CUTTING or *SCRAPPING?* Using Neural Networks to distinguish kinematics in use-wear analysis.

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ABSTRACT

In this paper, we apply supervised neural networks (Backprop. learning algorithm) to the classical problem of statistical hypothesis testing. Processing experimental use wear in lithics we have found some contra intuitive results using standard tests, which can be solved using the non-linear discriminant power of Neural Networks. Specifically when archaeological data do not fit parametric distributions, Supervised Learning algorithms appear as an alternative approach. Our particular case study is a set of digital images of experimental data showing use wear as a result of work actions. We have used replicated lithic tools in order to find similarities between use wear identified in experimental data. Previous studies shown that there is not an single discrimination rule to associate cause (kinematics) and effect (wear).

DESCRIBING USE WEAR AS TEXTURE PATTERN

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).

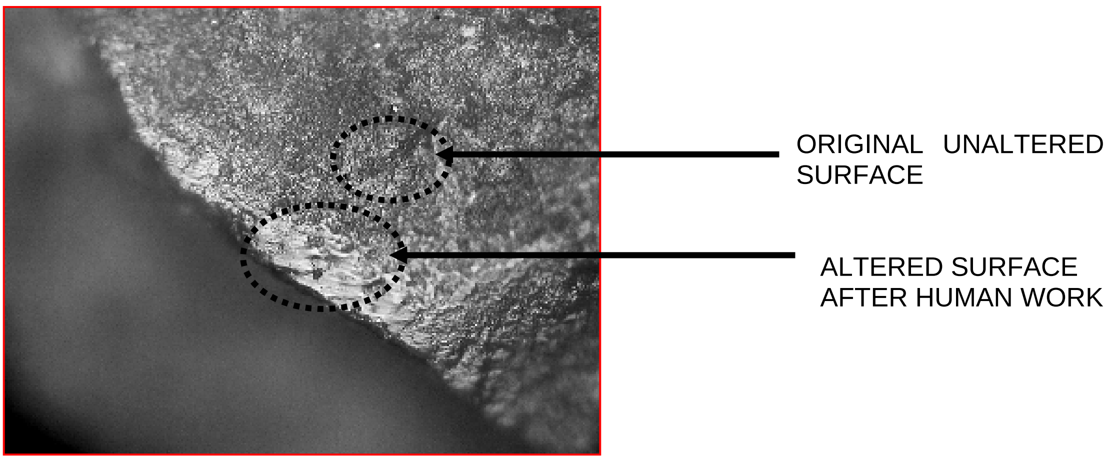


Fig. 1. Distinguishing altered from unaltered micro-surfaces.

The main assumption is that the surface of artefacts have specific features because of the way they have been made, or the way they have been used. Tools are made of solid materials and have rigid bodies which resist stress.

As any other physical entity, objects have surfaces, which can be defined in terms of their size, shape, composition and location. Texture can be defined then as the pattern of variability within this surface of those basic properties (Pijoan et al. 1999, Barceló et al. 2001, Adán et al. 2003).

In the case of tools, given that use and production make important alterations in surface features, we can use texture information to understand how the object was made and/or used (human work) (Fig. 2). Texture variations due to human work are evident, and vary according to the following causal factors:

- Movement: longitudinal (cut), transversal (scrape),...
- Worked Material: (wood, bone, shell, fur, etc.) the effects of its physical properties (hardness, wetness, porosity, plasticity, etc.) on the tool activity surface

