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The Automatic Morphological Description and Classification of Archaeological Monuments from Vertical Aerial Photographs

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Abstract. For most of this century, aerial photography has been an important technique for the discovery, recording and analysis of archaeological sites. For many regions there are vast archives of aerial photographs available; however, a critical problem for archaeology is the lack of time and resources available to adequately study this rich source of information by traditional methods. A problem that has more recently come to light with the advent of regional and national archaeological databases is the subjectivity inherent in the current techniques of recording and analysis. We have developed a software toolset in conjunction with archaeologists, which provides accurate, efficient and objective means to: extract and measure monuments visible in aerial photographs; provide topographic models of them; automatically classify them; and provide integration with geographical information systems (GIS). This paper describes the archaeological context of our research. It then introduces our object extraction approach, and discusses the development of an automated morphological-topographical classification scheme for earthwork monuments. This work represents a contribution to the automatic detection and extraction of low contrast, damaged objects, in scenes where significant noise and clutter are present. It also shows image processing, cluster analysis and artificial neural networks to be suitable and complementary tools for the automatic generation and implementation of an image-driven morphological classification scheme.

1. Introduction

1.1 Aerial Archaeology

Aerial photography, which has been used by archaeologists since Crawford's pioneering work in the 1920s [6], is today the single most important technique for the initial discovery of archaeological sites, and is also one of the most important for their

recording and subsequent analysis [7]. In recent times, as the number of excavations carried out has decreased, the need for non-invasive analytical techniques has become greater [2]. The importance of aerial photography today is greater than ever, as an increasing proportion of archaeological assessment is geared towards prioritising the importance of sites for preservation in the current climate of accelerating rural development [12], [14].

For many regions there are vast archives of aerial photographs available; however, a problem that is acknowledged to be of primary importance is the lack of time and resources available to adequately study this rich source of archaeological information by traditional methods [20], [22]. Digital image processing has the potential to improve the efficiency and objectivity of aerial archaeology, and a limited number of developments have been made to this end. Although Ireland has perhaps the most complete archaeological heritage remaining in Europe, it remains a largely unexplored archaeological territory. The potential for applying image processing techniques to the archaeological study of Irish aerial photographs is therefore particularly good.

1.2 The Need for Objective Classification of the Evidence

For aerial photography to have value as an archaeological discovery and interpretation tool, objective means of making sense of observations are required, even at a level as basic as determining which observations are likely to reflect archaeological material and which are likely to reflect small-scale geomorphological processes [19], [21]. For these purposes, a number of classification schemes for archaeological sites have been proposed. Crawford's work in the 1920s classified sites in terms of the nature of the evidence: for example, sites may be evident as crop marks, soil marks, or may be upstanding. Other schemes have attempted to classify archaeological features in terms of their morphology or other of their aspects: for example, enclosures can be classified in terms of their shape, number of banks and ditches, entrances, association with other features, topographical contexts, and so on [3], [9], [23], [30], [33].

While databases and Geographical Information Systems (GIS) are now being used to assist the collation of archaeological information at a regional and national level, the production and classification of this information has continued to be highly subjective. This is particularly troublesome for wide-area databases since these are invariably based on the work of many different archaeologists. Classification schemes such as MORPH, developed by the Royal Commission on the Historical Monuments of England (RCHME), certainly impose standardised description and classification, and provide centralised data access [9]: however, they still suffer from a lack of objectivity. It has been shown that groups of archaeologists working with MORPH, when independently presented with aerial images of archaeological monuments, are likely to produce widely disparate interpretations [15].

The technique of *numerical* morphology-based typological classification has been applied to archaeological artefacts since the 1960s, and more recently to monuments, in an attempt to reduce the subjectivity of their interpretation [31]. While the published

classification schemes have tended to rely on ground survey evidence, there have been convincing arguments made for classification based entirely on evidence from aerial photographs [28], [29]. The validity of attempting to classify monuments in this way has been heatedly discussed in the aerial archaeology literature for a number of years (e.g. [14], [31], [33]), though the advantages in terms of labour efficiency are undoubted. The primary weakness of numerical classification is that it produces archaeologically abstract classes, and it is also argued that this classification may disregard other important information about a site, such as cultural affinities. Numerical classification of monuments in general, and from aerial photographs in particular, is however regarded as being useful in a number of ways:

- As a means to produce *at least some* useful information from sets of raw morphological data, particularly in the case where no additional information regarding a monument is available;
- In order to allow effective querying of large (regional or national) monument databases, through the selection of groups by class, even if these classes are archaeologically abstract;
- To alleviate the problem of subjectivity in recording;
- As a first step in the progress towards dating, function designation and the deeper understanding of monuments;
- As a particularly effective technique for use by rapid wide-area discovery-oriented surveys from aerial photographs.

