors. If the associative mechanism runs properly, then the pattern of activation in the output neurons will be the pattern that was originally associated with the cue pattern. Therefore, the computational system acts like an automated archaeologist acquiring visual inputs in form of a vector of activity to the input neurons (shape, texture or composition feature detectors), which will be used as a cue pattern to retrieve its associated explanation, represented as a vector of activity in the memory’s output neurons.

This way of representing the function of archaeological observables is the consequence of *graduated learning* in a neural network: the definition of “function” emerges as the result of a number of different experimental situations or the gradual differentiation of a single function into two or more related ones. Therefore, as activation spreads from compositional input to behavioural output, the suggested functional answer *grades* according to how well the input exemplifies the existing experimental exemplars. Considering that several different prototypes can be stored in the same set of weights, a typical single prototype model may represent instances as sets of attributes (properties or features) with some numeric measure of both the importance of the attribute to that concept (sometimes called its "weight") and the extent to which the attribute is present. In this way, neural networks adopt a *probabilistic view* to functional categorization. The idea of defining necessary of sufficient properties is replaced with that of the probable properties for a member of a given class. A probabilistic view accounts for graded class membership, since the "better" members will be those exhibiting more of the characteristic properties. Instead of representing several concrete instances in memory, we judge category membership by degree of connection to an abstract model or *prototype*.

Such an associative memory, however, is not limited to the association of only those specific individual objects whose functional properties have been experimented before. If such were the case, the mechanisms underlying archaeological automatic explanation would be of limited use. As archaeologists, we must identify a range of novel visual data as corresponding to a given type of object. Generalization is part of our ability to identify objects and events; we typically can identify social actions having been performed in the past even when the visual appearance of its material consequences in the present does not exactly matches what we know of previously memorized cause/effect associations. The capability for archaeological recognition implies then the existence of some previous form of learning, in which the abstract potentially explanatory categories have been created and defined. The goal of recognition is to perform these identifications correctly, in the sense that identification reflects a meaningful property of the world that is independent of the particular data that is being interpreted.

Given the particular vector representation of input data, 2D shape contours and even 3D geometrical models of form boundaries can be easily transferred into a neural network. Shape vectors can be introduced into a neural network in different ways. The most usual is a list of discrete features of geometrical indices like those already discussed. Lengths, widths and depths have been used to input geometry into a neural network (Kulkarni, 2001), but also areas, perimeters, area ratios, Euler numbers, disperse degrees and moments related to the area of the window in which the object lies (Ji et al. 2005), and global shape parameters like elongation, angularity, roughness, or roundness (Kalliomäki et al. 2005; Martínez-Aljarín et al. 2005).

We can mention the use of ANN methodology in rock-art research (Barceló 1993, Díaz and Castro 2001), lithic arrow-point shape classification (Lohse et al. 2004; Keogh et al. 2010; Koutsoudis et al. 2010), the reconstruction of whole pottery vessels (Zweig, 2006; Kleber and Sablatnig, 2009), the historical classification of ancient Mesopotamian seals or Egyptian scarabs (Camiz and Venditti, 2004), the recognition of written characters in ancient documents, coins and epigraphic inscriptions (Kashyap et al., 2003; Maaten and Boon 2006; Maaten et al. 2006). Human and animal bone materials found in archaeological sites can also been investigated using neural networks (Gibson 1993, 1996, Bell and Jantz 2002, Corsini et al. 2005, Schmitt et al. 2001, Bignon et al. 2005, Gil-Pita and Sala-Burgos 2006, Coppa et al. 2007). This approach has also been taken into account for the classification of different properties of wheat grains based on image morphology (Li and Flenley, 1999; Wang et al. 2002) and in the identification of mineral inclusions and petrographic information from thin sections of geologic or archaeological samples (Fueten 1997; Fueten et al. 2001; Thompson et al 2001; Drolon et al. 2003; Marmo et al. 2005). Those examples give us a clue about how to apply neural networks for shape identification in palaeobotanical or archaeometric analysis (for instance, microscopy recognition). For more archaeological applications and examples of this paradigm see Barceló (2009, 2010b).

