SEMI-AUTOMATED LINEAR FEATURE EXTRACTION USING A KNOWLEDGE RICH OBJECT DATA MODEL

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ABSTRACT

This paper describes an approach to the extraction and classification of linear features from imagery using an object-oriented data model as a framework to store contextual knowledge. The work reported is the foundation of a three year project, funded by the UK Ministry of Defence, named Automatic Linear Feature Identification and Extraction (ALFIE). The project team comprises the UK Defence Evaluation and Research Agency (DERA), the University of Nottingham, and Laser-Scan Limited; DERA is leading the work. The research is driven from a requirement for rapid database generation for Synthetic Natural Environment (SNE) applications, although the potential for the research is not limited to these applications. The linear objects under investigation are described in detail in terms of the properties used to differentiate feature classes. The interrelationships between feature classes as observed in imagery are characterised in the form of a matrix. This will form the basis for an object schema that will allow contextual knowledge such as regional containment and the relationships between local neighbouring features to be modelled. The overall role of context in a strategy for geographical linear feature extraction is discussed and certain parallels made to approaches investigated in non-geographical domains.

1 INTRODUCTION

The work reported is the foundation of a three year project, funded by the UK Ministry of Defence, named Automatic Linear Feature Identification and Extraction (ALFIE). The project team comprises the UK Defence Evaluation and Research Agency (DERA), the University of Nottingham and Laser-Scan Limited; DERA is leading the work. The requirement for this research project was identified as a result of research into rapid Synthetic Terrain Database Generation. A prerequisite for this is the ready availability of suitable raw Synthetic Natural Environment (SNE) data (terrain elevation, feature and attribute data) for any area in the world that may need to modelled. Up to date and accurate source information at the required resolution is likely only to be available from remotely sensed imagery.

This offers a range of geographical information from regional contextual knowledge provided by low resolution multi-spectral imagery, to the large scale detail offered by digital ortho-photography and very high resolution satellite sensors. However, the abundance and detailed content of this imagery will remain inaccessible unless the information content can be readily extracted through automation. Tools to automate stages of the process of linear feature extraction from imagery are required. An approach to feature extraction is presented which uses an object-oriented data model as the framework to store contextual knowledge at a number of levels in an attempt to discriminate types of linear features and to reconstruct networks.

This paper considers the nature of the problem of extracting linear objects from imagery focussing on the use of contextual knowledge. The generic properties of the linear objects under investigation are presented which form the basis for defining the structure of an object schema. The interrelationships between objects are considered, to offer a framework for incorporating knowledge of the place within a scene of an object, in terms of both the context of its surrounding region and the local juxtaposition to other objects. Finally the role of context in an overall strategy for object recognition from imagery is discussed.

2 THE NATURE OF THE PROBLEM

The problem of geographic feature extraction has proved complex and may benefit from the incorporation of contextual clues similar to those used by human interpreters of imagery. Often feature recognition algorithms work at local levels, in a bottom-up fashion and lack the higher level control that would allow a more global understanding of parts of the image. The overall aim of the project is to extract vector linear map objects from imagery with a minimum of user intervention. Traditionally, the approach has been to adopt one or more algorithms, many of these employing local operators such as edge detectors alone to attempt to extract the linear components of the imagery. One aim of the project is to explore the use of more contextual information to aid the extraction and classification of linear features from a range of imagery.

Linear feature recognition has often been primarily concerned with pixel-based or region-based attribute-value representations, such as in Brown and Martin (1995), and Baraldi and Parmiggiani (1994). Linear objects are often represented in imagery by many pixels in width and as such their shape becomes dominant over the resolution of the raster image. However, not only is the radiometric character of pixels important, but the shape, dimensions and context become vital.

