Charlotte M. Gurney
*Systems and Applied Sciences Corporation*
*Hyattsville, MD 20784*
John R. G. Townshend
*University of Reading*
*Reading RG6 2AU, United Kingdom*

# The Use of Contextual Information in the Classification of Remotely Sensed Data

**Contextual methods can be used in the classification of urban areas and the identification of linear objects and separation of cloud and cloud shadow from the remainder of a scene.**

## Introduction

In recent years, considerable effort has been directed towards the extraction of information from digital remotely sensed data by computer-assisted methods. Although such information may be in the form of continuous variables such as percentage cover (Bentley *et al.*, 1976; Marsh *et al.*, 1980), usually the extracted information is in the form of classes. Procedures to extract such information commonly rely on use of a feature space whose axes are defined by the channels from the multispectral data set. Attempts are then made to sub-divide the feature space into mutually exclusive sub-spaces corresponding as closely as possible to the classes which need to be discriminated, using a proportion of the data for which one not only has spectral information, but also ground data. Assuming the latter proves possible, then the whole of an image may be classified relying solely on the spectral data. Implicit in this standard approach is that each pixel (picture element) is classified solely on the basis of its own properties without use of data from the remainder of the image; hence, the name per-point classifier.

In practice, per-point classifiers often achieve far from perfect classifications, errors of 25 percent or more being common for many classes (e.g., Townshend and Justice, 1980; Todd *et al.*, 1980; Shimabukuro *et al.*, 1980). The performance of per-point classifiers may well improve in the future with the use of sensing systems with better spectral and radiometric resolutions, especially those mounted on satellites (Salomonson *et al.*, 1980; Gaubert, 1978).

However, even with these improved sensors it is likely that far from perfect accuracies will be achieved, because not only will the data always contain noise, but also many classes have inherently similar spectral properties. For example, in terms of land use, a short herbaceous cover may represent agricultural use, recreational use, or a part of residential use.

Abstract: *A typology of contextual information as used in the classification of remotely sensed data is proposed. Procedures which use contextual information in the classification of remotely sensed data are defined as those where the spectral values or classes of pixels are used to assist classification of some other pixel or group of pixels. Procedures can be categorized according to whether they are applied to raw or classified data, by whether they apply to individual pixels or to groups of similarly classified pixels and objects, and by the form of spatial relationships between the pixels. Examples of applications of each type of procedure are given with reference to classification using Landsat data.*

Furthermore, improved spatial resolving power of satellites may not lead to improvements in classification accuracy (Townshend, 1981).

In order to improve classification it is natural therefore to use information not only from individual pixels but also from elsewhere in the image. Such spatial information is usefully subdivided into two types—textural and contextual.

*Texture* refers to a description of the spatial

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variability of tones found within part of a scene. Various measures of texture have been successfully used to define axes in a feature space, in a way similar to that described for spectral data (Haralick and Shanmugan, 1974; Haralick and Bosley, 1974; Hsu, 1978; Weszka *et al.*, 1976). A useful summary of texture is provided by Haralick (1979). One disadvantage of textural measures is that there is an effective reduction in spatial resolution of the final classified image because an area has to be defined within which the measurements of texture are made. This is particularly disadvantageous when low resolution satellite data are used. For example, in Haralick and Shanmugan's (1974) work on land-cover types in the Monterey Bay area, sample sites of 64 by 64 Landsat pixels were defined, producing units approximately 5.1 km by 3.6 km in size.

Whereas texture refers to the spatial variation within a contiguous group of pixels, the *context* of a pixel (or a group of pixels) refers to its spatial relationships with pixels in the remainder of the scene. Thus, contextual classification of any pixel can potentially at least involve the use of any other pixel or group of pixels from throughout the whole scene. A contextual decision rule can be applied either to raw image data, in which case the spectral or textural properties of other pixels can be considered, or to classified data, in which case a preliminary classification can be amended by considering classifications assigned to other pixels. This implies not only that classification error might be reduced by using contextual information, but also that additional classes could be recognized by separating pixels with the same spectral properties into additional classes according to their context.

Using these definitions, the structural or syntactic approach to scene classification (Grimsdale *et al.*, 1959; Fu, 1974; Fu, 1976; Pavlidis, 1979) involves a form of contextual classification. This approach relies on the identification of scene primitives, whose relationships are described using formal grammatical rules.

