Image Quantification in Use-wear Analysis

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Abstract In this paper we try to process microscope images in order to build the input data set for a statistical and machine learning experiment in use-wear discrimination. We look for the discrimination between different use-wear patterns based on observed differences in texture. This is a pattern recognition task. The problem is that pattern recognition methods are only applicable to a few types of quantitative variables, and subjective observation does not provide the necessary quantitative input data. Use-wear variables are usually 'identified' subjectively in the microscope image. Today, new advances in hardware and, principally, software, allow different approaches to image processing and texture quantification. Our goal is to obtain a series of numerical variables that can be used as objective description of the nature and properties of use-wear traces. Those variables will be used later in the classification and clustering stage.
Key words: Image Processing, Segmentation, Texture Analysis, Use-Wear.

1 Pattern Recognition and Functional Analysis

Archaeologists studying lithic remains usually wish to determine whether or not these stones have been used as tools and in what way 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.

Archaeologists have replicated prehistoric stone tools, and they have reproduced various actions (cutting, scraping, etc.) to see which patterns of use-wear are associated with specific actions. Stereomicroscopes and optical microscopes allow the description of the stone surface irregularities, referred to as *texture*. We look for discrimination between different use-wear patterns based on observed differences in texture. This is a pattern recognition task.

Pattern Recognition is an information-reduction process: the assignment of visual patterns (surface textures) to classes (use-wear) based on the form of these patterns and their relationships. Microscope images are then assigned to classes defined by a series of experimental replications. If the texture pattern of an experimental artefact image is similar to the image of an archaeological artefact, then the class (use-wear) related to the experimental item is assigned to the archaeological artefact.

There is a family of classification algorithms that allows such a procedure. They are part of the *supervised learning* category of machine learning methods. These systems process a preliminary data set (a *learning set*) in which the relationship between causes and effects is known. In our case, this is the action performed with a tool, and a description of use-wear patterning on that tool. The purpose of a supervised classification is to generalise (learn) what we have experimented (the learning set) to the entire data set (archaeological data). In other words, we are looking for a mechanism to *recognise* patterns in the data, using already stored patterns in of a sample of known cases.

A common characteristic of most pattern-recognition systems is the inherent variance of the traces to be recognised. The same action produces the same texture, but there are minor differences in regularity, location, morphology, size, and degree of formation. This inherent variation in texture is, however, much less important than variation between different actions.

In order to classify the inputs, we need to reduce *within-class* variation, and enhance *between-class* variation. Statistical methods and machine learning algorithms are used for this purpose. Principal Component Analysis, Discriminant Analysis and Correspondence Analysis have all been used.

The problem is that pattern recognition methods are only applicable to a few types of quantitative variables, and subjective observation does not provide the necessary quantitative input data. Use-wear variables are usually 'identified' subjectively in the microscope image; the researcher 'sees' *polishes, scars*, etc. Even worse, the 'intensity' of a trace is also determined subjectively, introducing attributes like 'poor', 'high', 'developed', 'greasy', etc.

All these identifications are not a qualitative description of texture. In fact, they are not a description at all, because there are no elements to link the visual patterns (texture) with the interpreted elements. The confusion between 'use-wear' and texture is then the cause of badly defined attributes.

Since the 1980s we can find the first objective approaches to texture description (Grace *et al.* 1985, 1988; Grace 1989). But those approaches were basically qualitative, and prevented the use of advanced statistical procedures. Because of the presence of *within-class* and *between-class* variation, the main differences in texture patterns are always fuzzy. Therefore, any qualitative approach, although statistically based (Multiple Correspondence Analysis, for instance) cannot get reliable discrimination patterns.

The studies in quantification of use-wear were centred principally on the quantification of polished textures: brightness, extension, elongation, and pattern.

The use of histograms for the representation of luminance intensities range is the most usual technique (Grace *et al.* 1988; Knutsson *et al.* 1988; Bietti *et al.* 1994; Vila and Gallart 1991, 1993; Ibañez and Gonzalez 1996, 1997; Lohse and Sammons 1999). However, in all those studies there is not a single common solution or a unified method for the quantification of the polish wear (Bietti 1996).

