The Characteristic Errar Apprmch to Conflict Resolution

Richard D. Ferrante

The Analytic Sciences Corporation
One Jacob Way
Reading, Ma. 01867

ABSTRACT

Conflict resolution is the process of reaching a decision using the opinions of multiple knowledge sources as input. It integrates two closely related concepts: reasoning about uncertainty and constraint propagation as applied to problems involving knowledge integration. This paper introduces the concept of characteristic error conflict resolution which is unique in treating each knowledge source as a separate entity whose validity b determined only from the information the knowledge source itself provides. The advantages of characteristic error conflict resolution are that the knowledge sources themselves provide the information necessary to determine the current context of the conflict and that the outcome of the resolution process is dependent only upon this locally determined context. This leads to an easily extensible generic approach to conflict resolution.

1. INTRODUCTION

Conflict resolution b the integration of alternate opinions about the state of the world into a single coherent world view. This operation b often performed by a separate entity (knowledge source) specifically designed for thb purpose. For example, a system which performs surface material classification in a remote sensing application may encounter conflicts when knowledge sources have differing opinions about the most appropriate classification of a given region. Remote sensing experts attempting to resolve these conflicts may employ such knowledge as 'the spectral signature of a road may have been shifted due to the presence of vehicles or an oil slick on the surface[9] or 'a portion of the road may have been obscured by trees'. Their approach to conflict resolution therefore consists of evaluating the classification errors which are most likely to occur in the given context.

Conflict resolution has been treated by a number of different authors who use various techniques and terminology such as reasoning about uncertainty or 'the integration of knowledge from disparate sources ' (4} Most of thb work takes a numeric approach to conflict resolution using, for example, Bayesian or Dempster-Schaefer techniques [5]. However, Bayesian techniques assume the ability to generate *a priori* a table of conditional probabilities (i.e. the probability of A given B), and only allow the source to posit a single probability at a time. Dempster-Schafer techniques, on the other hand, while allowing multiple beliefs, assume that all possibilities are independent, an assumption not often satisfied in reality. Other approaches to conflict resolution represent a more semantic knowledge-based approach and do not rely exclusively upon a numeric algorithm to resolve conflicts. Examples of these approaches include Cohen's theory of endorsements [2] and Tenenbaum and Barrow's Interpretation Guided Segmentation [6]. Even these approaches however, exhibit some limitations. They lack extensibility, function in limited domains and require either extensive preprogramming or interactive assistance for operation.

Thb paper describes a technique for conflict resolution (termed the characteristic error method) whose goal b to capture the reasoning process behind thb form of conflict resolution. Characteristic error conflict resolution integrates two closely related concepts: reasoning about uncertainty and constraint propagation. Reasoning about uncertainty determines the relative validity of beliefs, while constraint propagation uses the presence of contradictions to restrict the range of applicable choices. The characteristic error approach b unique in treating each individual knowledge source at a separate entity whose overall reasoning validity may be entirely self-determined. In other words, the knowledge sources themselves are assumed to provide all of the necessary information for the system to successfully resolve the conflict (given the local context).

2. THE CHARACTERISTIC ERROR APPROACH

The term characteristic error was chosen with the realization that certain error conditions are 'characteristic' of the environment in which the knowledge source expects to operate. Conflict resolution based upon the characteristic error paradigm uses knowledge-based semantic information, that is, information which b normally tacitly assumed by the expert during the knowledge acquisition process, both to develop the context for a given situation and to resolve differences of opinion. Thb b possible because information about characteristic error classes enables the resolution of a specific conflict to be dependent upon the Immediate context of the problem.

Characteristic error b based upon the idea that, within a multi-source system, each individual knowledge source is, to tome extent, the best judge of its own performance. The motivation for thii becomei apparent if one considers the factors which are normally embedded in the process of developing any given expert system:

- The knowledge of the context in which it expects to operate; i.e., an expectation of the form which the environment will take and the types of interrelationships that may occur.
- The type of boundary or limiting conditions it expects to encounter; i.e., what information can occur in the environment which is close to what is expected but is actually different.
- The type of misclassifications it postulates can occur; ie., what information may be present in the environment that is often confused with the desired information.