A persistent weakness of traditional (descriptive) morphological classifications lies in their definition of shape, since most archaeological features tend to fall between the geometrical extremes of the true circle and the true rectangle. Simplified descriptions of shape are typically adopted, for example to allow features to be classed as “essentially curvilinear”, “hybrid”, or “essentially rectilinear”. This paper describes the development of image processing and numerical classification techniques, in order to improve the efficiency and objectivity of archaeological monument description and classification from aerial photographs.

2. Automatic Monument Detection and Extraction

2.1 Overview of the Problem Area

It is only recently that domain-specific image understanding algorithms have been developed for automatically detecting [17] and mapping [23] archaeological monuments visible in aerial photographs. These tasks pose significant problems for digital image processing and image understanding. The causes of these problems, and the effects that they have on image segmentation techniques, include:

- The extremely low signal-to-noise ratio of most monuments visible in aerial photographs. This is the primary problem, which compounds all of the other problems. It causes low level domain independent techniques to fail: there is

simply not enough gradient information available in aerial photographs for local pixel analysis techniques to succeed.

- The fact that monument boundaries do not adhere to any strict morphological constraints, other than the fact that many can be loosely defined as 'sub-circular' closed loops. This means that higher level spatial techniques such as template matching have little domain knowledge to work with.
- The fact that nearly all monuments are visible only as thin boundary features, with no morphologically or texturally recognisable internal features. Successful approaches in other applied image processing domains in which low contrast features are sought - for example, medical image processing, or the analysis of remotely sensed urban scenes - often make use of these types of evidence.
- The presence of clutter - in this case, modern day objects of relatively high contrast, such as walls, houses, trees, and roads. This is a major problem in any natural scene analysis, but particularly in a domain such as archaeology, where the clutter objects tend to dominate the gradient evidence.
- Damage and occlusion, both of which further add to the problem of incomplete boundary evidence. Extracted boundaries become so fragmented that low-level neighbourhood based techniques such as relaxation cannot function adequately on these types of images.

2.2 A Sub-Circular Object Extraction Technique

In order to calculate the strength of evidence for a circle in a digital image, with centre point (x,y) and radius r , it is possible to approximate first derivatives of intensity in a truly directional manner. The first derivative (edge strength) at a point on the circle's circumference can be estimated by:

$$DI = \text{abs}(I(x+r.\sin(q),y+r.\cos(q)) - I(x+(r-1).\sin(q),y+(r-1).\cos(q))) \quad (1)$$

where $I(x,y)$ is the interpolated intensity of the pixel at location (x,y) , and q is the clockwise angle from a vertical line to a line from the circle centre to the circumference point. The strength of edge evidence for the existence of a circle of a specific radius and centre location may be calculated by summing the evidence at a number of points on its circumference.

While circles provide crude approximations of many archaeological monuments visible in aerial photographs, much more accurate approximations may be obtained by considering the arc. Our technique approximates the shape of archaeological monuments through the aggregation of many arcs, *with varying centre points and radii*. By applying sub-pixel accuracy edge detection to candidate arcs, a set of strong arcs may be identified, and these arcs used to build the final shape. These edge-detection efforts make use of domain knowledge in order to search small, tightly-defined regions, thereby minimising the effect of low contrast, noise, occlusion and damage.

Our technique is provided with a set of candidate centre points and candidate radii: these may be estimated from a user-defined bounding rectangle, or may be based on a

peak in a *Hough-transform* accumulator array [16]. For each combination of centre point and radius, 50 discrete 7.2° arcs are considered. The edge strength of each arc is calculated as the sum of the differentials at each of 12 evenly spaced positions on its circumference. The technique then rejects all except the 8 strongest arcs at each of the 50 arc positions, and also rejects outlying arcs (which are defined as those of significantly higher or lower radii than the average). It then draws the object boundary by applying weighted moving averages in order to calculate the centre point and radius at which to draw each of the 50 arcs making up the boundary shape. The strength of each arc is used as the weighting factor, thereby allowing arcs with good evidence to compensate for areas where there is little evidence for the monument's boundary. A variable parameter, the 'smoothing angle', determines the angular range of neighbouring arcs that are used to calculate the moving averages at each arc position.