As a pattern recognition methodology, artificial intelligence technologies allow the activation of functional assignments to a degree that depends both on available knowledge at each moment (the level of activation in all the neurons to which it is connected) and on the association between individual knowledge bits (the strength or weight of connections among neurons), which can be either positive or negative. Furthermore, in contrast with discrete Aristotelian logics, such computer models are more graded. The computer integrates information from a large number of different input sources, producing a continuous, real valued number that represents something like the relative strength of these inputs (compared to other inputs it could have received). The computer model then communicates another graded signal (its rate of firing, or activation) to other neurons as a function of this relative strength value. These graded signals can convey something like the probability of the cause in some specifically constrained circumstances.

7. LIMITATIONS OF CLASSIFICATORY APPROACHES FOR FUNCTIONAL ANALYSIS

Methods of functional explanation reviewed up to here are not entirely trustworthy. Functional explanation cannot be reduced to the task of finding the common structure in a given perceptual sequence, because such methods are limited by the natural grouping of the input data, and they are based on restricting knowledge production to finding literal regularities in the input. Such regularities are not generalizable out of the specific limits of the input data used. If the archaeological evidence happens to be untypical, or for instance the neural network misidentifies the relevant conditions, predicted behaviour may be permanently warped. Even human experts are vulnerable to inappropriate learning. We may be victims of self-reinforcing phobias or obsessions, instilled by a few experiences.

Therefore, we should take into account that artificial intelligence inductive techniques that rely “only on the input” are of limited utility, and we should integrate techniques that compare the functional assignments generated using different inferential mechanisms. Fucntional analysis is an inference process, whose very nature is beyond a mere mapping out of the statistical correlation present in the descriptive features of material evidences.

First of all, we should explore the possibilities of a different kind of learning which goes beyond standard induction. This is the case of relational learning. One way of understanding the idea of such relational learning is in “equivalence” terms: two objects are functionally equivalent (or analogous) if they do the same (or similar) things in the same (or similar) systems although they do not have the same shape, texture or composition. No other features of the objects should be relevant other than the fact that they do the same things under certain conditions: it is their potential behaviour what matters.

Therefore not only communalities are necessary for learning the past function of archaeological objects, but also some kind of contingent relationship between the observed examples, which will determine the type of association learned. The central problem of functional analysis is then to specify constraints that will ensure that the predictions drawn inductively are plausible and relevant to our general explanatory goals. Functional explanation is thus highly context dependent, being guided by prior knowledge activated in particular situations that confront the automated system as it seeks to achieve its goals.

The trouble with functional analysis based on implicit relationships is that this kind of input data is not always apparent. On the other hand, the number of potential relationships in a given scenario is generally unbounded, implying that the number of possible relational regularities is infinite. Given the fact that everything may be related with everything, this is, in principle, an infinitely hard operation. It is a good example of an ill-defined problem, whose problem space is infinite. To solve this situation there are only three approaches:
a) The experimental replication;
b) The controlled observation;
c) Or the simulation of the related factors.

Regrettably, not all social activities performed in the past can be replicated in the present. What cannot be replicated, in many occasions can be observed or has been observed and someone has witnessed it. Ethnoarchaeology has been defined as the observation in the present of actions that were probably performed in the past. Ethnographic and historically preserved ancient written sources can be used as observational situations in which some causal events took place and were described.

According to the theoretical framework discussed at the beginning of this paper, we should focus on processes, rather than on visual/non-visual components. Actions and intentions can have subtle relationships in the context of tool use. It is not sufficient to simply assign objects to roles in specific actions and call the behaviour object use (Kitamura & Mizoguchi, 2004; Erden et al. 2008; St. Amant and Horton 2008). Therefore, function cannot be reduced to a linear relationship between input and output, but a non-linear and non-monotone causal connection between changing intentions, design and uses. This constant interaction between task and object, between what users *can do* and what they *want to do* is what can be called the artefact-task cycle. The net effect is that a change in the design of an artefact may not only change practices and tasks, but lead to a change in the environments where it is being used and a change in the sub-populations who now make use of it. This regularly causes speciation of artefact and segmentation of user community (Kirsh 2009).