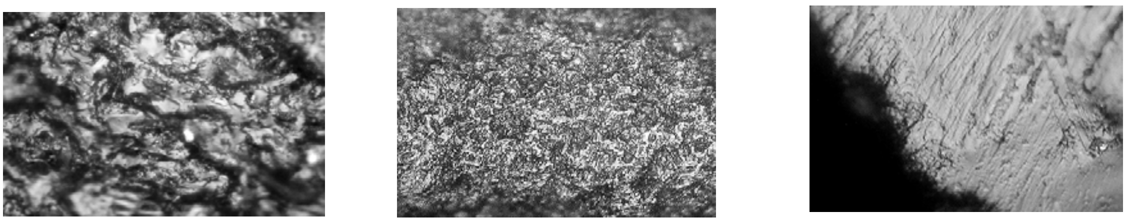


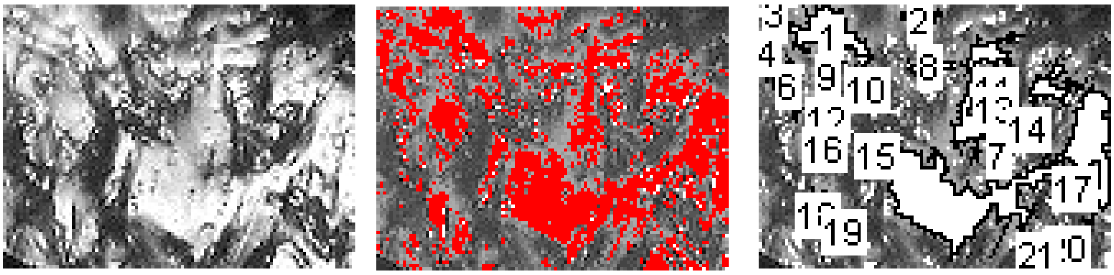
Fig. 2. *Texture differences between lithic tools used in different ways. A: original andesite texture before using; B, Result of the alteration in surface A when the tool was used scrapping fur. C, A different raw material (obsidian) with texture features produced through wood scrapping.*

We usually represent textures using images. What we are looking in that image is the patterning of luminance values across all pixels. Images have *texture* (luminance variation), which can be used to represent the variation of the object surface properties (surface texture). The texture of different images should allow us to discriminate between image groups with some characteristic pattern of luminance variation (Adán et al. 2003).

Texture is then described as the relationships of luminance values in one pixel with luminance values in neighbouring pixels (Pijoan et al. 1999, Barceló et al. 2001, Russ 1995, Fontoura and Marcondes 2001). These values can be modelled as forming a set of regions, consisting in many small sub regions, each with a rather uniform set of luminance values. In our case, these values are defined as grey levels. A group of related pixels can be considered as a texture minimal unit, sometimes called *texel* –texture element- Texture patterning in an image should be described as associations between *texels* .

We define luminance discontinuities (region in an image) as *texels,* if a set of local statistics or other local properties of the average density function are constant, slowly varying, or approximately periodic. Our goal is to segment those texture elements, in order to be able to study their variability in shape and spatial location (Fig. 3).

Texels may be geometrically described and measured or they can be “identified” subjectively in the microscope image as texture primitives; the researcher “sees” stries, polished areas, scars, particles, undifferentiated background. Even the “intensity” of a trace has also been determined subjectively, introducing attributes like “poor”, “high”, “developed”, “greasy”, etc. However, we should calculate their formal and relational properties, using their variables of shape, size, composition, and location.



Original image Image Segmentation Identified Texels

Fig. 3. *Segmenting micro-images using a fixed threshold algorithm.*

USING A NEURAL NETWORK

We have designed a neural network to use a quantitative description of use-wear texture to distinguish between lithic use (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 an 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).

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

Shape:

- -Elongation
- -Circularity-Thinness
- -Quadrature
- -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

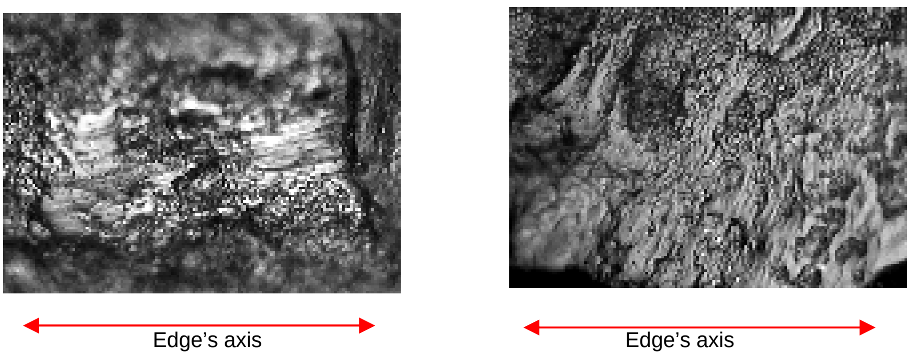
-Perimeter

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 (Fig. 4). Consequently, we have only used two outputs:

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



LONGITUDINAL TRANSVERSAL

Fig. 4. Longitudinal and Transversally generated original surfaces

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

We have used the standard back propagation algorithm for supervised training (Bishop 1995, Kulkarni 2001, Principe et al. 2000). As a supervised training, we need a subset of well known output-input patterns, that is experimental data, where the origin 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.*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 created another neural classifier (Pedra13), using this time 6 inputs (the most relevant variables: ANGLE, ELONGATION, CIRCULARITY, RECTANGULARITY (index A), RATIO PERIMETER/ELONGATION and COMPACTNESS (index B) The network was configured with 1 hidden layer made of 13 units. In this case, we have obtained the best results in all series of experiments (Testing: 73 % of correct longitudinal classifications).

To sum up, 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).

HOW GOOD ARE NEURAL NETWORK RESULTS?

We have interpreted the network's output as an estimate of the likelihood that a given pattern belongs to the LONGITUDINAL or to the TRANSVERSAL class. In order to definitely assign a class from the outputs, the network must decide if the outputs are reasonably close to 0.0 and 1.0. If they are not, the class is regarded as undecided. This highlights the intrinsically probabilistic nature of the use wear classification problem. However, the interpretation of output values as intensities, does not mean that we can use them as probability estimations. Only by using probabilities instead of intensities, we can build optimal classifiers which have the potential to create arbitrary discriminant functions that separate data clusters according to the a posteriori probability. To understand the network results and evaluate the network as an optimal classifier or not, we should work with numerical outputs as a posteriori probabilities of the class given the data. In so doing we can minimize classification error and calculate the best one can hope for.

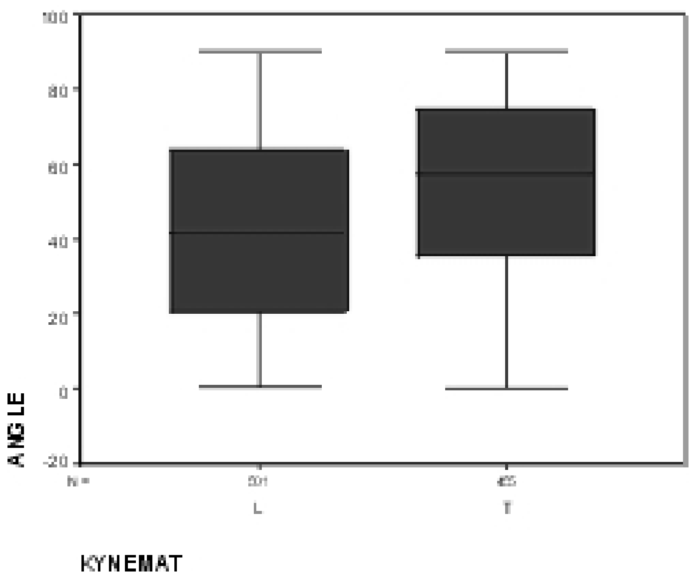
Up to now we have measured the performance of our neural network using classification errors. However, archaeological classification is never an "all or nothing" type of problem, therefore is is important to evaluate how close we are to the desired LONGITUDINAL or TRANSVERSAL.

The hypothesis to test is that ANGLE values should be the only ones allowing differentiation between longitudinal and transversal action, because it is the only feature related to the direction of the energy flow, which sharps the texel. Theoretically we should imagine that an angle between 45 and 90 degrees should correspond to transversal movement, whereas an angle between 0 and 45º corresponds to longitudinal movement. Ideally, scrapping is a transversal movement and angle values should be around 90 degrees. Cutting is a longitudinal movement, and its angle values should be around 0º. In the middle (45º) we should imagine an indeterminacy area.

In our experimental data, texels observed in longitudinally processed tools have a mean of 42.4 and a standard deviation of 25.7. More than 50 % of longitudinally generated data are below 45º.

Transversally processed tools have a mean around 53.6, and a standard deviation of 24.3, and 25 % of data are higher than 75º. Although distributions are not normally distributed, mean difference is statistically significant according Student *t* test and other non parametric tests. The problem lies in the number of outliers. Means and medians can be different, but some outliers seem to attenuate the differences (Pijoan et al. 2002, Toselli et al. 2002).

