Problem Description

Archaeologists studying lithic remains usually wish to determine whether or not these stones have been used as tools and how they were used. The best way to do this is through the analysis of macro- and microscopic traces of wear generated by the use of the tool (Fig. 1).

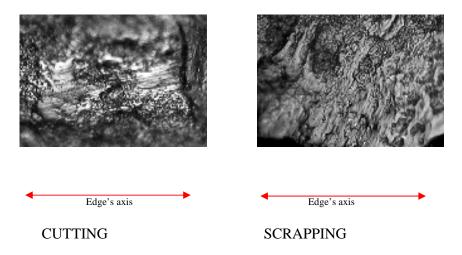
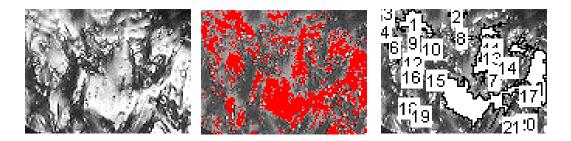


Fig. 1. Cutting and Scrapping generated original surfaces

We have designed a neural network to use a quantitative description of use-wear texture to distinguish between lithic (movement and worked material). In our PEDRA system ("pedra" means *stone* in catalan language), we wanted to distinguish those features produced by the movement of a lithic tool done on a specific material, from the macro and microscopic traces characteristic of the lithic surface alone. The idea was to calculate a non-linear discrimination rule for texel parameters, that is, how to distinguish texels generated because of longitudinal movement (*cutting*), from texels generated during transversal movement (scrapping).

Our goal is to segment texture elements, in order to be able to study their variability in shape and spatial location (Fig. 2).



Original image

Image Segmentation

Identified Texels

Fig. 2. Segmenting micro-images using a fixed threshold algorithm.

Texels may be geometrically described and measured. We have calculated their formal and relational properties, using their variables of shape, size, composition, and location.

As Input data, we have used the following texel measurements:

Shape: -Elongation -Circularity-Thinness -Ouadrature -Ratio Compactness/Thinness -Compactness, measured through two equations -Irregularity -Rectangularity, measured through two equations -Ratio Perimeter/Elongation -Feret diameter -Minimum rectangularity Composition: -Mean, mean of luminance -SD, standard deviation of luminance -Mode, mode of luminance -Min. minimum luminance value Size: -Area -Major axis -Major axis perpendicular to the major axis -Perimeter Location: -Angle (orientation of each texel's major axis in relation to the edge of the tool)

The output units correspond to classes we want to learn from training data. We want to verify whether the shape, composition and size features have some variability degree related to work kinematics. Consequently, we have only used two outputs:

LONGITUDINAL MOVEMENT (*cutting*) TRANSVERSAL MOVEMENT (*scrapping*)

Input vectors are quantitative values, which have been normalized to the range 1 to -1. Output values are binary.

Investigator's Background

Juan A. Barceló (PhD), Director of the Quantitative Archaeology lab, and Professor of prehistoric archaeology, works as main researcher of this project. He has a long experience applying Neural networks to different archaeological problems, as rock art classification, chronology, time series and pottery analysis (http://seneca.uab.es/prehistoria/Barcelo/.

Jordi Pijoan-López, PhD Student. He will present the results of this research as his PhD Dissertation at the end of the current year.

How NNs were applied

We have used the standard backpropagation algorithm for supervised training. As a supervised training, we need a subset of well-known output-input patterns that is experimental data, where the origins of texels are known. For this experiment, we have processed 10 images from 6 tools. 3 tools were submitted to longitudinal work (cutting wood), and other 3 tools were submitted to transversal work (scrapping wood). Three different images from the first tool from each set were taken, and one additional photograph from each other tool. Texels measurements were calculated using the NIH Image software and some additional programs for calculating ratios. All data was and stored in a spreadsheet where each row contains measurements for a discrete texel. In this way we can compare within-image texel variation, within tool texel variation, and between tools and functions texel variation.

Different topologies were examined using 70% of data (more than 650 texels) for training, and the resulting network was tested with the remaining 30%, which were not used for training. The best network had an input layer with 18 units (all shape/size/location variables, without the luminance intensity measures), 1 hidden layer with 24 units.

Results

PEDRA 7: 18 Inputs (Shape/Location only variables), 1 hidden layer (24 units)

TRAINING RESULTS 75.46 % right longitudinal classification. 24.54 % misclassified 58.3 % right transversal classification, 41.7 % misclassified TRESTING RESULTS 68.59 % right longitudinal classification. 31.41 % misclassified 54.23 % right transversal classification, 45.77 % misclassified

We have measured some degree of relationship, specifically when we analyse longitudinal movement. And this non-linear relationship explains (in average) more than 70% of total variance. Neural Networks reveal that LONGITUDINAL action (cutting) is easier to identify than TRANSVERSAL movement (scrapping) when controlling all other elements in the experiment (raw material, worked material, time, intensity of work).

Paper published

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