The extraction of objects from imagery is a problem common in other domains and is essentially a machine vision problem. Machine vision has been successful in non-remote sensing applications such as engineering but less common in remote sensing and GIS where, until recently, it has been limited to land cover classifications. Within the domain of engineering drawing recognition, object extraction can be very successful due in part to the high contrast and low noise of drawings on paper, but also because they are created by following an accepted code of practice, namely the drawing standards. Many of the same rules can be adopted by computer vision strategies. In the field of industrial object inspection the number of different object types under study is often limited and their shape and dimensions are predictable. Geographical objects do not conform to the rigorous standards of engineering drawings nor can the same assumptions be made regarding shape, size and orientation as with industrial inspection. The shape, size, orientation, complexity and reflective properties of geographical objects vary considerably, however some of the techniques and ideas applied successfully within other domains can be applied to geographical information. One idea crucial in other domains is the use of contextual clues such as the relationship between one object and its neighbours, or the containment of an object within a region. In the case of engineering drawings the containment of a linear feature within the linework already recognised as representing a machined part will, for example, limit the possibilities for labelling this linear feature. Also key features such as junctions with arrowheads are vital contextual clues which suggest that certain line types may be found connecting to these features. The role of similar contextual knowledge in aiding an object recognition strategy for geographical information, primarily linear features such as roads, railways and rivers, is the focus of this paper.

3 THE ROLE OF CONTEXT

3.1 Defining context

The ability of humans to recognise objects or parts of objects can be illustrated by viewing the images in Figure 1 from left to right. At the pixel level in the first image, it is difficult to identify the object, but as the view is widened then more 'supporting evidence' from the immediate context of the object is incorporated and so the object can be identified more confidently.

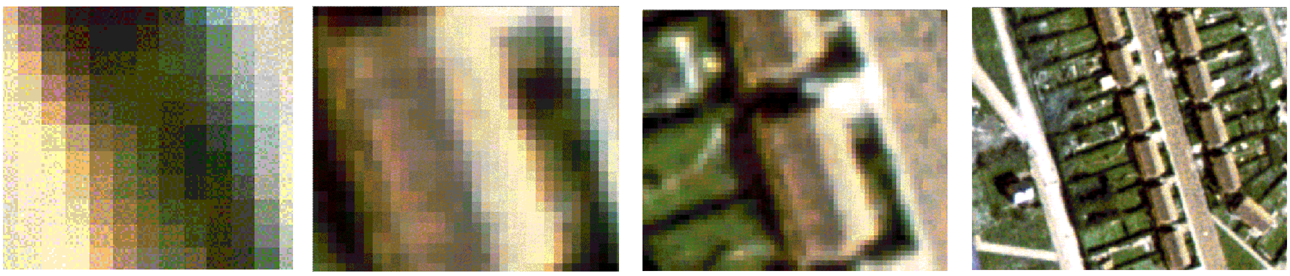
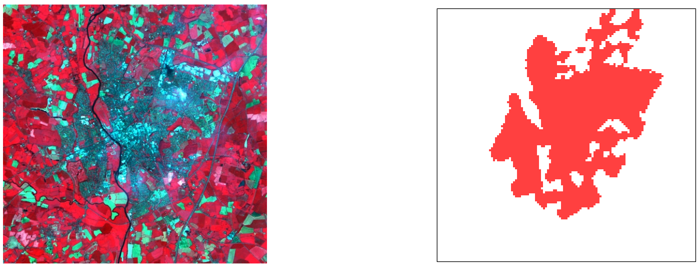


Figure 1. The introduction of context (© NRSC, 1996)

The word 'context' can be used in several different ways. One use of the word is to describe the existence of knowledge not only about the object of interest but also about other relevant facts and their relations to the object of interest. With respect to image analysis for example, every piece of information about the image (resolution, sensor), image conditions (viewing, lighting), object (geometry, radiometric properties, functionality), and relations between objects can be regarded as contextual information (Baumgartner *et al*, 1997). Tonjes (1998) describes a knowledge based approach for the interpretation of aerial images that combines context from multiple sensors (visual, infrared, SAR). The integration or fusion of the contextual information (regional classifications based upon different scales of imagery) from different sensors allows multi-resolution extraction schemes to be devised. The derivation of contextual clues of a spatial nature such as containment can be achieved using relatively coarse resolution multispectral imagery to reclassify the image into broad land cover regions, for example using the SPOT image in Figure 2 below. Here, the urban region has been classified. The characteristics of linear features within this region (roads for example) may differ from respective linear features in rural areas. If the rules defining these characteristics can be encapsulated for each regional context area, the identification and differentiation of linear features could be made easier.