Most modern quantification approaches are partial, because only polished textures have been taken into account, and other use-wear traces have been forgotten (Grace 1993; Lohse and Sammons 1999). Some authors seem to think that polished textures are the most significant evidences for use identification. Other texture elements (striations, microscars, etc.) have been neglected, because they are more difficult to quantify.

Today, new advances in hardware and, principally, software, allow different approaches to image processing and texture quantification. Expert systems have been used to prove the impossibility of getting results using subjective 'identifications', and the need to improve objectivity in texture description (Grace 1993; Van den Dries 1994, 1998). Image processing software advances and Neural Networks techniques are opening up the possibility of direct comparison of microscopic images, without the compromise of qualitative description.

For the moment, we do not know how to relate observable textures to use-wear traces. Our objective in this paper is a preliminary step towards obtaining a reduced list of statistical texture characteristics to be used in discriminating use-wear. Image processing, texture analysis and Neural Networks are used to acquire data, and to deal with redundancy and within-class/between-class variation. In this paper we show only the first part, that is, image quantification as pre-processing for the creation of fully quantitative discriminant functions and to implement an easy to use expert system.

2 The Risk of Redundancy in Image Quantification

Redundancy occurs when many indicators have little influence on the output, or some of them have a larger influence than others.

Redundancy also appears when two identical or 'similar enough' input patterns have entirely different outputs. We should not delete the source of data conflicts, but instead examine how those conflicts affect the relationship between image description and functional attribution.

Consequently, we question any discrimination method based on the assumption that *all* observed texture features (whatever the scale, macro- or microscopic) have *equal* relevance or that they all contribute in the same way to discriminate between different uses. Since many indicators at first glance appear to be relevant, we should perform sensitivity analysis with respect to the different inputs.

But there are other sources of redundancy. Not only the different information content of descriptive features, but also, the quantity and nature of inputs. To avoid the influence of *within-class/between-class* variation, we need a sufficient number of experimental cases. In most research works, experimentation is reduced to a few cases, that is samples, where normality cannot be tested. These problems were analysed in a previous paper (Barceló *et al.* 1996).

The last source of redundancy comes from the data acquisition procedure itself, and is caused by the light environment in which images are acquired and the view angle between the surface of the object and the microscope lens. Many image quantification studies have not taken into account the luminance environment in which the microscopic image was acquired. Different light intensities and different viewing angles give different histograms (Grace 1989). There is also place for a *dark noise* in images, that is isolated pixels with extreme values, which is produced by microscopic lens distortion in poor illumination conditions, or as a side effect in image processing.

In all cases redundancy is expressed as a random pattern when enough cases are considered (Barceló *et al.* 1996), so we can deal with *noise* as a stochastic process. The goal is to reduce this redundancy, enhancing the real discriminant and hiding other attributes and elements that create distortion.

3 The Setting of a Pattern Recognition System

Pattern Recognition involves many stages:

1. The initial stage in any pattern recognition study is *data collection*. In the real world, an image is a pattern of luminance and contrasts. In a computer, the same image is represented as a matrix of numbers. Each number is the measure of the intensity of luminance (grey-level or colour) for a specific point.
2. In the *registration* of data we must locate the area of interest on the input image. To do this, we use *a priori* knowledge from the experimental data. In use-wear analysis, this phase includes the selection of the surface to be explored, the size of the image window, the limits of the background area (the tool's unmodified surface or the area outside the microscope observation field), the resolution of the image, the alterations produced by other factors not related to use, and the nature of the lithic material. Differentiation of linear features can be also included in this stage.
3. Input data always contains some noise and *pre-processing* is needed to reduce this effect. The term noise is to be understood broadly: anything that hinders a pattern recognition system in fulfilling its goal may be regarded as noise, no matter how inherent this 'noise' is in the nature of the data. In our case study, we have detected a large quantity of noise produced by the separation bands between grey levels (256 levels), or those isolated pixels with

outlier values (low or high) randomly produced by the reflection of light on the stone surface.