Human photointerpreters have long exploited context very thoroughly, and recently attempts have been made to incorporate context in computer-assisted image classification. However, context has only been defined in very imprecise terms, and it has not been clear to the user just what procedures use contextual information and what advantages might attach to its use. The initial objective of this paper is to propose a typology of contextual information in order to demonstrate the variety of choices open to analysts as well as to provide a framework so that the relationships between different uses of context are clarified. In the following sections we illustrate how these various procedures can be implemented with examples from our own and others' investigations. In several of the latter the term "context" was not explicitly used in the original papers, but we believe that the development of a typology enables these methods to be explicitly identified and related to other, similar, procedures. In addition, the examples described provide some indication of the levels of accuracy, or improvement in accuracy, attainable through the use of context.

## A Typology of Context

For the sake of comprehensiveness, we should first distinguish between contextual information within an image and context derived from non-image sources. The latter includes knowledge of the geographic context of the image as a whole, the time at which the image was obtained, and the definition could even be extended to include information about individual parts of images from registered areal data sources, such as topographic or geologic maps. Welch and Salter (1971) have suggested that contextual information can also include appearance modifiers due to sensor limitations and to levels of solar illumination. In the present paper we restrict our attention to contextual information from within the image itself.

As stated in the previous section, a contextual procedure can be applied either to raw or to classified data. In the latter case, in addition to reclassifying a single pixel, it is also possible to take a decision with respect to a group of contiguous pixels which belong to the same class. Such a group of pixels can be termed an "object." There is, therefore, an important distinction between procedures involving objects, relevant only to classified data, and those applied to individual pixels, useable with either raw or classified data.

In either case the assignment made to a pixel or object will be contextual if it considers the values of another pixel or set of pixels with a given relationship to the pixel(s) in question. Contextual procedures can, therefore, be categorized on the basis of the type of spatial relationship involved. Four basic forms of relationship—distance, direction, connectivity, and containment—are illustrated in Figure 1.

Both *distance* and *direction* can be applied both to single pixels and to objects and can, therefore, be used on either raw or classified data. Very commonly, all pixels within a given distance of the pixel of interest are considered, and an assignment is made on the basis of either their spectral or class characteristics, possibly combined with their relative arrangements. Alternatively, pixels or objects separated by a specific distance and/or direction can be considered.

The concepts of *connectivity* and *containment*, as used here, apply strictly only to objects and can, therefore, only be used where some preliminary segmentation of the data has been made. One object may be said to be "contained" in another if it

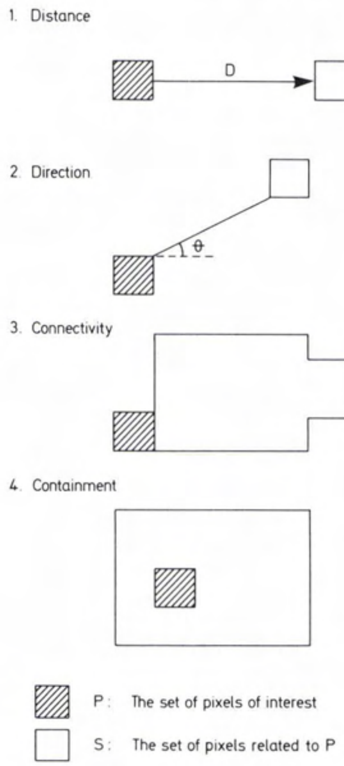


FIG. 1. Types of spatial relationship.

is completely surrounded by that object. Connectivity describes the relationship between a pixel and the other contiguous pixels of the same class. If a pixel is connected to a very large object, or an object of a particular shape, it could be assigned to a particular class.

Consideration of all the above factors leads to the typology of context shown in Figure 2. Procedures can be categorized by the use of raw as opposed to classified data, by whether they apply to individual pixels or to objects, and by the form of spatial relationships considered.

## CONTEXTUAL CLASSIFIERS

### TYPE 1: PIXELS WITHIN A LOCAL AREA

In theory, the classification of a pixel may be made to depend upon the spectral properties of all the other pixels in the scene. However, not only would this be computationally unwieldy, but also there is not necessarily a relationship between land-cover types some distance apart. Therefore, it is frequently assumed that only pixels within a given distance can affect a classification, and the majority of contextual classifiers are based on the use of local windows. These may be divided into two types, those which consider both the values and the internal arrangement of the pixels in the window and those which consider only the values.