SPOT XS Image
(© SPOT Image Copyright 1998)

Urban Context Region

Figure 2. Imagery suitable for derivation of regional contextual information

Spatial context can be considered at several 'levels', from the regional (above) to the more local, where the relationships between an object and its immediate surroundings become important. Baumgartner *et al*, (1997) discuss the general distinction between the different 'levels' of spatial context, using the terminology of context ***regions*** and ***sketches***. On a regional level three kinds of context regions are introduced: urban, rural and forest. Context regions can be defined or classified by segmentation and texture analysis. Results of texture analysis can be combined with other GIS data if available, for example urban boundary data sets. For each context region special relations exist between linear features and background objects. For example buildings are more likely to run near and parallel to roads in urban regions and shadows from trees are likely to affect forest regions. Background objects can therefore have a strong influence on the characteristics of linear features. Background objects on the one hand support and on the other hand hinder road extraction.

On a more local level, context sketches can be used to model the relationship between linear objects and neighbouring objects. Context regions and sketches may potentially be defined by any contextual clues used by humans when interpreting images. An example is the 'occlusion shadow' where a hypothetical road part is required to bridge the gap left by a shaded area. Another example can be seen in Stilla and Michaelsen (1997) where the local relationships between roads and linear groupings of buildings are discussed.

The ALFIE project considers the use of regional context both in terms of limiting the choice of acceptable feature recognition solutions and in effecting the parameters used by feature extraction algorithms. Local context, at the scale of the 'sketches' discussed above, is introduced in the form of a matrix of feature interrelationship rules. The co-operative use of other collateral information in a feature extraction strategy is discussed below.

3.2 Target imagery and collateral information

Despite the increasing number of remote sensing satellites currently in operation and planned for launch in the near future, there still remains a risk that the most appropriate imagery may not be available worldwide, for the specific area of interest. This may be due to cloud cover or simply that a particular sensor has yet to acquire data in the given region. As such, optimal and minimal target datasets have been determined. The minimal target dataset includes; 30m, 7-band multispectral imagery; 10m panchromatic imagery; and an elevation model at around 100m post spacing. This dataset is assumed to be available for all parts of the world and will provide the basic source data from which to extract linear features. The optimal dataset includes; 4m, 3-band multispectral optical imagery; 1m panchromatic imagery; and an elevation model at around 30m post spacing. In essence, the minimal dataset should allow major linear features to be extracted and the object schema populated to the object class level (see section 5), while the optimal dataset should allow the extraction of fine detail linears and allow the population of the object schema in its entirety. In practical terms, a mixture of these datasets is likely to be available. The key is to ensure that the extraction system has the capability to work within the bounds of these two target datasets.

As shown in Figure 2, the coarser resolution multispectral imagery (defined in the minimal dataset) will be useful for determining the urban/rural context regions. A further use will be the extraction of collateral information prior to the actual linear feature differentiation. Water, for example, is relatively straightforward to classify from multispectral imagery given its reflectance properties in the near infra-red. If fine resolution imagery is available, hedge lines and field boundaries may be extracted (for example by segmenting the image). These features, although not necessarily required for the final application, provide important collateral information in as much that if linear features extracted by the extraction algorithms can be confidently assessed as not being roads or railways, then the classification of the remaining linears becomes significantly easier.

4 CHARACTERISING THE OBJECTS TO BE EXTRACTED

The first step towards incorporating context, both at a regional and local level, is to characterise the objects under study, assigning properties which include both the typical shape, size and radiometric character but also any contextual clues which may be associated with a particular class of object.

The first stage is to define a generic set of feature properties and then to consider how these can be translated into rules for each class of feature under study. These feature classes will include not only those required in the final database but any other classes of feature which are deemed important for assisting the feature recognition process.

For extracting features from imagery the need to consider factors other than the spectral reflectance properties of the surface material alone has been clear. By attempting to incorporate more knowledge, techniques become less reliant upon assumptions based upon spectral consistency alone. By combining spectral character, with local geometry, and knowledge of how that geometry builds up into connected networks, a less local view is taken. Steger et al (1997) recognise the need to construct a topologically complete road network.

Vosselman and de Knecht (1995) characterised roads using five properties: photometric, geometric, topological, functional and contextual.