This technique provides for the automatic (and therefore objective) edge tracing of archaeological monuments: see fig. 1. We have conducted extensive tests, validating its accuracy and superiority in this domain over more generic object extraction techniques. Of particular importance to the current task is the fact that the technique approximates an object's boundary where evidence is weak due to damage, low contrast, or occlusion: this capability is not rivalled by generic techniques such as relaxation. For an in-depth treatment of our technique, see [24].

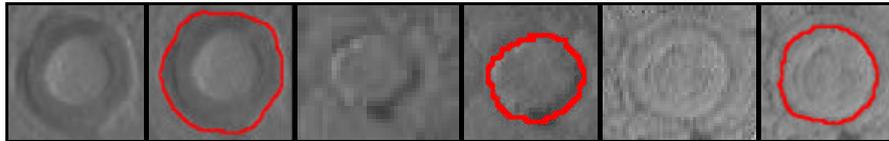


Fig 1. Sample automatic boundary tracings of relatively high contrast features.

3. Morphological and Topographic Measurement

3.1 Archaeologically Relevant Measurements

A variety of morphological and topographic metrics are considered to be significant to the classification of archaeological earthwork monuments, though some of these cannot be objectively collected because of the varying level of preservation of sites. This point is particularly relevant to our purposes, since previously unknown sites are invariably those which survive as faint markings visible only from the air.

Ground slope and aspect (facing) are important: ringforts, for example, tend to be on well-drained slopes. Slope, altitude and aspect together indirectly account for most of the physical constraints on land use, and are therefore important in terms of site function. Size and overall shape are significant: it is suggested that larger, more

accurately circular enclosures, for example, tend to be of prestigious ritual nature rather than domestic.

A number of other measurements, though considered significant to archaeological type designation, present problems in terms of objectivity. The compass direction of entrance(s) is considered to be important, though entrances are often hard to define, particularly from remote imagery, and it is often hard to tell if they are original. Bank and ditch size (height, depth and width) are highly dependent on preservation. Measurements describing more complex structures (for example, systems of banks and ditches, or the nature of internal buildings) are notoriously difficult to collect, even from field survey, since neither structural changes that occurred during the period of occupation nor subsequent modifications of a site after its abandonment can be assessed [3].

A variety of spatial analyses between archaeological monuments and other environmental data, for example nearest neighbour analysis, line-of-sight statistics, distance to nearest ecclesiastical site or to water, are relevant to site classification. This type of analysis is a higher level task in the domain of GIS, and is therefore beyond the scope of the type of classification systems under current discussion. It is worth noting, however, that anything other than preliminary classifications of archaeological sites cannot be attempted without a study of the wider landscape and inter-relationships between sites [31].

3.2 Morphological Measurements from Monument Boundary Tracings

Our classification scheme is based on a number of morphological and topographic measurements which are derived from a monument's extracted shape and from its digital elevation model (DEM): see section 3.3 for the latter. These measurements, which are summarised in tables 1 and 2, are those that (a) are deemed to be relevant to the morphological-topographic analysis of archaeological monuments, and (b) can be collected objectively from aerial photographs [3], [9], [18], [30], [33].

Table 1. Morphological measurements derived from monument edge tracings.

Measurement	Calculation	Notes
Circularity	$(\text{Area})/(\text{Average distance of interior points from boundary})^2$	Maximised at 4P for a circle
Rectangularity	$(\text{Area})/(\text{Area of minimum enclosing rectangle})$	Maximised at 1.0 for a rectangle
Elongation	Length/Width	Length and width are calculated with respect to the principal axis of the shape
Total area	Pixels x area in photo of 1 pixel	The area represented by a single pixel in a photo is calculated automatically from user-supplied control points

3.3 Topographic Measurements from Photographic Stereo Overlap

Vertical aerial surveys normally provide an overlap of at least 60% between successive pairs of exposures. This allows parallax measurements to be made, and the topography of the landscape to therefore be modelled. The softcopy topographic photogrammetry techniques used to generate DEMs incorporate geometric correction, cross-correlation, blunder and obstacle removal, and $x/y/z$ scale estimation. It is beyond the scope of this paper to discuss specific implementations.