Archaeological observables should be explained by the particular causal structure in which they are supposed to have been participated. The knowledge of the function of some perceived material element should reflect the causal interactions that someone has or can potentially have with needs, goals and products in the course of using such elements. This approach has been called the affordances view of function, because it can be traced back to Gibson's formulation of *affordance theory* (Gibson, 1979, Norman, 1989). This theory states that information available from the perception of an object gives clues as to its function and possible manipulations. According to Turvey (1992), affordances are dispositional properties of the environment, that is to say, "tendencies" to manifest some other property in certain circumstances. "Being fragile" is a common dispositional property. Something is fragile just in case it would break in certain circumstances, particularly circumstances in which it is struck sharply. Thus dispositional properties are conceivable only when paired with circumstances in which the disposition becomes manifest—the glass is fragile only if there are possible circumstances in which it might shatter. That means that an object's physical structure and an agent's action specify an affordance jointly, constituting the immediate causes of a perceived function.

On the other hand, the term affordance designates the range of possible actions which objects or other elements of the surrounding offer to an agent. Therefore, it may also refer to relationships between structural properties of objects and specific components of their use (Bozeat et al., 2002; Chaigneau et al., 2004). In tool use, however, the function determined by structural properties may concern interactions of the tool with other tools, recipients or material rather than with the animate actors themselves. Comprehension of such interactions has been conceptualized as 'mechanical reasoning' or 'mechanical problem solving' (Hegarty, 2004). Consequently, affordances are not properties, or at least not always properties (Chemero 2003). Affordances are relations between the abilities of people, physical characteristics of solids, and features of the environment. Therefore, affordances are partly constituted by functional properties,

To put it shortly, archaeological entities should be described not only in terms of their intrinsic properties (form, texture, and material properties) but also in terms of their *affordances*: relationships between these properties and the properties/abilities of the intended users. The affordances of any archaeological evidence become obvious in its use and/or formation process. Both involve establishing and exploiting constraints: between the user/producer and the artefact, the user/producer and the environment, and the artefact and the environment. Physical affordances, closely related to constraints, are mutual relationships that involve both the agent and the artefacts she/he manipulates (and the environment he/she operates). An object's function should reflect the actions that can be performed on it, given both its physical structure and the physical structure of the agent interacting with it. Consequently, reasoning about the affordances of physical artefacts depends on the following factors and senses (Bicici and St. Amant 2003):

- *Form/Texture/Material:* For many tools, these are decisive factors in their effectiveness.
- *Planning*: Appropriate sequences of actions are basic to tool use. The function of a tool usually makes it obvious what kinds of plans it takes part in.
- *Dynamics*: kinematic and physic relationships between the parts of tools, and between the tools and their targets provide cues for proper usage. For reasoning about a tool's interactions with other objects, and measuring how it affects other artefacts, we need to have a basic understanding of the physical rules that govern the objects.
- *Causality*: causal relationships between the parts of tools, and their corresponding effects on other physical objects, help us understand how we can use them and why they are efficient.
- *Work space environment:* a tool needs enough work space to be effectively applied.
- *Design requirements:* using a tool to achieve a known task requires close interaction with the general design goal and requirements of the specific task.

A possibility to add affordance knowledge into archaeological functional analysis would be through the decomposition of use-behaviour processes into chains of single mechanisms or operations, each one represented by some part (or Physicochemical/mineralogical component) of the studied object. Zlateva and Vaina (1991) have noted that decomposed parts relate to the most obvious operations an object may be submitted. They claimed that in order to know the use of an object, we need to infer its proper usage position, the direction of the action, and the pressure to be applied by a prospective user. These cannot be learned without spatial relations between parts and subparts, which imply that the parts and subparts directly relate to behaviours made with the object. Changing the direction of forces, torques, and impulses, and devising plans to transmit forces between parts are two main problems that arise in this framework. To solve these, we need to integrate causal and functional knowledge to see, understand, and be able to manipulate past use scenarios. We have already defined functional analysis as the application of an object in a specific context for the accomplishment of a particular purpose. Thus, we should consider the modality of the operation, which will be reflected by the task description and context of application (Bogoni, 1995; Brand 1997). That means, we should add the rules of physics that govern interactions between objects and the environment to recognize functionality. The functional outcome cannot occur until all of the conditions in the physical environment are present, namely the object(s), its material, kinematics and dynamics. Once these conditions exist, they produce and process the relevant behaviours, followed by the outcome (Barsalou et al. 2005). That means we need to integrate material, form, and texture models with representations of dynamic physical relationships to recognize the functionality of objects. The recognition process is enhanced by the consideration of causal relationships between objects, such as the predictable or observable effect on some target object, by carrying out an action with a tool or object.