4. The registered and pre-processed input data will have to be split into subparts that make meaningful entities for classification. This stage of processing is called *segmentation*. In our case, this requires separating the use-wear traces from the background (the unmodified surface of the tool). Consequently, use-wear traces should be described as visual elements (or *textels*: texture elements): *polish, microscarring, striations* and other *linear features* on the surface and edges of the lithic artefact.
5. In the *feature extraction* stage we enhance those features of the input data (image) that discriminate between classes. The diverse possibilities for feature extraction in the recognition of use-wear traces include:
   - area measurements (number of pixels *within* a 'textel' or element of texture)
   - perimeter measurements (number of pixels around the edge of a textel)
   - perimeter shape. A pattern of changes in edge orientation
   - convex hull: the smallest region which contains the textel, such that any two points of the region can be connected by a straight line
   - Euler-Poincaré characteristic: difference between the number of regions (textels) and the number of holes within them
   - texture: a pattern of changes in luminance variations in a scene with nonuniform reflectance. This can be described using
     - the frequency and entropy of brightness (histogram of grey levels)
     - the frequency and entropy of contrast: local change in brightness (ratio between average brightness of the trace and the background brightness
   - Topology of use-wear. A pattern of discrimination between edges at different spatial positions, distance and adjacency relationships between different textels:
     - Coarseness: edge density is a measure of coarseness. The finer the texture, the higher the number of edges present in the texture edge image
     - Contrast: High contrast textures are characterised by large edge magnitudes
     - Randomness: it may be measured as entropy of the edge magnitude histogram
     - Directivity: Entropy of the edge-direction histogram. Directional textures have an even number of significant peaks, direction-less textures have a uniform edge-direction histogram
     - Linearity: It is indicated by the co-occurrence of edge pairs with the same edge direction at constant distances
     - Periodicity: Texture periodicity can be measured by co-occurrences of edge pairs of the same direction at constant distances in directions perpendicular to the edge direction
     - Size: texture size measure may be based on co-occurrence of edge pairs with opposite edge-directions at constant distance in a direction perpendicular to the edge-directions.

4 Image Quantification as Data Description

(The software used for microscopic image processing have been Corel Draw 8.0, Corel PhotoPaint 8.0 and National Institute of Health IMAGE 1.6.2.)

In the following examples we have controlled the appearance of the following features and attributes of texture in different experimental observations:

1. pattern, extension, maximum length, microtopography, brightness of polish
2. number, orientation, length and width of striations and linear features
3. size and clustering of microscarring

The goal is to obtain a series of numerical variables that can be used as objective description of the nature and properties of use-wear traces. Those variables will be used later in the classification and clustering stage.

Experiment 1: Wood Cutting

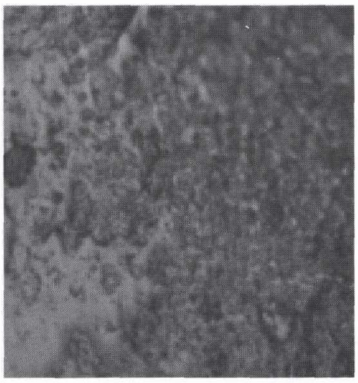

Photo 1A. Original Image of Wood Cutting (Microscope: x200)

This image displays three features of polished areas: pattern, extension and maximum length. The first task is the *segmentation* of polished and non-polished areas, both discriminated in two contrasted luminance.