### TYPE 1A: INTERNAL ARRANGEMENT NOT CONSIDERED

Classifiers which employ some modification of the commonly used per-pixel statistical classifiers are frequently based on the use of the spectral values of the immediate neighbors of a pixel (Welch and Salter, 1971). Kettig and Landgrebe's ECHO classifier relies on a two-stage procedure whereby homogeneous objects are recognized in local areas, and each object as a whole is spectrally classified using a non-contextual algorithm (Kettig and Landgrebe, 1976), In contrast, Bryant (1979) describes a contextual method for recognizing both homogeneous areas and boundary pixels (see Type 1b) followed by contextual reclassification. Such methods can lead to significantly improved classification accuracies, and the results have a less noisy appearance than those produced by per-pixel procedures.

### TYPE 1B: INTERNAL ARRANGEMENT CONSIDERED

Extension of the approach of Welch and Salter (1971) has been developed (Swain *et al.*, 1980; Swain *et al.*, 1981) which permits consideration of the position of pixels in the local area for the purposes of land-cover classification.

Where the relative locations of pixels in the

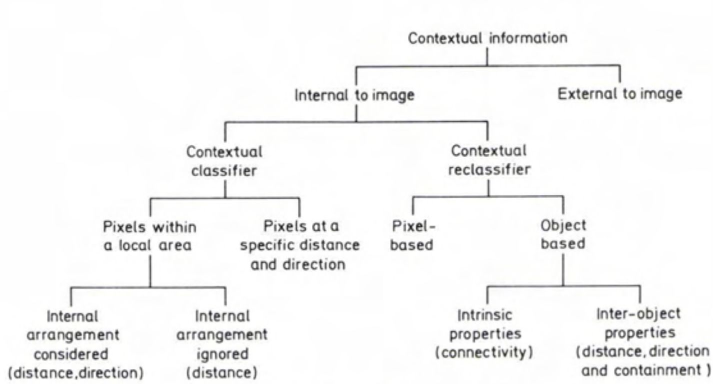


FIG. 2. A typology of context.

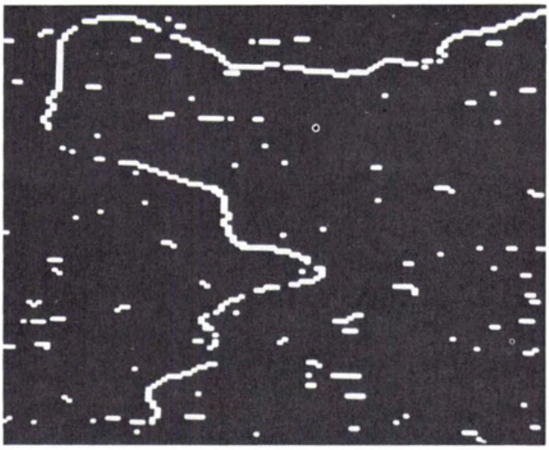

FIG. 3. Results of linear feature detection on a Landsat scene of Henley, England.

local area are considered, it is possible to determine whether the pixel under consideration forms part of an edge or boundary between classes, or is part of a linear feature.

Linear feature detectors may be used to identify roads and rivers (e.g., Bajcsy and Tavakoli, 1976; VanderBrug, 1976; Montoto, 1977; Gurney, 1980). In the last work quoted, a variation of the procedure developed by VanderBrug was used. Consider the array labeled

$$\begin{array}{ccc} a & b & c \\ d & e & f \\ g & h & i \end{array}$$

A vertical dark line is considered to be present at $e$ if

$(a + d + g) > (b + e + h) < (c + f + i)$ by some threshold $T$ and also that $d \geqslant e \leqslant f$.