- Road surface is homogeneous (photometric)
- Road surface has good contrast to its adjacent areas (photometric)
- Roads are elongated (geometric)
- Roads have a maximum curvature (geometric)
- Roads do not end without a reason (topological)
- Roads intersect and form a network (topological)
- Roads are a means of communication between locations (functional)
- Roads may be indicated by a special distribution of trees (contextual)

The category of 'function' could be viewed as a contextual property but also as a feature of a topologically complete network. In working towards the definition of an object schema, a further property 'Confidence' can be included. This relates to the current 'belief' in a particular feature labelling in terms of the ***type*** of feature and the ***strength of belief*** i.e.: the confidence associated with that labelling. This property is potentially updateable continuously during the feature recognition process and would represent the current state of knowledge about one feature in the image.

Using a structure adapted from the broad categories defined by Vosselman and de Knecht (1995) the characteristics of linear features that will be used to discriminate between different feature types are described below. These characteristics contribute to the definition of object classes used to store properties and interrelationship information.

4.1 Geometric characteristics

Geometric rules regarding length, curvature, angle, orientation and density have been incorporated in most feature extraction studies in recent years, typified by Wang et al (1991). Geometric and photometric rules can be adopted by techniques which work on extracted vector primitives, or can operate 'on-the-fly' in the form of rule-bases and parameters built into road tracking (Grossman and Morlet, 1984) or line following programs such as VTRAK (Laser-Scan Ltd.). The geometric characteristics can be defined as:

- *Width:* of a linear feature segment, derived during pre-processing and carried forward.
- *Consistency of width:* the variation of width along the length of the feature.
- *Shape, size, and orientation*: the degree to which the feature is elongated. Orientation may be common to neighbouring roads in certain urban environments (for example gridiron street patterns).
- *Curvature*: sinuosity or fractal indices as discriminators of roads, rivers and railways, assigned to features in whole or in part. Typical expected curvatures vary in different environments and terrains.
- *Patterns:* such as junctions can be important clues relating to the interrelationship of features and can form triggers for spatial searches to complete portions of the network, especially like features comprising a network. Section 5 considers a range of junction configurations between different object types.

4.2 Photometric characteristics

Rather than being solely the typical reflectance characteristics of a linear feature pixel, this category provides a summary of the character of a feature along its length, in profile, and in comparison with its background. This could include any characteristic response to radar for example. Photometric characteristics include the 'average' spectral character of a feature, homogeneity, and the contrast with the background and the cross-sectional histogram.

4.3 Topological characteristics

This category includes the degree to which a linear feature is complete in terms of satisfying part of a network, and also the type of connectivity at junctions. Several approaches (including Wang and Trinder, 1998) have used the topology of a road network to reduce the number of false road segments and to give clues as to filling in the gaps (see 'completeness' below). Characteristic junction types (T, +, and Y junctions) can be used as triggers for searches to reconstruct segments of the network. Characteristics are:

- *Completeness:* an indication of the degree to which the road segment is connected. When combined with the length of the feature, this could contribute to methods of resolving imperfect continuity (Zlotnick et al, 1993).
- *Connectivity*: the type of connectivity and whether the road network segment is part of a 'legally' connected network. This is important both for network reconstruction and to differentiate roads from rivers and railways. Both completeness and connectivity will aid the re-construction of a topological road network beginning with road segments with the highest confidence values.

4.4 Contextual characteristics

Context is taken to mean both regional containment and information from the local area. Characteristics include:

- *Regional contextual environment*: the environment through which the linear feature passes or is contained, would effectively represent the regional context as supported by several multi-resolution approaches in the literature including Baumgartner *et al* (1997) and Tonjes (1998). These context regions could be conceptualised as being high level objects within which features are contained. They can be derived through a basic classification of urban / rural (extendable to woodland, desert and other land covers) areas.
- *Local contextual clues*: proximity to linear groupings of buildings could in many cases be important. Possible attributes of building classes include size, orientation, 'type', roof material, function (inferred from other clues), and alignment with neighbours (belonging to a string of building objects). Relationships between objects of the same class, for example the density and alignment of road features in urban and rural areas falls within this category.
- *Elevation profile*: overlaying linear features onto a Digital Elevation Model (DEM) will not only give estimates of gradient for sections of the feature but will allow trends in elevation along the whole profile of the feature which could be a useful discriminatory attribute.

4.5 Confidence level

This attribute represents the confidence which can be placed upon an object's classification at any particular time and which stores the degree to which the rules for a particular feature type have been satisfied. It will change as new clues to confirm or deny a classification are derived, although an initial allocation of a confidence level based upon geometric and photometric properties will be important in prioritising the later network building stage.