This task has been done by *thresholding,* that is, a binary transformation of the original image. Thresholding is a pixel transformation operation that changes original grey values according to the following function:

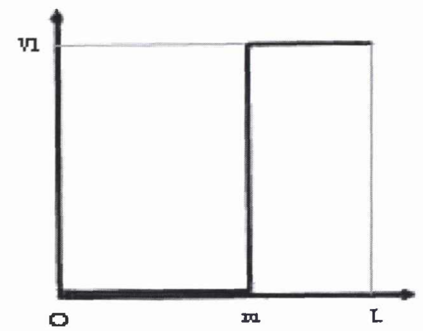

Fig. 1. Stepwise function for thresholding

Original grey values (pixels) have 256 different intensities. The transformed image has only two values: 0 for polished areas, and 255 for background.

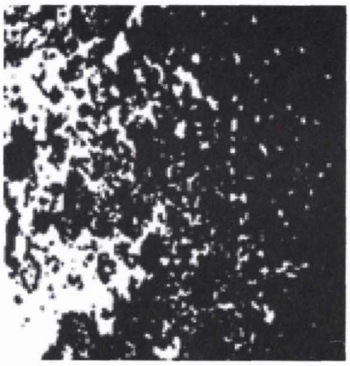

Photo 1B. Binary image showing segmented polished areas

Once polished areas have been segmented, we can extract the following quantitative properties:

1. Extension: number of pixels corresponding to the white areas in the image
2. Pattern: Ratio between total number of white pixels and the number of single areas with white pixels
3. Maximum length: largest distance between the white area outline and the edge of the tool.

Experiment 2: Wood Cutting

Photo 2A. Original Image for Wood cutting (Microscope: x200)

This image displays the topographical variations of the polished area surface. A problem is that microscopic images have only two dimensions, but what we want to measure exists only in the third dimension. The solution is to use local changes in brightness as a surrogate for the topography of polishes. The computer has grouped the areas with the same grey level to obtain a three-dimensional representation of the original polished area. This information can be seen in the following histogram:

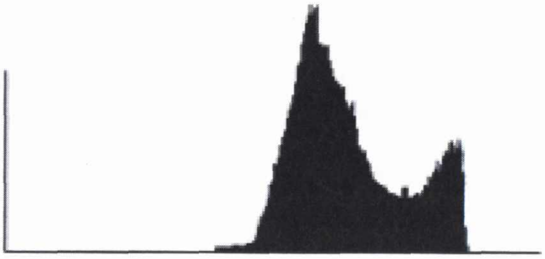

Fig. 2. Histogram of grey intensity levels in Photo 2A

To extract the third dimension from the difference between grey levels, we need a two steps algorithm:
First step: A *convolution filter*: Each pixel in the original image is transformed according to the following function:

$$g(x, y) = G\ [f\ (x, y\ )] = \begin{vmatrix} \delta f / \delta x \\ \\ \delta f / \delta y \end{vmatrix}$$

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

$$mag\ [G[f(x,y)]]=[(\ \delta f/\delta x)^2+(\delta f/\delta y)^2]$$

This operator increases grey level values in areas with sharp luminance and brightness contrasts, and decreases in areas with soft luminance and brightness contrasts. As a result, isolated areas are segmented whose pattern and extension will represent the micro-topography in the original polished surface. The resulting transformed histogram appears in Fig. 3

Fig. 3. Histogram of transformed grey intensity levels

And the transformed image is displayed in Photo 2B:

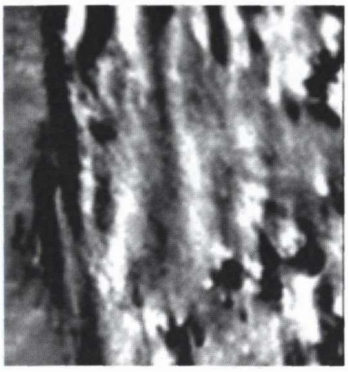

Photo 2B: First step: A preliminary three-dimensional representation of contrasts between grey levels

Now, we can segment the topography features displayed in the image as the zones with the maximum contrasts of luminance. But there are still other problems. If we look at the histogram of transformed values (Fig. 3), we can see two significative groupings: two peaks at the extreme values, and an equalised distribution for non-extreme or intermediate value. It is obvious, that microtopography cannot be adequately represented in those terms. The image should be transformed again, in order to enhance existing contrasts in the intermediate values.