Lines of different orientations can be identified using similar equations. An objective choice of values of $T$ was based on the likely spectral reflectance values of lines and backgrounds as well as the probable width of the linear features. Thus, information from the pixel, $e$, itself is utilized along with its contextual relationship with surrounding pixels. Figure 3 shows the results of such a line detection procedure applied to a Landsat scene 150 by 110 pixels in size near Henley, U.K. The most prominent linear feature detected is the River Thames, which is approximately 55-m wide in this area. Tests of 220 randomly chosen pixels which had been classed as "linear" indicated that at the 95 percent confidence level between 74 percent and 82 percent of these pixels actually correspond to some recognizable linear feature on the ground. 90 percent of the pixels traversed by the Thames were classed as "linear" by the detector. The confidence limits quoted here and elsewhere in this paper are based on the single-sample lists of proportions as described by Cochran (1963). These limits are symmetrical, unlike many quoted in the literature (Hord and Brooner, 1976; Hay, 1979), because with the large sample sizes which are used, the distribution can be assumed to be normal rather than binominal.

Related procedures can be used to recognize edges, which can be used to enhance images for interpretation of their geologic features (Goetz *et al.*, 1975), to detect geological lineaments (Burdick and Speirer, 1980), to assist regional delimitation (Strong and Rosenfeld, 1973), and to aid in the registration of images from different dates (Nack, 1977). Using the labeling of the array above, an edge may be considered to be present at pixel $e$, if the values on one side of it are significantly different from those on the opposite side. For example,

$$G_x = (a + 2b + c) - (g + 2h + i)$$
$$G_y = (a + 2d + g) - (c + 2f + i)$$
$$G = \sqrt{G_x^2 + G_y^2}$$

High values of $G$ denote the presence of an edge. Many modifications of this procedure have been developed; for reviews and comparison see Davis (1975), Fries and Modestino (1977), and Shaw (1979).

TYPE II: PIXELS AT A SPECIFIC DISTANCE AND DIRECTION

Although the use of local windows is more generally applicable, there are cases where pixels in a specific position at a given distance and/or direction can provide information for classification. As an example of this, we examine a procedure for identifying cloud and cloud shadow from Landsat multispectral data (Gurney, 1982). Identification is based on the assumption that all cloud pixels have a value greater than a threshold $T_c$ (though not that other objects cannot have such values) and that similarly all shadow pixels have values less than a threshold $T_s$ (though not that other objects cannot have such values). The distance between clouds and their shadows is calculated from a knowledge of sun elevation, solar azimuth, satellite heading, image geometry, and, where available, cloud base height. Cloud base height can be obtained either from meteorological data, or by measuring a sample of cloud to shadow distances and substituting for the cloud base height in the equations. All the other variables are available from Landsat header records. Figure 4 gives a diagrammatic representation of the method used. Essentially, bright pixels are identified, and on the assumption that they are clouds, cloud shadow is searched for in a window centered at the appropriate distance and direction. If a sufficiently dark pixel is found, then it is classed as shadow and the bright pixel as cloud. Dark and bright pixels without this spatial relationship are assumed to belong