The local topography of an archaeological monument can be used to derive slope and aspect information: our approach is based on a 3-dimensional linear regression of the $x/y/z$ points in an elevation model.

Table 2. Topographic measurements derived from local digital elevation models.

Measurement	Calculation	Notes
Slope	Slope of best-fit plane	X,Y,Z ground co-ordinates of the points in the monument are submitted to a 3D linear regression (after [25]).
Aspect	Compass direction of best-fit plane	Orientation of photo/DEM is automatically calculated from user-supplied control points.

4. The Development of a Classification Scheme

4.1 Introduction

There are a number of requirements that should be met by a computer assisted classification scheme of archaeological monuments, if it is to be applicable to wide-area assessment and regional or national database development [1], [28]:

- The scheme itself should be statistically significant. Archaeological significance cannot be ascertained in the short or medium term;
- Individual monument classifications should be reproducible. The wide range of monument preservation states therefore precludes incorporation of information such as entrances, and bank and ditch heights, widths and depths. While this is undoubtedly useful information, from a classification stance it is simply too subjective and affected by outside factors;
- The scheme should assist in the preliminary interpretation of monuments. It should therefore at least provide a data summary role, assisting the user to make sense of the sheer bulk of information.

4.2 Cluster Analysis

Cluster analysis is a statistical technique of numerical taxonomy that is commonly employed in an exploratory manner for the identification of structure in complex, high dimensional data sets, for which there is no prior knowledge of groups or their characteristics [10]. As a classification procedure, cluster analysis seeks to determine natural groups (or clusters), which reflect the underlying structure of data sets by relating similar measures of observed variables.

Agglomerative clustering progressively groups individuals into fewer and larger clusters. Given a set of observations, each of which has m variables measured, the similarity between a pair of data points in the m -dimensional data space can be estimated in several ways: the most commonly used is simple Euclidean distance. The chosen distance measure is used to build a similarity matrix which tabulates the similarity of each individual with each other individual. The next stage is to link individuals and groups. It is necessary to define similarity between groups of points: again, there are a number of ways of doing this. A popular method, developed by Ward [32], adds an item to the group that produces the least increase in the total sum of squared deviations between individuals in groups and group averages. The linkage process continues until a chosen threshold distance is reached, thereby yielding a number of groups.

4.3 Data Collation and Classification Development

In order to develop a typology of archaeological enclosures and sub-circular features visible in vertical aerial photographs, a set of 125 monuments were selected from the *Bruff* Aerial Photographic Survey. This survey was initiated in 1986 by the Office of Public Works (OPW) and the Dept. of Archaeology, U.C.C. The aim was to assess the potential of medium altitude vertical aerial stereo photographs for the recording of hitherto unknown archaeological sites [8]. The study covers a 70 km² area centred on Herbertstown, Co. Limerick, and extends slightly into Co. Tipperary. The monuments selected for our study were deliberately chosen from those that had been identified by the members of the Discovery Programme, Dublin: any previously unidentified monuments, visible with or without image enhancement, in the scanned photographs, were not used. A set of 7 morphological and topographic measurements regarding each of these monuments was generated, using the techniques described in this paper. In the case of the aspect (facing) measurement, the data were vectorised into a north component and an east component on the unit circle, since a simple angle is clearly not useful as it is not a continuous numerical measurement. Any monument on a ground slope of less than 1 in 100 (0.01) was considered to have *no aspect* value. In addition, we used the following estimation of radius, as a replacement for area:

$$radius = \sqrt{\frac{area}{p}} \quad (2)$$

Radius rather than area is normally used in archaeological classification schemes, since this cancels the propensity for size to dominate the classification when there are some monuments many times the size of others. The data generated were normalised so that each variable fell within the range [0,1] (in order to ensure that all variables were of equal importance in the clustering process), and then submitted to agglomerative cluster analysis using Ward's method, in order to objectively define typological groups.