Implementing the concept of characteristic error requires that each knowledge source posit an *a priori* estimate of the error classes which it might encounter. This estimate is an explicit ranking of its expectations for the immediately local context, and is independent of the strength of the knowledge source's opinion in any particular instance of its application. It to based only upon the expert's knowledge of the underlying structure of its environment and decisions. For example, a region growing knowledge source, designed for road finding within an image understanding system, will know that local classification error may occur because a portion of the road may be partially obscured by trees. By the same token, it will also be aware of the fact that it is very uncharacteristic for any region designated as deep water to actually be a road. The same source will, however, have no real opinion as to the likely misclassification of shallow water. These considerations are independent of its specific belief of the existence of roads in any particular instance.

This error class information is dependent only upon the context *assumed* by the knowledge source. It is independent of the *actual* context of any particular instance in which the knowledge source is utilized. In other words, the knowledge source's characteristic error list explicitly states the context which was assumed to be part of the underlying structure of the environment during knowledge acquisition. Therefore, no *a priori* controls need be imposed upon the overall system using the knowledge source, since all context information is explicitly stated by the knowledge source itself.

To illustrate these points, Table 1 shows the structure of two road finders. The road finder which anticipates being called upon to process satellite information might expect partial road covering by treetops. The ground level road finder on the other hand, has no expectation of such a conflict.

Such *a priori* identification of errors also promotes the graceful performance degradation of a group of knowledge sources, if and when any knowledge source is operating outside of its area of expertise. A source operating in an unfamiliar area should not have the conflicting class appearing anywhere in its characteristic error list. This absence serves as an immediate flag for the conflict resolver to investigate the situation further.

The minimum implementation of the characteristic error technique requires the following information:

- The characteristic *a priori* errors expected to be encountered by the knowledge source in the environment
- The knowledge source's strength of opinion in a particular instance
- A methodology for evaluating the error list and determining the context.

The system works by comparing the characteristic error lists of the conflicting knowledge sources. This determines the conflict's local context. This context is, in essence, an indicator of the similarity and structure of these error lists. The implementation is such that similar error lists create a context controlling the relative strength of opinion necessary from the knowledge sources to alter a decision. For example, if all sources agree that a given error is characteristic of the situation, it will not take a large (absolute) opinion strength to shift the decision in another direction. By the same token, if the context is relatively incoherent, a knowledge source's opinion must be stronger for the opinion to change. The interaction of these two factors is the basis for the implementation of the most likely error approach.

The items listed above serve as bask information for knowledge (rule) based management of the conflict. However, given the existence of a central (top level) conflict resolving system, additional rule based manipulation is possible. The rules used for this manipulation/management of the conflict will be specific to a given system, and perhaps even a specific instance of its use. It should be noted that these manipulations

* Sidewalks would not appear oa the overhead expert due to lack of resolution

Classes for structural knowledge sources				
Knowledge Source	target class	characteristic error	uncharacteristic	neutral
ROADS (overhead)	concrete asphalt	oil-slick tree-tops	deep water	shallow water patchy snow
ROADS 1 (ground)	concrete asphalt	oil-slick tires	deep water sidewalks*	shallow water patchy snow 1

Table 1: Knowledge source structure.

require no overall ranking of the knowledge sources in the system. Their general thrust is to drive the system results in a specific direction thereby establishing a strategy for the system. This strategy embodies more general criteria i.e. always err on the side of caution. Strategy setting is implemented by moving error terms from characteristic to uncharacteristic or neutral, thereby altering the source's *a priori* opinion toward this error type.

3. AN APPLICATION OF CHARACTERISTIC ERROR

This section presents an example application of the characteristic error concept. The focus of our application is TASC's Multi-Spectral Image Analysis System (MSIAS) [3]. MSIAS is a knowledge-based system that interprets cartographic surface attributes using information obtained from remotely sensed imagery. The MSIAS classifier utilizes the relative spectral signature of an individual pixel location (i.e., its relative intensity in various spectral bands), to determine its surface material class eg. concrete, vegetation, water. Conflicts will only occur when new knowledge sources, using other criteria, are introduced into the system. These knowledge sources may start with the latter spectral identification, but may base their own classification opinion upon some alternate criteria (e.g. structural measures). The important feature of these knowledge sources is that they use the same initial information (the spectral classification), but apply independent criteria to obtain their individual results. These results generate alternate possible classifications for any given pixel/region. In the example below, alternate classifications represent the conflicts. The process of obtaining a final classification is conflict resolution. Using the nomenclature of Clancy [1] this is a problem of heuristic classification.