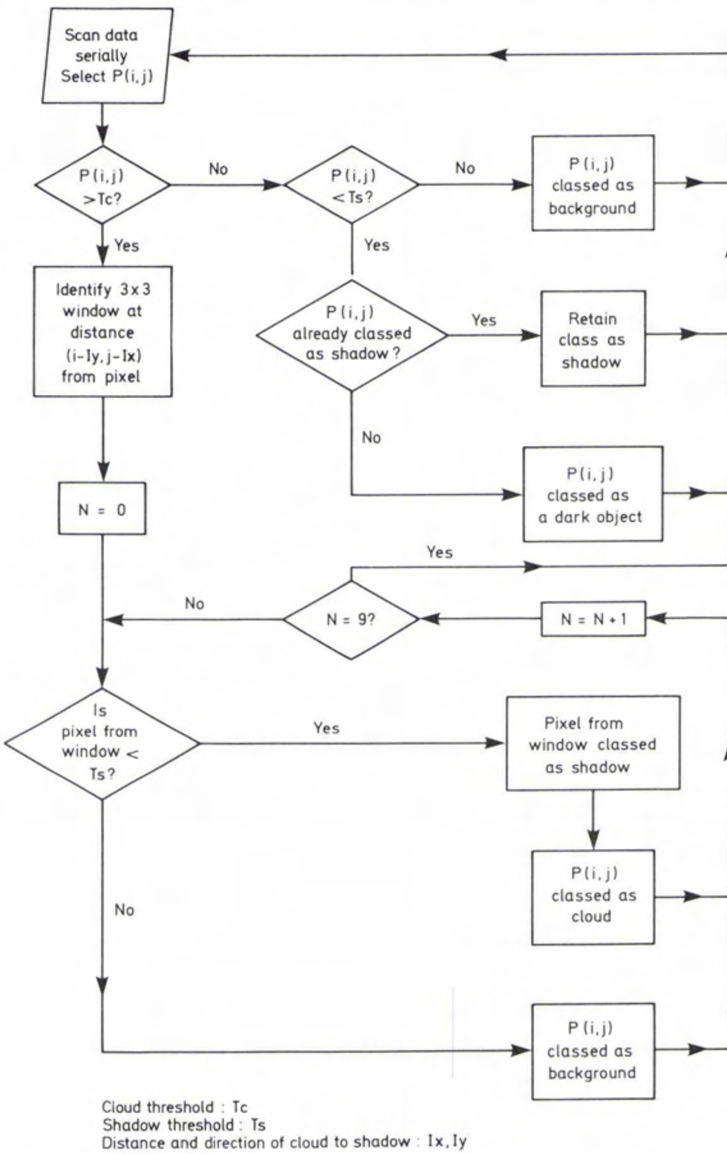


FIG. 4. Cloud and cloud shadow recognition.

to other classes. Thus, the introduction of contextual information allows pixels with the same tonal properties to be separated into distinct classes. An example of the results of such a procedure applied to Landsat data for March 1973 covering Beachy Head is shown in Figure 5. The area of sea on the lower left of the image has been successfully separated from the spectrally similar cloud shadow in the upper left of the image.

## CONTEXTUAL RECLASSIFIERS

The results of any classification will inevitably contain error. By employing contextual information, at least a proportion of this error may be corrected by reassigning classified pixels to another class. Additionally, the use of object based procedures can lead to the identification of additional classes.

### TYPE 1: PIXEL-BASED RECLASSIFIERS

Amendments of preliminary classifications made of individual pixels can be carried out using the same type of procedures as those employed for classifying raw data using context (see Figure 2 and the previous section). However, rather than

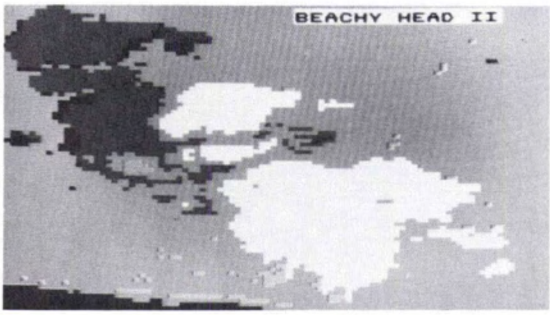


FIG. 5. Results of cloud and cloud shadow recognition on part of a Landsat scene near Beachy Head, England.

considering the spectral values of the pixels, their classes are considered.

Most pixel-based reclassifiers are based on the use of local windows of varying sizes. A widely used assumption is that pixels of a given class are likely to be surrounded by pixels of the same class. This assumption may often be valid where the underlying size of the classes is large relative to the pixel size, though it may not hold where single land-use classes contain many different spectral classes, as is more likely with higher spatial resolution data. Thus, for example, a procedure can be adopted in which the central pixel in a window is assigned to the class which occurs most frequently within the window (e.g., Itten and Fasler, 1979). This process is directly analogous to the use of local averaging on raw data, and has a similar effect to that of smoothing out isolated noise. In theory, a window of any size could be used, and rather than using a simple majority rule, different thresholds could be adopted for each class. Thus, for example, one class might require a large number of pixels present before reassigning a pixel, whereas for another class only a few pixels would be required. Such a procedure might be applicable where different error rates are associated with different classes.

The procedure may be illustrated, for binary data, by the following equation:

$$x'(i,j) = \begin{cases} 1 \text{ if } \sum_{m=-a}^{a} \sum_{n=-a}^{a} x(i+m, j+n) > T \\ 0, \text{ otherwise} \end{cases}$$

where $x(i,j)$ = class of pixel at $i, j$;
$x'(i,j)$ = new class at $i, j$;
$W^2$ = area of square window of side $W$;
$a = ((W + 1)/2 - 1)$; and
$T$ = number of pixels of class 1 required to change central pixel to 1.