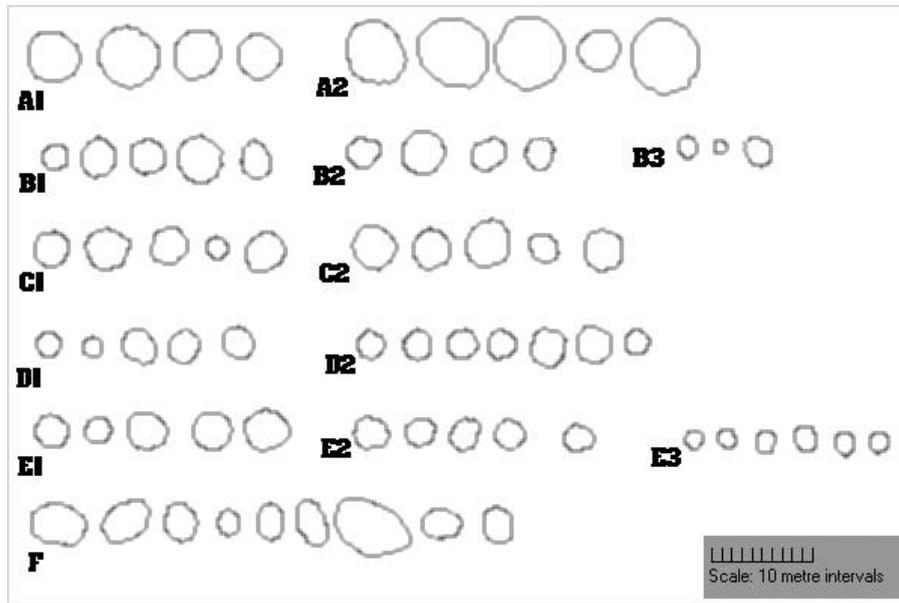


Fig. 3: Tracings of sample monuments from the resulting classes.

Table 3 A summary of the 6 typological groups resulting from cluster analysis. 'Tightly defined' measures are those that unify a group (i.e. have low standard deviation) without actually being of unusually high or low mean value.

	No.	Radius	Circular.	Rectang.	Elong.	Slope	Facing
Group A	11	high	high	low	low		
Group B	20					high	not N
Group C	26				tightly defined	low	
Group D	29	low				tightly defined	N or NW
Group E	28						SE, E, or NE
Group F	11		low		high	low	

The resulting *dendrogram* is presented in fig. 2: this is a tree of hierarchical relationships, which is used to graphically depict the clustering of data. One axis (in this case, the vertical axis) plots the individual observations. The distances at which linkages are made between groups can be measured along the other axis: the more similar two observations or groups are, the closer to the origin of the horizontal axis they are linked. Sample tracings of monuments from the resulting groups are provided in fig. 3. Table 3 summarises the characteristic features of the 6 groups we have defined from the dendrogram.

4.4 Verification of Statistical Significance

A coefficient, C , that measures “tightness of clustering” was defined as follows:

$$C = \frac{\left(\frac{\sum D_g}{P_g} \right)}{\left(\frac{\sum D_a}{P_a} \right)} \quad (3)$$

where SD_g is the sum of Euclidean distances between each of the within-group pairs of objects, P_g is the number of within-group pairs of objects, SD_a is the sum of Euclidean distances between each pair of objects disregarding group membership, and P_a is the number of pairs of objects disregarding group membership. This coefficient measures the average ratio of the distance between objects in the same group, to the distance between objects disregarding grouping, and is minimised by a strongly clustered classification.

Clearly, without proof of statistical significance, any numerical classification scheme lies on shaky ground. Therefore Monte-Carlo simulation was performed, in conjunction with the use of the C coefficient, in order to verify the statistical significance of the Bruff monument classification. In order to carry out this simulation, 500 sets of test measurements were generated, where each set comprised 125 “fake” monuments, whose measurements were selected randomly from correctly distributed data (the distribution of measurements for each variable was taken from that of the real Bruff data). Since radius and rectangularity were significantly correlated in the Bruff data (correlation coefficient -0.387), the rectangularity measurement of each “fake” monument was adjusted as follows¹:

$$rect_{new} = -0.387radius + rect_{old}\sqrt{1 - (-0.387)^2} \quad (4)$$

A similar adjustment was made to the elongation measurement of each “fake” monument, since in the Bruff data elongation was significantly correlated with circularity (correlation coefficient -0.456). The 500 sets of simulated data were

¹¹ The formula for generating correlated data was taken from: http://www.uvm.edu/~dhowell/StatPages/More_Stuff/Gener_Correl_Numbers.html.

submitted to cluster analyses, and C was calculated in each case. It was found that just 13 of the simulated sets produced stronger clustering than the real Bruff data. Our classification may therefore be accepted at a 97.4% level of statistical significance.

