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Image Processing Strategies for Artefact Classification

1 Introduction

It need hardly be stated that the identification of objects (usually artefacts) is a fundamental requirement for the practice of archaeology. In particular, when the identification takes the form of assignment of the artefact to a classification (pre-existing or not) the information associated with the artefact is greatly increased. In the case of assignment to a pre-existing classification, the task may be called recognition, but the procedure(s) are the same. Classification, which may be defined as the division of a set of artefacts into subsets containing objects that are more like each other than other members of the set (Doran/Hodson 1975: 159), is very closely related to identification/recognition.

Identification has traditionally been carried out by experts in the field. The task requires a large amount of training and experience, because although in many cases specific features are diagnostic of a particular class of artefacts, the identification often rests on a visual judgement by the worker. Of course every method has its pros and cons, but for our purposes the most important disadvantage of the traditional approach stems from the limitations of the human brain when it comes to large data sets. Humans find it difficult to think of more than 3 or 4 things simultaneously, let alone several hundred (or even tens of thousands as is often the case with pottery). Large data sets also take time for the human to consider, introducing the possibility that fatigue may affect the results. A third factor is the lack of repeatability of this method. As the results depend on human judgements, there is no guarantee that a different person will produce the same result, or that the same person will produce the same result at a different date. We have been looking at ways of producing an automatic aid to classification that will alleviate these problems.

Much work has been done on computer-based classification in archaeology (e.g. Doran/Hodson 1975; Gero/Mazzullo 1984; Main 1988; Wilcock/Shennan 1975). However these methods have not been as successful as might have been hoped when applied to practical situations.

Our work has concentrated on using the shape information contained in images of the artefacts. Shape is an important factor in identification. Visual identification as we have implemented it, requires a 2 stage strategy (see fig. 1). The first stage is to use an image processing algorithm to extract shape information from the image. This information may then be used individually to identify the object, or when this information is extracted for a set of objects, to classify that set. It should be noted that the image processing algorithms can be used on any shapes, not just whole objects. Thus, although the case study in this paper is concerned with the identification of the profile shapes of whole artefacts (pots), the methodologies used can equally well be applied to other categories of shapes, such as partial/broken artefacts, or surface decoration motifs.

Figure 1. The 2 stages of visual identification and classification.

In the remainder of this paper, we describe and compare the abilities of several different strategies that have potential for classifying a set of artefacts on the basis of their profile shapes. These strategies are different combinations of alternative algorithms for each of the two stages of the procedure, both for extracting the shape information, and for identifying the object statistically on the basis of this information.

2 SMART

The first part of the work was to create a visual lookup front-end for a database. Such a system could be used by the excavator in the field to help identify newly-excavated objects. A prototype of this interface was implemented as the System for Matching ARTefacts (SMART see fig. 2; Durham *et al.* 1995). This uses a pattern matching algorithm known as the generalised Hough transform (GHT) to compare the unknown image to a set of known library images. The GHT calculates a value for the similarity between two images. The similarity of the

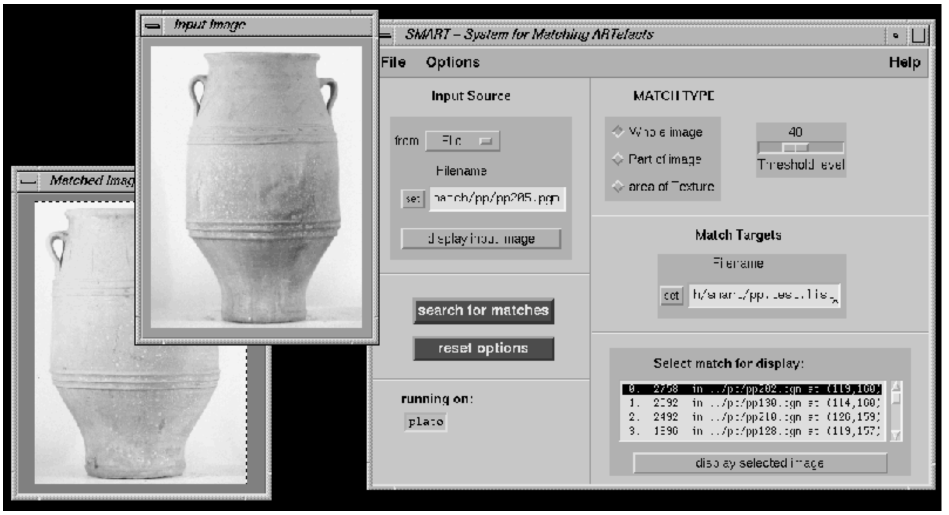

Figure 2. The SMART interface.

unknown image to each of the library images is calculated, and a ranked list of the library images is displayed.
It should be noted that the system does not assign the unknown image to a specific class, but indicates which library images have shapes most similar to the unknown.

In the SMART identification method, the calculation of the similarity values is the first of the 2 stages mentioned above, the ranking of the list is the second. To extend the method to classification, only one set of images is used. Every image in the list is compared to each of the others, and the table of similarity values so produced is used to classify the artefacts (Durham *et al.* 1994).