5 BUILDING AN OBJECT MODEL

Having defined the properties of different classes of object, an initial Object Database Schema has been created, identifying the need for methods attached to particular classes to derive many of the local contextual and geometric properties. The desire to incorporate context requires object interrelationships to be studied and represented. This results in the need for extended topology and the use of object classes to store junction information.

An object schema has been devised which defines the classes and associated attributes of both the linear features of interest, and of other features that provide important collateral information. At the highest level, two base classes are defined; 'unknown line' and 'known line'. Initially, the results of the linear feature extraction algorithms will populate the unknown line class. The aim then will be to move the lines from the unknown class to the relevant known class based on the rules associated with that class. Figure 3 shows the basic schema together with an example for a road object.

Base Class → (Known Line)
Object Class → (Road)
Sub-Class → (Motorway)
Geometric Attribute → (Centreline, width)
Non-geometric attribute → (Number of lanes, surface material)

Figure 3. Object schema and example categories

Junction features will hold vital network topology details and can form good starting points for searches to complete linear segments and begin growing the network. This section discusses the interrelationships between objects and how they might help define local contextual rules (which in turn can be influenced or constrained by the regional context in which an object finds itself). In addition to the rules for an individual feature in terms of its geometry and other properties, the spatial relationships between different feature types can be summarised, as in Table 1. These feature interrelationships relate to the context sketches described earlier (Baumgartner *et al*, 1997). Furthermore, many of these rules for interrelationships benefit from the knowledge of containment within urban or rural context regions as highlighted by comments within the matrix, for example, single carriageway roads often display near parallel grouping within urban regions.

	Railway	**River**	**Motorway / Dual C-W**	**Single Track Road**	**Tree line**	**Building Line**	**Hedge Line/ Field Boundary**
Railway	Rounded junctions, low curvature. Near parallel only in urban (goods yards)	Independent, often near-normal bridging or tunnel	Independent, often near-normal bridging or tunnel	Independent, often near-normal bridging or tunnel	Near parallel in urban, weaker in rural.	Near parallel in urban, weaker in rural.	Near parallel with feature, particularly in rural. Forms edge of field. 'T' junction more common than cross.
River		Often 'Y' junctions elevation profiles of rivers at juncs may resolve direction	Pass ***under*** motorway, usually normal	Pass ***under*** motorway, usually normal	Vegetation follows river often close and near parallel, often obscuring river line	Occasional near parallel grouping but set back unless channeled in urban area	Near parallel, less likely to obscure but still possible with trees in hedge. Hedges normal to river lines common.
Motorway Dual Carriage - Way			Distinct junctions large roundabouts with slip roads	Largely independent of single track roads, crossings often normal	Few parallel tree lines but near parallel forest edge set back	Few parallel linear groupings of buildings in rural;	Possible near parallel hedge line set back. Normal hedges less common.
Single track road				Many types of junction but 'T' and '+' junctions common. Near parallel roads in urban	Occasional near parallel tree lines especially in rural. Can obscure road.	Near parallel groupings of buildings in both rural and urban.	Occasional near parallel and proximal hedge line in rural regions. Normal hedge boundaries common.
Tree line					Largely independent	Occasional near parallel esp. in urban (boulevard)	Mixing possible. Quite difficult to discriminate
Building line						Near parallel groupings in urban. Often road ìnferred' between two rows of buildings	Largely independent although occasional near-parallel pairs
Hedge line / Field Boundary							Topology similar to roads T and + junctions common. Proximal near parallel pairs rare

Table 1. Matrix of linear object inter-relationships

6 THE PLACE OF CONTEXT IN THE OVERALL STRATEGY

The role of contextual information is seen to be important at several levels. Firstly, by classification of medium resolution multi-spectral imagery, a simple set of context regions based upon broad land cover categories can be produced. Polygonised versions of these regions form objects in the hierarchy and can be used to allow containment of objects within them to be represented. The degree to which the choice of linear feature extraction algorithm, at least the associated parameters of an algorithm, is influenced by the context region, is under investigation. Vector primitives extracted from the imagery can be given an initial attribution based upon geometry, photometric character, topology (presence of junction) and contextual clues based upon containment in a region and elevation profile information if available.