Fig. 5. Box plot of original angle values for longitudinally and transversally generated texels.



Some texels from longitudinal tools have angle values greater than expected, whereas some texels from transversally processed tools have angle values lesser than expected.

Those statistical results can be compared with the neural network output values, to test its classification performance. We have used the best network (Pedra13), using a subset of input variables, where the influence of angle inputs on output probability estimates are easier to explain, and coincide with previous statistical results. The diagram below shows, schematically, both outputs (longitudinal, transversal), as a function of angle values input (this is a 1-D representation of the *n*-D input) (Fig. 6).

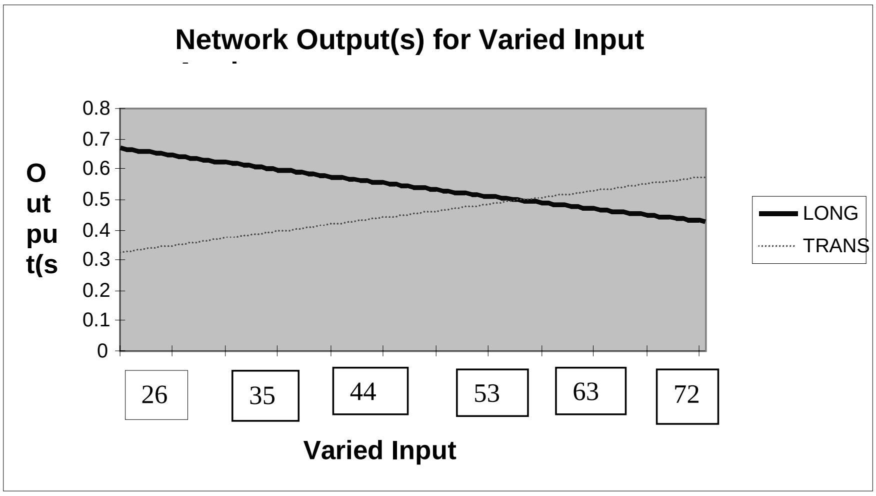


Fig. 6. Output-Input Diagram for ANGLE input. Pedra 13 Network: 6 inputs, 1 hidden layer with 11 units

Here, the probability estimate for longitudinal movement based on angle values is above the 0.5 threshold for the range of “parallel” texels (angle between 10º-55º), and below that threshold for orthogonal angles, related with transversal movement (higher than 55º). The opposite is true for transversal outputs, with below the threshold results for the parallel range, and around the threshold for higher angle values. In any case, transversal output never goes beyond 0.6.

To compare the influence of the texel’s major axis with other variables, we have considered circularity values, whose results seem to be correlated with angle probability estimates (Fig. 7).

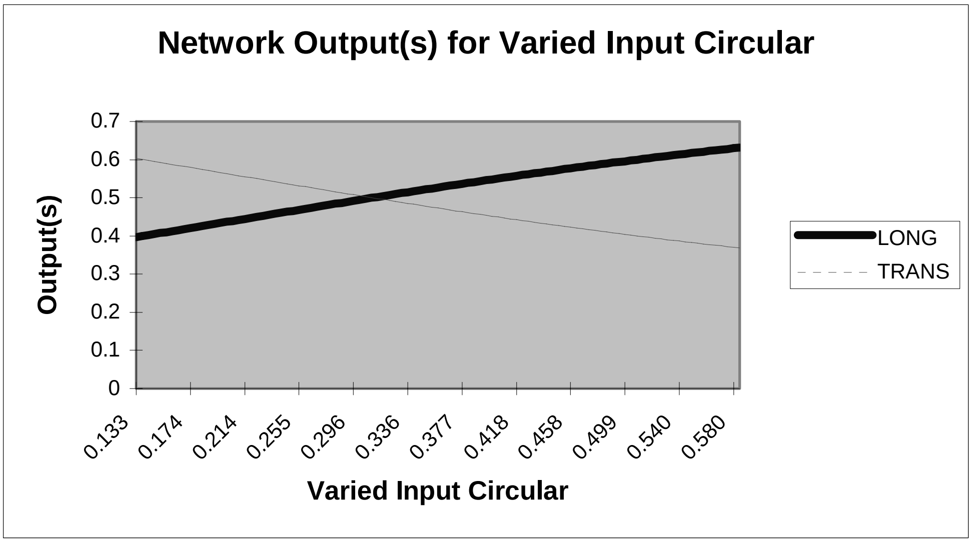


Fig. 7. Output-Input Diagram for CIRCULARITY input. Pedra 13 Network: 6 inputs, 1 hidden layer with 11 units