DiManzo et al. (1989) regarded functional reasoning as the ability to integrate visual/non-visual data and function with the help of planning. They described the difficulty of separating the function of a tool from the plan it takes part in, since plans and tools evolve together, and differentiate with time. More research on this domain of integrating knowledge of physics, the mechanics of the task, and perceptual data (visual and non-visual: shape, texture and/or material) has been advanced by Far (1992), Deshmukh et al. (1993), Cooper et al., (1995), Hodges (1995), Rivlin et al. (1995), Froimovich et al. (2002), Zhang et al. (2002), Peursum et al. (2003, 2005, 2007), Pechuk et al. (2005), Erden et al. (2008). Alternatively, it is possible to build a model of function based on a description of the physical structure (shape/form) of the known ancestors of this object, namely certain reproduced physical dispositions. In that sense, both the artefact and its ancestors are part of a genetic reproduction history and are thus products of processes. In some cases, it can be proved that the physical structure of the element is approximately similar to the physical structure of those ancestors, including the dispositions that correspond to the proper functions ascribed to the artefact. Only malformed, and consequently malfunctioning, are an exception of the principle that the genetic structure of the causal history provides partial justification for the belief that: artefact A has the physical disposition (shape) that corresponds to the ascribed function (Vermaas and Houkes, 2003). Obviously this approach cannot be applied in all circumstances, because it is wrong in the case of *new* objects and the introduction of novelty and revolutionary changes, but it can be useful for understanding the causal history (or "genetic" reproduction) of a historically connected series of objects.

8. FUNCTION FROM OBJECT INTERACTION

More than integrating knowledge of physics with the appearance of the archaeological object in a deductive way, we need to interact with the object to learn in a proper way what we can do with it. *Interacting* means here *using*, that is to *intervene* in the empirical world changing and modifying the solids around us. As it has been suggested many times in psychology, to "interact" directly with a solid material entity gives much more information than simply "seeing" it (Lacey et al. 2007, Deshpande et al. 2010).

The major interest in object direct interaction lies in the recognition of additional properties, which determine the possibilities and limits of what can be done with the object (Goldenberg and Spatt 2009). Where each property tells us something about the reaction an artefact would have gone through, in case prehistoric people brought it into a certain environment and used it in a certain way.

There are different modalities of direct interaction with an archaeological object that can be here mentioned, and from which we can analyze distinct aspects, namely:

- *Static*: involves displacements, reaction forces, strains, stresses, and factor of safety distribution;
- *Frequency*: involves stresses caused by resonance; buckling, large displacements and failure due to axial loads;
- *Fatigue*: implies calculating the total lifetime, damage, and load factors due to cyclic loading; displacements, reaction forces, strains, and stresses at incrementally varying levels of loads and restraints, in the case of non-linear studies;
- *Dynamic*: refers to the object's response due to loads that are applied suddenly or change with time or frequency. This permits defining parameters such as gravity, type of contact and position relationship between components or assemblies.

To interact with past evidences of human behaviour in that way, we can manipulate virtual surrogates of tools, structures, and other objects. In any case,

a) The constructed representation should represent unambiguously the corresponding physical object;
b) The representation should support (at least in principle) any and all geometric queries that may be asked of the corresponding physical object.