As a result of the initial feature attribution, confidence levels would prioritise a cycle of further labelling and network building. Starting with high confidence features such as strong 'T' junctions for example, linear segments can be followed, initiating spatial searches to gain further local contextual clues and to bridge gaps in linear features.

Figure 4 shows how a similar search triggered by the presence of high-confidence junction structures is implemented in an engineering drawing application (Priestnall et al 1996). Here the search is initiated at A, detects contextual clues at B (in the form of characters), bridges gaps C-D and terminates at another junction, E. The search continues from this junction. All entrant lines to junctions are automatically placed on a 'stack' and are visited later.

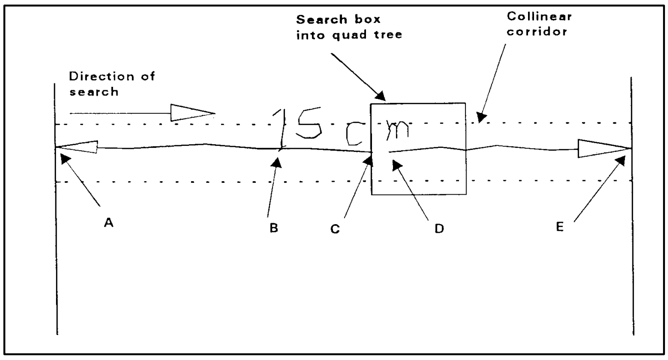


Figure 4. Feature labelling of vector primitives triggered by confident junction

Gaps are bridged by following broken segments along a 'collinear corridor' although here there is a strong expectation that the lines are straight. For geographical linear features the bridging of gaps using a 'least cost path' algorithm or a snake operating on the underlying imagery could be considered. When applying the approach outlined in Figure 4 to satellite imagery several possible local solutions may exist and the use of sequential operations and 'hard' thresholds should be avoided.

Figure 5 illustrates a re-working of Figure 4 applied to geographical data using an equivalent numerical labelling scheme. In this case junctions are still the trigger, although their detection relies more upon the intersection of linear features of a certain character rather than the presence of clues as with the arrowhead in the engineering example. As features may constitute several broken segments at first, the properties described in section 4 will have to be recalculated for newly 'merged' features through an amalgamation of the attributes of the input feature segments. The confidence level of each object should be dynamically updated. The junction objects will hold information regarding the types of linear features and the angles of entry and can effectively store the information to enable the category of object relationship to be evaluated.

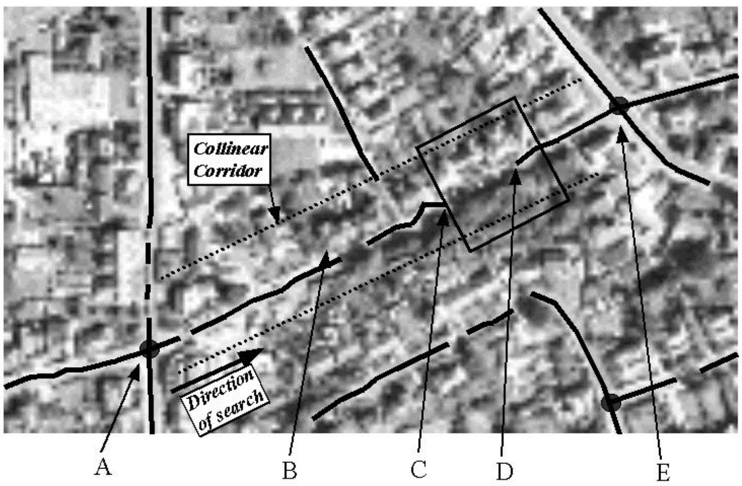


Figure 5. Use of junctions applied to the extraction of geographic objects

7 SUMMARY AND CONCLUSIONS

The general concept of context has been discussed. The co-operative use of medium and high resolution imagery is seen to offer an effective mechanism for deriving context at a number of levels. These include regional land cover units used to influence object extraction and guide the expectations of the type and interrelationships of objects found in these regions. Local context, in the form of rule-based object interrelationships, have been detailed. The use of an object oriented data model offers the necessary flexibility of structure to allow both object properties and their interrelationships to be stored. Both the contextual knowledge and the functions necessary to extract such contextual knowledge can be associated with object classes and offers a powerful framework for developing a feature extraction strategy.

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