Assigning the central pixel to the majority class of surrounding pixels is therefore equivalent to using $T = W^2/2$. The use of expand and shrink procedures (Rosenfeld and Kak, 1976), which are often used for data smoothing, is also a special case of this method using $T = 1$ and $W = 2E + 1$ where $E$ = the number of expansions. In general, use of a large value for $W$ and a small value for $T$ will have a very marked effect on the data and is, therefore, suitable where error rates are known to be high. Conversely, correction of a smaller error might only require a small $W$ and/or a large $T$.

The effects of varying the size of $W$ for a reclassification of land-cover types in southern Italy are shown in Figure 6. As might be expected, improvement declines with increasing size of window and there is a small decline as more distant pixels are considered. Unless some form of weighting is introduced so that the more distant pixels have progressively less importance, such a decline will inevitably occur. An example of such weighting is that suggested by Thomas (1980) who uses a gravity model to assign relative weighting. The actual degree of improvement attained will be a function of the relative sizes of the pixels and the areal units at ground level.

An alternative procedure for correcting classification error by using information from a local area is the use of relaxation labelling (e.g., Schachter *et al.*, 1977). Such procedures consider the probabilities that assignments are correct. Rather than making an immediate discrete decision, as above, the probabilities are iteratively updated using the set of probabilities contained in the local area. After a finite number of iterations, a stable solution is reached (Peleg and Rosenfeld, 1978) in which

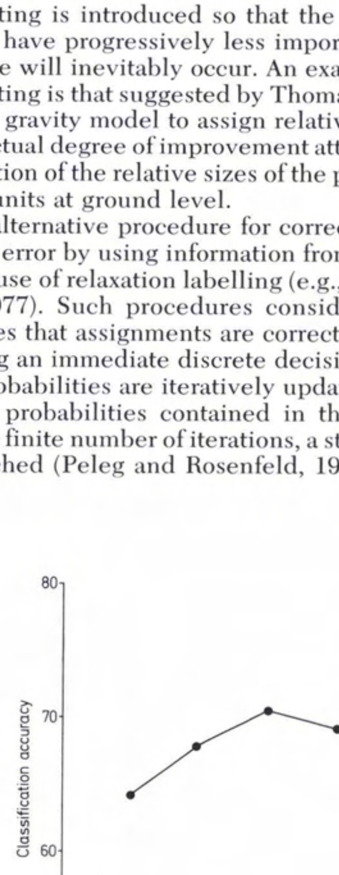


FIG. 6. Variation of final classification accuracy for reclassification of landcover types in southern Italy using a range of cell sizes.

correct assignments are reinforced and errors are reduced in probability (Zucker and Mohammed, 1978). Both edge or line data and general classified data can be reclassified using such procedures.

As mentioned above, the assumption that pixels of a given class are likely to be surrounded by pixels of the same class does not always hold. Some land-cover classes may be characterized by a heterogeneous assemblage of component cover classes. This is likely to be the case, for example, for scenes of residential areas, which are composed of roof tops, trees, herbaceous cover, and roads, especially where the imagery is of high resolution. In such circumstances, reclassification into land-use classes according to the frequency distribution of ground-cover classes found within a window has been proposed and successfully implemented by Wharton (1982).

In practice, use of either a window-based contextual classifier, or a reclassifier may give similar results. The use of a reclassifier may be preferable in some cases because the use of windows larger than 3 by 3 pixels is readily possible, whereas for contextual statistical classifiers much greater computational demands are made. Reclassifiers are, therefore, more viable and, in addition, it is possible to restrict attention to only one class. However, the use of discrete classes rather than spectral values does decrease the amount of information available for a decision. In this respect, the use of raw data for the recognition of linear features and edges is distinctly preferable to the use of classified data.

The following section contains a further example of a pixel-based reclassifier combined with an object-based procedure.

#### TYPE II: OBJECT-BASED RECLASSIFIERS

A classified data set may be regarded as an arrangement of discrete objects of class $C_k$, where $k = 1, \ldots, N$ and $N$ is the total number of classes. Each object contains one or more connected pixels which have been assigned to the same class. The contextual arrangement of these objects can be used to reclassify them.