The GHT gives good results but is very slow, especially when classifying large sets of objects. This is because it calculates a relationship between two images which needs to be done for each possible pair in the set (in the classification case this calculation is Order $\mathbf{n}^2$). It would be much quicker if the shape information calculated were a property of the individual images rather than a comparative measure between images. This would only require the calculations to be made **n** times, and would have the added bonus that the information could be calculated in advance, as it is a property of the individual image itself and will be independent of the other images. Thus the incorporation of a new artefact would only require a single set of calculations to be made.

Many such measures exist, but the one we have concentrated on is shape moments. These are statistical characteristics of the shape, based on the arrangement of its parts. Many different moments can be calculated, and the more that are used, the more detailed the description of the shape will be. An infinite set of moments will completely describe the shape (cf. Fourier harmonics). In practice it is sufficient to use a subset of lower-order moments to give a fingerprint for each shape with the desired level of detail.

A commonly used set of moments is the set of invariant moments (Sonka *et al.* 1993: 228ff). When considered together these moments provide a description of the shape that is translation-, scale-, and rotation-invariant (that is, the result will be the same irrespective of where the shape is, what size it is and which way up it is in the image). These moments have been used successfully to identify aeroplanes, etc. (Cash/Hatamian 1987; Mertzios/Tsirikolias 1993). However early experimentation revealed that the invariant moments were inappropriate for symmetrical shapes, such as pot profiles as they consist of combinations of a few low order moments most of which are zero for symmetrical shapes. A simpler form of moments, known as normalised central (NC) moments do not suffer from this problem as they may be calculated to any order. However, they do not possess the property of rotation-invariance, but this is not a problem if care is taken to ensure that all the shapes have the same orientation.

In our 2-stage scheme for visual identification, the GHT or the moments are used to do the first stage: to extract the shape information. Several techniques can be used to perform the identification based on this information. The GHT produces a single number for each comparison, so a simple ranked list can be used here as related above. A set of moment values can be thought of as a set of features of the shape, and the object can be identified by the use of classical statistics such as the well-known k-nearest neighbour method (looking at its nearest neighbours in the feature space defined by the moments, the neighbours being known examples). Alternatively, the moments can be used as the inputs to a back-propagation neural network, which is

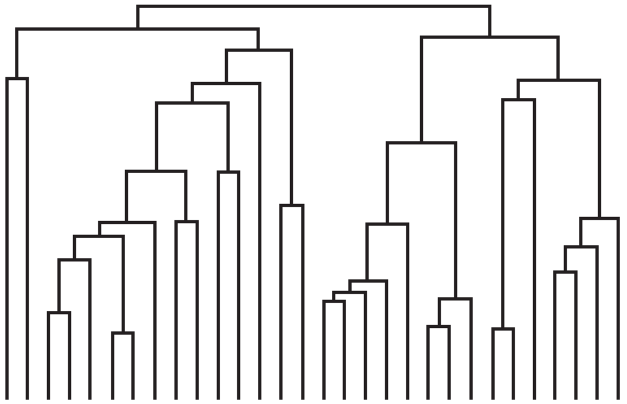

Figure 3. GHT dendrogram.

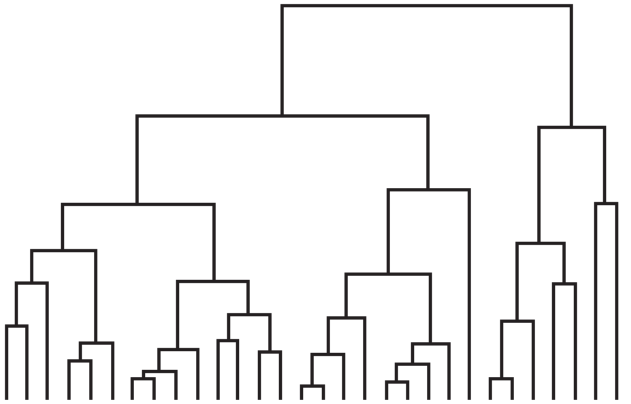

Figure 4. NC moments dendrogram.

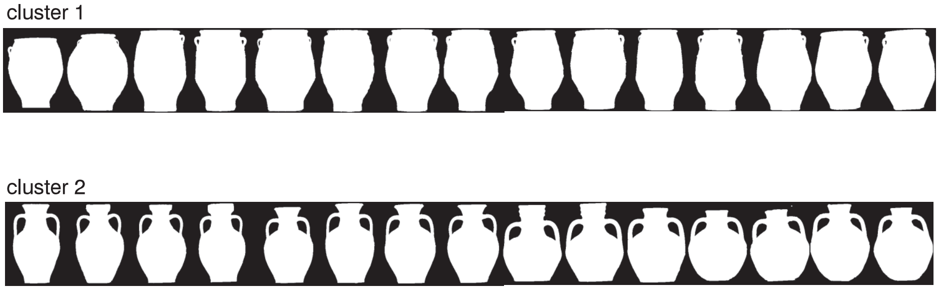

Figure 5. GHT group assignment.

trained to identify shapes using known examples. Both of the methods have been implemented, and their performances were compared to the GHT method.