It is obvious that there is a difference between statistical significance and archaeological significance. Statistical significance allows our morphological and topographic observations to be made with some conviction; however, that is not to say that the factors causing these observations are necessarily archaeological -- "statistical significance is a necessary but not a sufficient condition for [archaeological] type designation." ([1] p.177). Further archaeological research is required in order to determine the archaeological significance (if any) of the groups.

5. The Application of the Classification Scheme

5.1 Artificial Neural Networks

Artificial Neural Networks (ANNs), which are essentially complex transfer functions based on simplified emulations of biological neural networks, have been well proven in the area of numerical classification, particularly in cases of 'noisy' data, where other classification approaches are more susceptible to error. They consist of one or more layers of nodes (artificial neurons). Numerical system inputs are received by an input layer of nodes, which operate on these values and output the results. The typical operation of a node involves a weighted summation of its inputs, and the application of a continuous non-linear function, in order to provide a bounded and differentiable output value.

The chosen ANN topology specifies connections between the nodes of the successive layers: the outputs resulting from the input layer become the input values to connected nodes in the other layers of the ANN, where further operations are performed. This feed-forward process continues until the outputs of the final layer, which represent the ANN's overall 'understanding' of the system inputs, are computed. The most widely proven ANN topology for pattern recognition tasks is the multi-layer perceptron (MLP): this specifies that the nodes in each layer are connected to *each* node in the preceding layer. It is common to use 3 layers of nodes in a MLP: the second layer, which has no connections to the 'outside world', is referred to as a *hidden layer*. It is this layer which adds sufficient internal complexity for complex patterns to be recognised.

In order to train a MLP to accurately match input values to target output values, the weights at each node are modified iteratively, most commonly through the 'back propagation' of errors from the output layer through the preceding layers [26], which is essentially a credit-blame approach allowing the error attributed to each node to be used to modify the weights of its connected nodes.

It is a simple matter to devise a MLP with sufficient internal complexity that it can be trained to the point where it almost perfectly reproduces results from its own training set. This is referred to as *overfitting*, and it leads to a loss of generality. In practice, the

point at which training should be terminated, in order to produce optimal generality, is proportional to the size of the MLP (number of nodes) and the number of training cases used [4].

5.2 The Automatic Determination of Monument Class Membership

In order to apply the developed typology as an automatic interpretation task, a MLP approach was used. The validity of cluster analysis followed by neural network classification has been previously proven for astronomical applications [11]. In designing the MLP architecture, i.e. the number of layers and the number of nodes in each layer, the fact that the end result was to represent discrete outputs was considered important. It would not be sensible, for example, to model the output from the network through a single node, even though this model was found to work well on the training and subsequent test data, since this implies a continuous output value. See [13] for a general discussion of ANN architectures.

Training experiments were carried out using a backpropagation MLP with 7 input nodes, 1 hidden layer, and 13 output nodes, where each output node was trained to respond to one particular monument sub-class. The training proved to be impossible with this many outputs. The same task was attempted with 6 output nodes, responding only to the 6 major monument classes; training still proved to be difficult, and the resulting accuracy of the network not satisfactory. The final model, which proved to be highly reliable, involves a hierarchy of eight co-operating neural networks, as illustrated in fig. 4. This is essentially a layered variation of the mixture-of-experts modular system [5]. A similar hierarchy-of-networks approach is described by Snorrason & Ruda [27].

A hierarchical collection of MLPs is considered to be particularly suitable to the current classification task, since the groupings resulting from cluster analysis were inherently hierarchical in definition. The discrimination task to be trained for each network was derived directly from the classification dendrogram (fig. 2). The top-level network, therefore, concentrates on separating monuments according to the three weakest linkages of the dendrogram, which distinguish (i) groups A and B, from (ii) groups C, D and E, from (iii) group F. On the second level of the hierarchy are two networks: the first separating group A from B, and the other separating group C from D from E. The bottom level of the hierarchy consists of a network for each of the groups A to E, which determine sub-group membership. Group F does not have any subgroups, and is identified by the top level network, since it is quite different to the other groups (the very last, i.e. least significant, linkage of the dendrogram is the one that joins group F to all of the others).