Second step: We have made a 4-level thresholding on the first step result, reducing the 255 grey levels into only 4 levels. The result is a contour plot of irregularities in 4 levels of intensity.

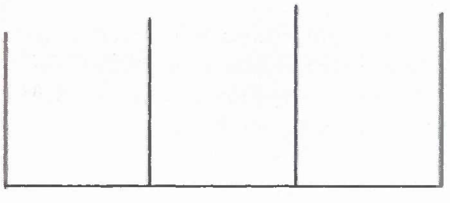

Fig. 4. Histogram of second step transformed grey intensities

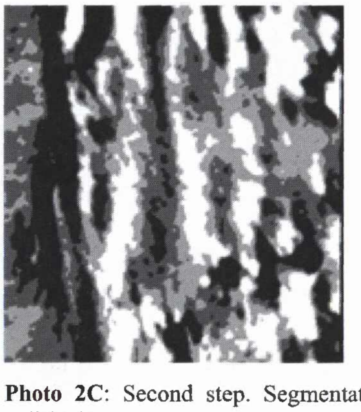

Photo 2C: Second step. Segmentation of irregularities in polished areas

Photo 2C shows how microtopography can be represented as a contour plot of enhanced luminance and brightness contrasts. Now we can use the global parameters of each contour as quantitative variables for image description:

1. Extension of Microtopography: number of pixels corresponding to each contour in the image
2. Pattern of Microtopography: average number of isolated areas with the same contour value.

Experiment 3: Bone Processing

Photo 3A: Original Image for bone processing (Microscope: x200)

This image displays linear features (*striations*) generated by the use of the tool on a hard material (bone). Linear Features are pixels where brightness changes abruptly. They mark locations on the image of discontinuities in grey level; these discontinuities have a linear nature, because their brightness values change linearly in the edge of an object. Linear features seem clearly detached in the original image, but as we will see, some features are hidden because of the dominance of the most developed striations.

Image sharpening has the objective of making edges steeper. The sharpened output image is obtained from the input image g as:

$$f(i,j) = g(i,j) - C\ S(i,j)$$

where C is a positive coefficient that gives the strength of sharpening and $S(i,j)$ is a measure of the image function sheerness, that is calculated using a gradient operator. This operator can be expressed using a convolution mask. We used a gradient operator in a similar way in Experiment 2, in order to obtain a 3D representation of the original 2D image. In the present case, segmented edges represent linear features present in the original image.

The three-dimensional transformation has been processed to enhance linear contrasts and to segment edges. The goal is to group local edges (linear features on the image) into a transformed image where only edge chains exist. We have *vectored* the linear features detected in the previous bit-map image. Vectorisation proceeds by looking for linear paths of pixels with the same grey level, and reducing them to a one-pixel-width line. This line is then defined as a vector.

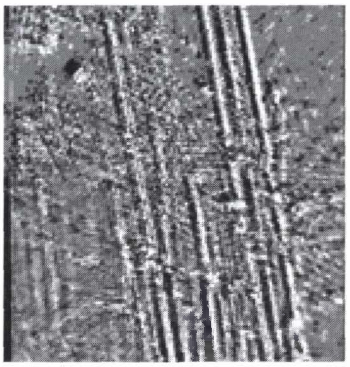

Photo 3B: A three-dimensional representation of linear features

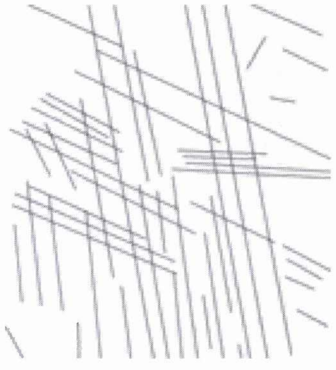

Photo 3C: Vectored linear features

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

Experiment 4: Wood Processing

Photo 4A: Original Image for wood processing (Microscope: x200)

This image displays microscarring features. These features appear only on the working edge of the tool. They are micro-fractures produced by the resistance of the material. However, the microscope field of vision is always too small to include the whole worked edge. Microscope sharpening is also problematic given differences in height between different areas of the same used edge. As a result, the edge appears distorted and microscarring features cannot be detected.