To build such a surrogate integrating visual and non-visual – described earlier –, we need a full digital *solid model* based on a volumetric mesh defining both the exterior surface and the interior volume of the object (Figure 8). Solid models emphasize the idea of informational completeness, physical fidelity, and universality of representations. This surrogate can be defined in terms of a

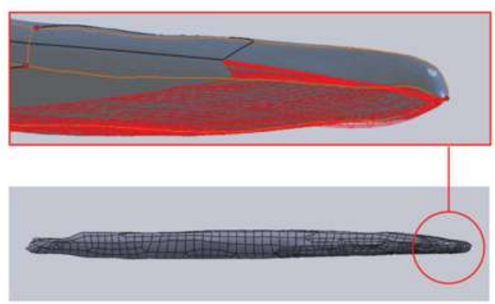


Figure 8 3D digital solid model of wooden artefact D01-KD89-10, from La Draga (Moitinho de Almeida and Barceló 2012b). It has been functionally analyzed as a spear. The point cloud data was captured using the same scanner, with the shortest FOV available for this scanner, the 90 mm set of lenses, which has the highest resolution (50 μm), and gives the maximum level of detail. Fixing surface continuity errors (top, detail). It is not a solid model with a mesh on it, the mesh of elements is now the model.

digital model of a physical entity, with computable mathematical properties allowing the emulation of distinct behaviours on the real world.

When inserted in a simulated interaction, the digital solid model has to be first subdivided into a finite set of connected elements. This fundamental theory was outlined by the mathematician Richard Courant in 1943 and developed independently, and put to practical use on computers during the 1950's by aeronautical structures engineers. Since then, the Finite Element Analysis (FEA) computational technique has been widely used in various disciplines that draw on solid mechanics.

Given its potentialities, archaeology should not be an exception.

The basic concept of Finite Element Method (FEM) lies in that a body or structure may be considered as an assemblage of many smaller cells, typically parabolic tetrahedral solid elements (Figure 9).

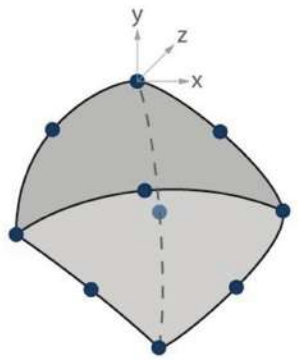


Figure 9 Parabolic tetrahedral Finite Element (FE), defined by: 4 corner nodes, 6 mid-side nodes, and 6 curved or straight edges. Each node has 12 variables and degrees of freedom: 3 variables take care of translation, 3 of rotation, leaving 6 to describe the deformation.

The original body or structure is then decomposed into finite dimensions, whose elements are connected at a finite number of joins called nodes or nodal points, with determinable degrees of freedom.

Nodes are assigned at a certain density throughout the digital model, depending on the hypothetical stress levels of each particular area. Regions which will receive large amounts of stress are modelled having a higher node density than those which experience little or no stress. Points of interest may consist of: fracture point perceived at the archaeological object, corners, complex detail, and high stress areas, among others.

The resulting mesh of finite elements acts like a spider web carrying the material and structural properties for each region in which we have decomposed the object, so that those properties can be formulated and combined to obtain the properties of the entire artefact. Equilibrium equations for the entire artefact are then obtained by combining the equilibrium equation of each element, ensuring the continuity at each node. The necessary boundary conditions are then imposed and the equations of equilibrium are solved to obtain the required values of Stress, Strain, Temperature, Distribution, or Velocity Flow, depending on the functional problem to solve. Additionally, such dynamic decomposition of the model enables the analysis of how each node or the whole assembly will react to distinct forces and magnitudes. Thus, instead of solving the problem for the entire structure or body in one operation, the attention is mainly devoted to the formulation of properties of the constituent elements. In this way, we increase the prediction accuracy in important or critical areas, by reducing it in others not so relevant functionally speaking (Rao 2005; Strang 2008). Yet, one must keep in mind that although the geometry of the model has to be optimized before a simulation can be achieved, the final solid model must necessarily carry all the relevant information. The accuracy of the simulation results is intrinsically linked to the quality of this new finite element model.