In order to generate optimal ANNs for the sub-tasks, different amounts of nodes in the hidden layers were experimented with. Two sets of data were constructed from the 125 classified monuments available: one set (80 members) was used exclusively for training, and the other (unseen) set (45 members), for determining the point at which optimal generalisation had been reached. It was found that using ANNs with 7 nodes on the hidden layer produced optimal generalised results: this is clearly not only a

function of the system being modelled, but also of the number of training cases available. Using the final ANN models, none of the 45 unseen monuments were misclassified, and in addition the "strength of conviction" for each of these classifications had been maximised (each of the ANNs have either 2 or 3 output nodes, where each node represents a classification decision, and is represented by a real number in the range [0-1]. The node with the highest output value is the one which represents the overall decision, and the value at this node, minus the values at the other output node(s), provides a "strength of conviction" score).

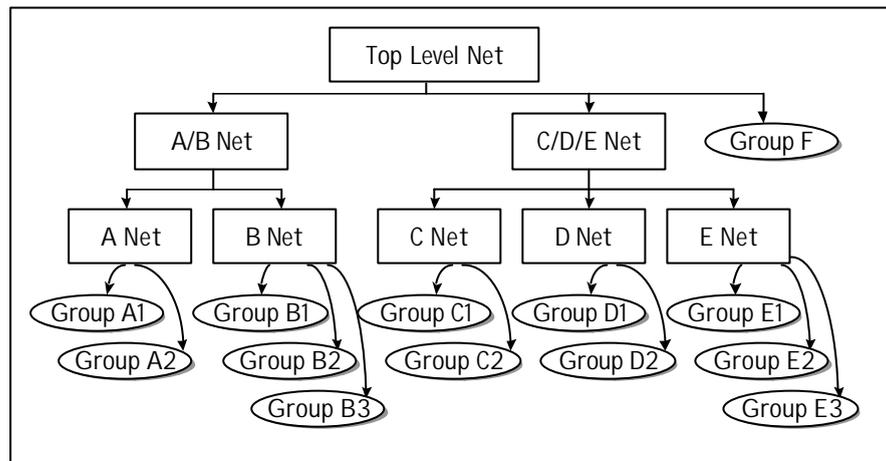


Fig. 4. The hierarchy of eight MLPs used to classify monuments. Rectangles represent neural networks, while ovals represent final classification decisions. Group F is sufficiently different from the other groups to be determined by the highest level network.

6. Conclusions

Early work on the morphological analysis of archaeological sites presumed that once all sites in a particular study had been categorised according to shape, one could then look at the existing excavation material and on that basis provide a date range for sites of similar shape. Unfortunately, so few sites have been excavated that there is not enough information on which to base chronologies. It is now widely believed that morphological studies cannot progress beyond a certain point without the support of dating evidence. Systematic excavation of selected representatives of morphological types is required, in order to test the categories that have been developed, and to allow the refinement of classifications [31]. We are currently analysing the correlation of our archaeologically abstract classification with existing independent classifications of previously known monuments. Sites and Monuments Record (SMR) data from an

important archaeological region in Co. Roscommon, for example, has allowed us to suggest a tentative designation of class 'A' monuments as 'ritual', and class D' monuments as 'domestic'.

The monument boundary extraction technique described in this paper may be of direct use to other applications requiring the extraction of low contrast and/or damaged sub-circular shapes, for example computer-assisted mammogram interpretation. The technique however has one important drawback in that it is a mapping function only: it requires as input an approximate centre point and size of the feature of interest. We are currently researching the goal of automating monument mapping *and* detection, through the application of preprocessing stages including the use of a gradient-direction assisted Hough transform. There is also potential for the development of more robust weak-arc estimation functions, which could for example look at the rate-of-change (derivative) of arc centres and radii, local to an arc being estimated, rather than performing simple weighted averages.

The implementation of the monument classification scheme, involving a hierarchy of co-operating ANNs each trained to perform a logical section of the overall monument classification task, illustrates a natural exploitation of the inherently hierarchical groupings resulting from cluster analysis. Hierarchies of co-operating ANNs have been used before, but their use for inherently hierarchical pattern recognition is believed to be new.

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