#### TYPE IIA: INTRINSIC OBJECT PROPERTIES

The principal intrinsic object properties are those of size and shape. A simple example of the use of such properties is where a pixel of class $C_k$ is considered to be present in one context if attached to $N_p$ other pixels of class $C_k$, and in another context if attached to $M$ other pixels of the same class where $M >> N_p$. Using such a method, objects can be classed on the basis of their size.

Reassignment of an object below a given size to whichever class forms the majority of its perimeter can be used to reduce classification noise (e.g., Kan *et al.*, 1975; Carter and Stow, 1979) or to smooth data for presentation at different scales (e.g., Davis and Peet, 1977). This technique of error correction coupled with a pixel-based reclassifier has been used to improve classification of urban land use of Reading, England, using Landsat data for June 1973 (Figure 7) (Gurney, 1981). Random samples of 400 pixels classed as urban and 400 pixels as non-urban were sampled for accuracy assessment. When a simple per-pixel classifier was utilized, the errors were estimated as being 19.6 ± 4.0 percent for the urban class and 15.5 ± 3.6 percent for the non-urban class at the 95 percent confidence level. Figure 8 shows the effects of applying an error correction procedure with a window size of 7 by 7 pixels, considering the central pixel only if it had been classed as non-urban, reassigning it to the urban class if at least 14 urban pixels lay within the local window. Subsequently, urban areas of less than 100 pixels in size were classed as non-urban, using the procedure described above, so that only major urban areas were retained. Error in the non-urban class was reduced to 5.2 ± 2.2 percent and in the urban class to 6.1 ± 2.4 percent. This is a significant change in error at the 95 percent level, illustrating the considerable improvement of classification that may be achieved utilizing such procedures.


FIG. 7. Classification of urban land cover of Reading, England, using Landsat data.

A pixel of class $C_k$ may be considered to have different contexts if attached to pixels $C_k$ which are arranged in different ways: in other words, the objects have different shapes. This forms the basis of syntactic procedures to identify linear features in classified scenes, where the local shapes of linear features are considered (e.g., Li and Fu, 1976; Lu and Fu, 1976). A global shape measure has been used by Carter and Stow (1979) to separate motorways from urban areas. Jackson *et al.* (1980) suggest the use of a shape measurement to distinguish fields which are usually rectangular, from urban areas of undefined shape, where the

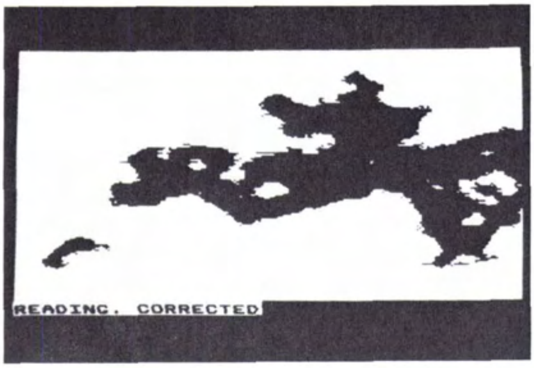


FIG. 8. Results of applying error correction procedures to the urban classification shown in Figure 7.

categories are tonally inseparable. However, accurate measurement of shape in low resolution data from current satellite data is hindered by imprecise definition of object boundaries. Moreover, in any data, the presence of classification errors will themselves obfuscate the shape of objects. Shape measurement will probably, therefore, prove to be a less common use of context than many of the other procedures discussed in this article.

TYPE IIB: RELATIONSHIPS BETWEEN OBJECTS

We can use three basic contextual relationships between two objects of different classes to improve classification, namely, whether they are adjacent, separated by a given distance and/or direction, or whether one contains another. If both objects have the same class, then clearly only the second property can be used.

In classification, it may happen that a proportion of the pixels are not assigned to any specific class, but are placed in an unlabeled class. In such cases, the unclassified objects may be assigned to whichever class forms the majority of the objects' perimeter. For example, Gurney (1980b) describes a procedure where objects initially classified as cloud or shadow were assigned to whichever land-cover class made up the majority of the perimeters. Recognition and classification of complete objects in this way avoids a large number of iterations through the data which would be necessary if the reclassification were carried out pixel by pixel.