Once created the virtual model integrating all observed and measured properties of the real object, we can recognize the function of an object interactively, by observing the deformations that happen on the model when submitted to simulated forces (Stark and Bowyer, 1996, Stark et al., 1996). The causal effect of such forces can be efficiently represented algorithmically using physical and mechanical equations. In this domain, we should mention pioneering work by Ernest Davis (Davis 1990, 1993) formalizing the kinematics of cutting solid objects, among other functions. He showed the geometric aspects of various cutting operations: slicing an object in half, cutting a notch into an object, stabbing a hole through an object, and carving away the surface of an object. He also gave a list of geometric relations between the shapes and motions of the blades and targets. For example, he suggested that a blade needs to be sufficiently thin and hard, but he does not discuss its elasticity or sharpness (see also Duric, Fayman and Rivlin 1996, or Atkins 2009, for a more exhaustive analysis of the mechanics of "cutting"). In archaeology, Johan Kamminga and Brian Cotterell applied mechanical sciences to understand the kinematics and dynamics of shaping, throwing, pressing, cutting, heating, etc., in prehistoric and ancient times (Cotterell and Kamminga 1990). Although such an approach is not at the core of mainstream archaeology, there are already important and relevant applications (Kilikoglou et al. 1997, 2000; Tite et al. 2001; Richmond et al. 2005; Miller 2007; Hopkins 2008; Kuzminsky and Gardiner 2012; O'Higgins et al. 2012).

Running the adequate simulation, allows testing the accomplishment an object had in the past to effectively fulfil a specific action, that is, a task which has been previously formally described. Depending on the archaeological problems one wants to address, and the objects to be studied, some types of simulation might be more or less suitable, not suitable at all, or should even be used in conjunction with each others.

To illustrate such approach, we present here a very short abstract of our current work on the functional analysis of prehistoric wooden artefacts. We intend to test the functional hypothesis of bows, arrows, and spears from the Neolithic archaeological lakeside site of La Draga (Catalonia, second half VIth millennium cal. b.C.). Some of our preliminary studies consisted in reproducing the motion of some of these artefacts, and analyzing its behaviour by also incorporating the effects of force and friction – e.g., ballistic: where both parameters and settings of possible trajectories, elements positions, velocity, acceleration, friction, and distance have been successively changed and tested, in order to reveal, among other issues, if a

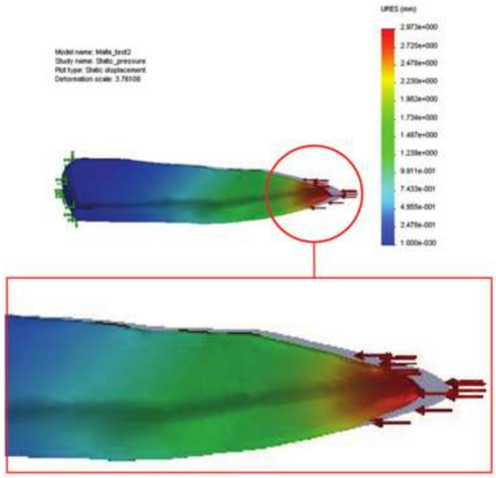


Figure 10 3D digital solid model of an experimental wooden spearhead (PC3-A1), scanned with the same 3D scanner, and a 90 mm FOV set of lenses. Preliminary pressure-displacement simulation test: the direction of pressure is indicated by the red arrows; the grey silhouette indicates the original form before deformation, whereas the blue-to-red colours indicate areas with lower-to higher levels of deformation (detail at bottom image).

hypothetical spear was capable of penetrating (Fig. 10).

When the use behaviour and the corresponding mechanical process are simple, we can suggest a *linear model* using parameters that are constant over the entire simulation and independent of each other. In real world, however, parameters are always dependent upon other parameters to some degree, but in many cases the dependency is so small it can be well ignored.

Nevertheless, the physical world where objects were once produced and used is not a flat, linear domain where structural responses are always proportional to the applied forces. We can decide for a *non-linear model* to bypass such difficulties, by introducing dependent parameters that are allowed to vary throughout the course of a simulation run. To model non-linearities, we must update the simulation parameters at each iteration, recalculating displacements, reaction forces, strains, and stresses at incrementally varying levels of forces and restraints. Non-linearities generally arise from two major sources: *non-linear materials* and *non-linear geometries*. Such non-linearities can occur due to large displacements, large strains, or large rotations, and these enter the formulation through the strain-displacement relations as well as the equations of motion. Non-linear boundary conditions are often included in non-linear geometries because the area of contact is a function of the deformation (Reddy, 2004).