The goal is to detect and to trace the outline of microscarring features. Small edge values correspond to non-significant grey level changes resulting from microscope distortion, so we have reduced the quantity of grey levels. Thresholding to 10 levels (see also Experiment 2) can be used here to change original grey values into a contour map of the microscarring areas. The edge of the tool and the edge of the microscarring area is easily detected.

Photo 4B: Thresholded image showing 10 grey levels

Thresholding has allowed the smoothing of distortion, so edge and outlines can be easily visible. The step is to trace outlines of detected areas (pixels with the same grey-level) as contours. Pixels around the border of areas are assigned a grey-value of 1, whereas all the rest of the pixels receive a grey-value of 0. This binarization of the thresholded image is based on the definition of outlines and *edges* as a path of pixels (connected pixels) around areas with the same grey-value.

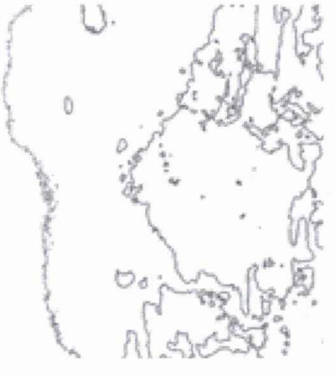

Photo 4C: Outlines of Microscarring

Once outlines have been extracted, we vectored the image, to calculate different geometric properties of the microscarring. Outlines have been converted to irregular vector polygons, in such a way that the size and the shape of the microscarring features can be measured.

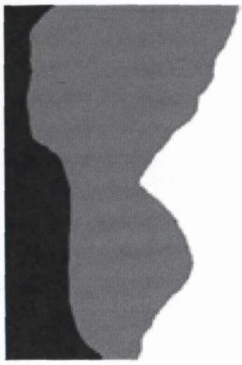

Photo 4D: Microscarring areas

Microscarring features can be described as polygons, so they have the usual geometric properties of vector objects: surface, curvature, convexity, etc. In addition, we can count the number of microscars and the average length of the edge showing microscarring.

5 Conclusions

In this paper we have tried to process microscope images in order to build the input data set for a statistical and machine learning experiment in use-wear discrimination. Subjective and/or qualitative features and attributes give misleading results in use-wear analysis (Barceló *et al.* 1996), and the only possibility is to work with real quantitative variables. In our preliminary experiments, we have selected:

1. pattern of polish: Ratio between total number of white pixels and the number of single areas with white pixels.
2. extension of polish: number of pixels corresponding to the white areas in the image
3. maximum length of polish: largest distance between the white area outline and the edge of the tool
4. microtopography of polish: Ratio between number of pixels corresponding to each contour in a enhanced brigthness and contrast image and the average number of isolated areas with the same contour value
5. number of striations and linear features
6. orientation of striations and linear features
7. length of striations and linear features
8. width of striations and linear features
9. size of microscarring areas: number of pixels corresponding to each contour
10. convexity of microscarring areas
11. average length of the edge showing microscarring.

The first five attributes in our list have been also used by other authors (Grace 1989; Vila and Gallart 1993; Bietti *et al.* 1994; Ibañez and Gonzalez 1997; Lohse and Sammons 1999), but in a different way. But we have increased the number of quantitative variables to define, beyond the reduced list of variables related to polish wear. Quantifying only polish wear, we cannot deal with all variation related to use-wear. We have introduced also the texture quantification of other use-wear traces (striations and microscars), to increase the reliability of potential discriminant functions.

In this paper we have only discussed how microscope images should be pre-processed before 'textures' can be used as input data for use-wear discrimination. Image quantification is the only way to obtain numeric inputs to be used in Neural Network processing or any other supervised learning algorithm.

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