3 Testing

To compare the methods a set of 30 pots were used. The pots are modern, from Crete, and have been classified by a human (S.J. Shennan) into two groups. These groups are obvious to even the untrained eye, the pithoi being jars with very small handles, and the amphorae having large handles. Although the methods are quite capable of using the raw images, the images were pre-processed to give a solid shape. This was easily accomplished by extracting the edge map of the image, then joining the gaps in the profile, filling in the interior of the shape and removing noise from the background, using an image painting package. Thus the images used were ideal shape representations, and the quality of the images would not affect the results. The first 7 NC moments were calculated for each image and the neural net which was used had 7 input nodes, 2 output nodes and 4 nodes in the hidden layer. The 3 methods were compared using the leave-one-out method, where each member of the set is identified on the basis of the others, and the percentage of correct identifications is recorded.

4 Results

The relative performances of the 3 methods were as follows:

GHT	100%
NC moments - k-nearest neighbours	97%
NC moments - neural net	63%

It can be seen that the NC moments were slightly less successful than the GHT when used with the k-nearest neighbours method. The neural net results were rather poor, but this work is still at a very preliminary stage and it is expected that further work on this will produce better results by using a different net topology and experimenting with different parameters in the back propagation algorithm.

The reasons for the different performances of the GHT and the NC moments becomes apparent if the shapes are classified on the basis of these methods. As mentioned above, the shape information derived in the first part of the

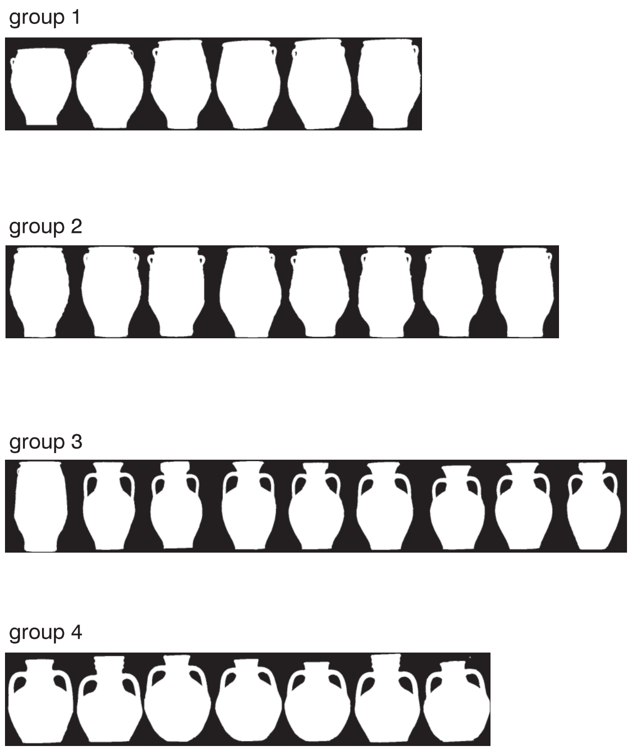

Figure 6. NC moments group assignment.

identification procedure can also be used to classify the objects. To do this the second stage is to use Principal Component analysis and Hierarchical Agglomerative cluster analysis (Shennan 1990: chs 12, 13) to group the objects into clusters based on the shape information. The Principal Components extracted from the shape information variables are used for a Group Average Cluster Analysis. (More details of this procedure can be found in Durham *et al*. 1994). The relationships between the pots are shown in the accompanying dendrograms (figs 3, 5).

The GHT successfully divides the shapes into two groups, which correspond exactly with the pithoi and amphorae (figs 3, 4). The level of resolution of the GHT is demonstrated by the fact that the two shapes on the extreme left of the dendrogram are in the pithoi group, but are markedly separated from the other pithoi. From inspection of the pithoi cluster in figure 4 it can be seen that these two pots on the left are noticeably different from the rest, while still being obviously pithoi.

On the other hand, the shape information from the NC moments does not produce such a clear classification (figs 5, 6). The pots are divided into 4 groups. Two of these correspond to pithoi and two to amphorae. However, one of the amphorae groups (group 3, the third from the left) is classified as being more similar to the pithoi than to the other amphorae. In addition, one of the pithoi has been classified in this group. This is because the set of moments used does not give a sufficiently detailed description of the shape to make the necessary distinction. The moments can only distinguish that group 3 are tall and thin, groups 1 and 2 tall and fat and group 4 are short and fat, but cannot distinguish more subtle differences. The use of more, higher-order moments should alleviate this problem.

5 Conclusions

We have shown that automatic identification and classification of artefact shapes is feasible, if rather slow, using the GHT. Our preliminary results suggest that other methods exist that have a performance approaching that of the GHT, and will be much quicker to use. These results promise to produce a practical tool for automatic classification of artefact shapes in the foreseeable future.

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