While the term *non-linear* primarily refers to the nature of an object's physical response, the forces and boundary conditions that elicit non-linear responses can either be static or dynamic in nature. When the applied force is a function of time, and the material response is a function of displacement or temperature, an object can respond in ways that are difficult to predict. Predicting the impact of time-varying forces and other load-related effects, such as damping and inertia, which can occur with alternating forces, sudden applied forces, or intermittent loads, requires dynamic analysis capabilities.

Of course, an archaeologist should face this kind of challenges. We may analyze an elastic material — such as a prehistoric bow made of flexible wood — in a form that constitutes both material non-linearities, where the response varies disproportionately to the applied forces; and geometric non-linearities, where displacements alter the structure's stiffness. The practical applications of non-linear materials analysis vary widely. In a non-linear analysis of a component, "failure" may be defined by the extent that a material yields rather than if the materials yields, as in linear analysis. We may also want to examine different failure modes. Many ancient materials, such as bone, shell, ceramic, stone, or wood have unique properties that require non-linear materials analysis to capture their complex load response behaviour. When we are dealing with non-linear materials in a flexible structure, we will need to combine large displacement and non-linear material analysis. An important consideration for these simulations is that as the part changes form, it can experience a phenomenon known as "stress stiffening". Stress stiffening can either increase or decrease the components stiffness, depending upon the applied loads and the component geometry. At times — as is the case with membrane effects — a relatively small change in form results in a substantial change in stiffness.

Such complexities and non-linearities do not mean that functionality problems are beyond the scope of computer simulation.

Hitherto we have seen that interaction modalities in conjunction with the form and dimension of the model, the properties of the materials, including weight and density, the relation between the artefacts' components, kinematics, the type of medium, and physics, are all to be considered when conducting simulation tests, analyzing, and predicting how the virtual archaeological artefact would have behaved as a physical object in possible scenarios of real world operating conditions.

Investigating prehistoric or ancient mechanics through computer simulation may provide new insights into the complex dynamics of certain phenomena, such as event-based motion or kinematics. The analysis of the used mechanics allows us to understand how the behaviour with the object was performed in the past, quantifying the needed forces to activate a specific mechanism, or to exert mechanical forces to study certain phenomena and processes.

If necessary, one can modify the mesh density and other characteristics, redefine parameters, assign new values and settings, or any other input data, select another simulation study or run a new simulation test, to troubleshoot problems or question the validity of the model itself. After all, these analyses are based on experiments of both functional hypothesis and knowledge obtained so far.

9.FUNCTIONAL ANALYSIS AS REVERSE ENGINEERING SUM UP

Function-based reasoning can be seen as a constraint satisfaction problem where functional descriptions constrain visual appearance and structure, or visual appearance and structure constrains functional possibilities. Available mappings between perception and function are actually many-to-many, and recovering an object by matching previously recognized functionalities, may experience combinatorial growth, what may constrain us not to infer the actual functionality in the past, but some more improbable action(s) or behaviour(s).

Model-based recognition has been thought as a possible solution. Another view may consider reasoning about functionality as a planning module that is composed of helper procedures for recognition. In this view, the functional description is done at a higher level discarding the complete representation. A complete representation of the physical world could attempt to represent the forces governing the universe, and reach from gravitational forces between planets to forces between chemical compounds and atoms.

The alternative we have presented in this paper is *Reverse Engineering* (RE), which can be defined by the process of extracting missing knowledge from anything man-made, by going backwards through its development cycle and analyzing its structure, function and operation (USAITA; Dennet, 1991, Eilam, 2005, Raja, 2008, Wang, 2011). It consists of a series of iterative steps, each addressing different questions regarding to an object or structure. These steps may be repeated as often as needed until all steps are sufficiently satisfied.