However, in the case of the ratio between texel's perimeter and texel's elongation, the plot is very different (Fig. 8). Here probability estimates have not any discrimination power.

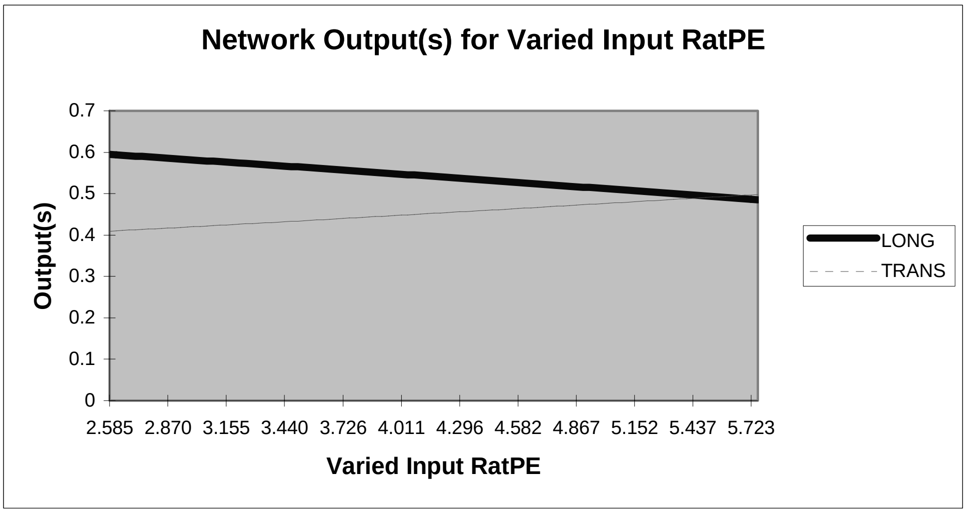


Fig. 8. Output-Input Diagram for Ratio PERIMETER-ELONGATION input. Pedra 13 Network: 6 inputs, 1 hidden layer with 11 units

CONCLUSIONS

Our neural networks models can be described only partially as optimal classifiers. Neural computing shows the specific non linear relation between texture and work movement. The specificity of this relationship may arose from the fact that between images variation depends on within-images variation. That is, not all texels from an image have the same features, nor the different pictures from the same tool have similar texels. Luminance maps may be not entirely related to movement, because there are three sources of luminance variations:

- one of them is generated by the object's surface and it should be explained in terms of the original texture of the object's surface before processing,

- a second one other is also identifiable with the object's surface, but it should be considered as the result of modifications on the surface generated by work activities (cutting, scrapping, etc.) and worked material,

- the third one is grey level variations in the image which are not related to the object's surface, but to the image acquisition process (photography). Furthermore, we should also distinguish luminance variations produced during the perceptual stage as a consequence of microscope functioning.

Statistical analysis proofs that the quantity of texels within an image and their size (area in pixels) are not normally distributed. All that points to the fact that not all texels in the sample are good indicators for movement: some of them and some of their features have been generated through specific kinematics, but other can be properties of the original surface of the flint tool, or even reflection consequences during microscopic image acquisition (see Barceló et al. 2001, Pijoan et al. 2002).

Texture is a phenomenon generated by a dynamic process. Consequently, the direction of the energy flux produced by movement determines the shape of texture elements. If the movement is longitudinal, then the energy generated by this movement will tend to create elongated texels, and their orientation according to the original movement is clearer. Transversal movement is much more irregular, and consequently energy flux is less focused at a single direction. The consequence is a higher dispersion and variability of texel shapes: elongated, and circular texels appear together.

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