The distance and direction between two objects can be used either to reclass one or both of the objects, or to reclass some other portion of the data. An example of the former is given by Brayer *et al.* (1977) to identify clouds and shadows in classified data. An example of the latter can be found in the interpolation of missing segments of linear objects or edges. Where two segments together have similar orientations and for which the missing segment would also have a similar orientation, then they can be assumed to be part of the same object, and pixels lying on the path between them may be reassigned as part of a linear object. Interpolation procedures of this type can be based on tracking a segment to its end, searching over a given area for a new segment, and then continuing (e.g., Bajcsy and Tavakoli, 1976). Alternatively, stored information about each segment's size, orientation, and position may be used (e.g., VanderBrug and Rosenfeld, 1978; Gurney, 1980a). Exemplification of this type of procedure is provided by its application to the results of the line detection (Figure 3), the results of which are shown in Figure 9. Following interpolation, segments less than five pixels in size were removed. The accuracy of the results has been significantly improved by this procedure, the change in error being 17.5 percent.

Reclassification of an object may also be carried out on the basis of whether or not it is contained within another object, For example, Brayer *et al.* (1977) used such considerations in identifying "commercial" areas. These were assumed to lie within the "downtown" area, so that any pixel classed as commercial which lies outside this area may be assumed to be in error and reclassification performed. Definition of the downtown area was by operator interaction rather than by relying directly on classified information within the data. In effect, such reclassification is relying on some form of hierarchical subdivision of the data (Fu, 1976). This type of approach is closely related to the decision-tree approach proposed by Wu *et al.* (1974) in which classification takes place at a number of sequential stages, possibly relying on non-remote sensing data at one or more stages.

## CONCLUSIONS

A wide variety of contextual classifiers and reclassifiers are available which can provide improvements in accuracy beyond those achieved by simple per-point classifiers. Despite the number of methods available, it is possible to categorize

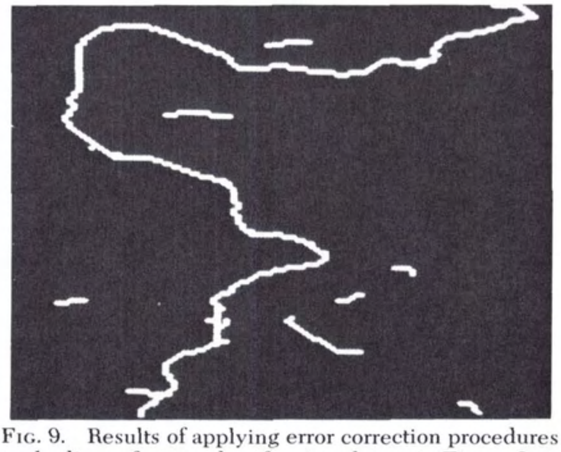

FIG. 9. Results of applying error correction procedures to the linear feature classification shown in Figure 3.

them into a relatively small number of types on the basis of the character of the context used. Relatively sophisticated contextual classifiers have been proposed based on extension of the maximum likelihood rule. However, it is possible to develop very simple contextual rules which can substantially improve upon conventional classifiers. Specifically, we have shown how contextual methods can be used in the classification of urban areas and the identification of linear objects and separation of cloud and cloud shadow from the remainder of a scene.

It is important to note that, although contextual information will often be of substantial value in classification, design and use of appropriate contextual rules is primarily dependant upon the analyst's knowledge of the spatial relationships actually existing on the ground and the on the relation between pixel size and object size within a scene.

Frequently, contextual classifiers and reclassifiers involve additional computation compared with simple per-point classifiers. In view of this, application of contextual relationships should usually be adopted only after there has been a preliminary classification of samples of the total data set, or if there is reasonable *a priori* knowledge of contextual relationships which can be exploited.

We have been concerned principally with the application of contextual methods to Landsat MSS data. Such methods are likely to be of even greater relevance in the future. There is clear empirical evidence that future satellite sensors, with their finer spatial resolving power, may not necessarily lead to improved classification when simple per-point classifiers are used (Townshend, 1981). This arises because of the higher internal spectral variability of classes, which becomes apparent as resolution becomes finer. For this reason also, simple pixel-based contextual reclassifiers may also be unsuccessful in such situations. However, full and successful use of higher resolution data from satellites such as Landsat-D and SPOT will rely on the appropriate application of classifiers relying on context.

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