Our approach to document the functional aspects of archaeological objects involves applying Reverse Engineering from the physical-to-digital stage to the interpretation stage, by simulating the artefacts' function and inferring possible inherent working processes (Figure 11). Throughout this process, it is important to analyze and evaluate its potentialities, constraints, quality, robustness and effectiveness, by controlling the flow of information and vulnerabilities of the

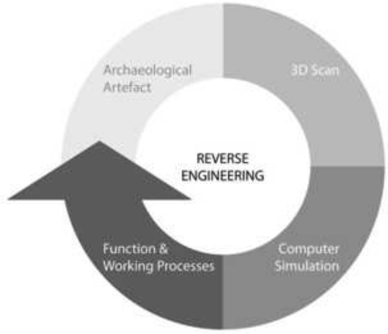


Figure 11 Proposed framework (Moitinho de Almeida, and Barceló 2012a).

model. At the end, we aim to use these processes in the effort to achieve more efficiently better results, as well as to decrease research time and efforts.

Investigating prehistoric and ancient mechanics through computer simulation may provide new insights into the complex dynamics of certain phenomena. Would the object have behaved as expected? As we have been discussing, this depends on several interrelated issues, for these

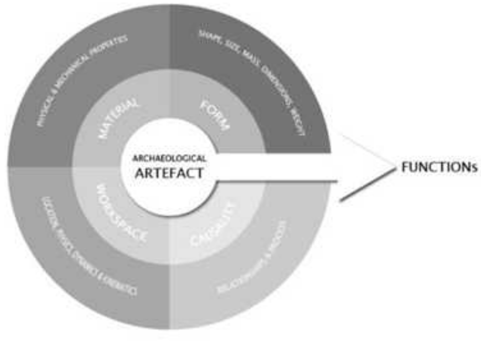


Figure 12 Functionality from an enhanced virtual multidimensional model (Moitinho de Almeida, and Barceló 2012a).

determine possible outcomes. Its form, its material, for many properties have been characterized by hypothetical statements, it is then important to quantify them. But the object must also be used in a certain manner. An object having the required properties therefore functions in the intended manner, only if used in the environment and in the way the manufacturer/craftsman has thought up and prescribed. The use of an object is not a given for the craftsman, like the function, but is thought up – together with the form and material of the object – and thus comprise an essential part of the solution to the design problem (Fig. 12).

The functioning, or actual behaviour of an object, depends both on its form and structure, as well as on the mode and conditions of its use. Given the form, the material properties, and the use of an object, then, by physical or virtual experiment, we should try to evaluate the implied functional behaviour(s). Given a desired function, the craftsman must think up the form and its use. The reasoning from perceptual data to function is usually called "analysis", whereas the reasoning from function to perceptual data is called "synthesis". In spite of the importance of analysis, in design the essential mode of reasoning is synthesis, for without an idea of perceptual data (material, form, texture) and use (kinematics and dynamics) there is nothing to analyze (Chakrabarti 2002). This reasoning from what we "see" in the archaeological present to function in the past – or from structure to behaviour – is based on deduction (Roozenburg, 2002).

Our approach can be related with M. Schiffer's recent proposal for a "behavioral analysis" of technological choices (Schiffer 2003): Our discussion in this paper has concerned what he (and us) have called *material* properties, a product of technical choices, which can be defined and measured without reference to post-manufacture activities. In addition to directly affecting material properties, functional analysis also determine such measurable attributes of an artefact as shape, size, weight and so forth, what Schiffer denotes as *Formal properties.* We have tried to show how material properties can influence formal properties, but also how formal properties can influence on material ones, not only through "technological choices, but also as a result of goal-direct intention.

Logically speaking, perception of function, and categorization, should be independent of one another. One can perceive that an object is throwable, for instance, without knowing that it is an arrow. Conversely, one can know that an object is an arrow without necessarily knowing what it is for. In practice, however, knowing how to categorize an object generally implies knowing what it is for, as well where it is likely to be found and when. In this sense, we can argue that rather that "form determines function", it is better to say that "function causally explains form, and texture, and material, and any other perceptual property of the artefact".

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