It is planned that the conflict resolver will be activated late in the image classification process. The late activation occurs because a number of different knowledge sources must be polled for a conflict to occur. Conflict resolution is only applied to those objects which are the subject of conflicting opinions. The frequency of these conflicts will increase as the semantic level of the program increases. That is, the use of the resolver will be lower, on a percentage basis for pixels than for regions. Upon activation, the resolver first looks at the pixels/regions* immediately adjacent to the one currently under investigation and searches for other opinions as to this pixel's classification. Every adjacent pixel b marked with both a specific classification and characteristic error list. The list summarizes the characteristic error classes posited by the knowledge source which identified it. This information serves as the basis for conflict resolution, attempting to address such issues as:

- How do the other conflicts and their characteristic error classes relate to the identification of this pixel?

* Although the term pixels will beused for the remainder of the dis-OMSJOO, the process applies equally to regions.

- Do they reinforce the current designation or contest it and in what way.
- The error classes may also be completely mute about this possible pixel classification.

As shown in Figure 1, a pixel can have up to eight nearest neighbors in a digitized image.

Pixel layout		
1	2	3
4	x	5
6	7	8

Figure 1: Pixel Locations.

There are two extreme cases for the possible opinions of these neighbors: First the original pixel classification (at x) may be a member of the "uncharacteristic* error class of each and every neighboring pixel; second, the pixel's class appears in the "characteristic" error class of all neighboring pixels.

In the first case, the conflict resolver would not, under any circumstances, alter the pixel's classification, as as all of the knowledge sources agree that it is unlikely that this pixel is misclassified. Therefore, even if all knowledge sources felt that their regions were worthy of extension, no regions would be extended as they all have preagreed to abide by this pixel designation. That is, they have all agreed that an "x" class pixel is both something which they expect to see in the environment and something which could be a boundary of their regions. This corresponds to the general case in which an expert would say "I use x as an indicator of this condition, y is an indicator of an other condition, x and y are rarely confused".

In the second case however, the conflict resolver will change the classification of this pixel to the competing class with the highest relative likelihood (opinion strength). Such a change will occur even if the relative likelihood is fairly low in an absolute sense. This is because there is complete agreement that initial misclassification of this pixel is often characteristic of the situation. This corresponds to the general case in which an expert would say "I use x as an indicator of this condition, however y is often confused with x, so if you have doubts about y you may also use it as an indicator".

Fundamentally, the characteristic error paradigm gives one a methodology for joggling cases intermediate between these two extremes. For example, for seven neighbors to agree b less strong a case than all eight, or if one has the class on its uncharacteristic error list it can possibly be excluded.

There are three basic ways of performing this integration. The simplest method merely tabulates frequency of appearance for the pixel class in question, combines the two frequencies (characteristic and uncharacteristic) and decides to go with the highest combination of relative frequency and opinion strength.

This is t relatively simple approach with weights being heuristically determined.

The second approach judges the relative coherence of these opinions. For example, if three divergent region types had found that the class in question was on their characteristic error list, it is a stronger case for misclassification than if a single type of region had reached the same conclusion three times. This approach attempts to compensate for systematic bias on the part of the experts.

The third method which might be considered involves merely discounting the opinion of any region having this class on its uncharacteristic error list. This is however not a valid method as in such a situation a region is actually giving a strong vote for retaining the current classification.

The characteristic error paradigm allows the extraction of information about the characteristics of the knowledge source itself. First, it is important to recall that although we have been discussing three classes there actually are four specific class lists in existence. The fourth class being the class(es) for which the structural knowledge source (region grower) was actually designed. For example, a road grower would have concrete/asphalt in this class, some other examples appear in Table 2.

The characteristic error class is a group of pixel identifications in which one would expect an error to occur in the environment As shown in the table, if one was growing highways, it would be expected that some road areas may have been misclassified due to overhanging trees, oil slicks etc. The 'uncharacteristic* error classes are the ones which are expected to form a hard boundary between the given class and an alternate. These would be such classes as deep water and rock for roads. Neutral classes are classes which may exist in the expected environment but about which no intelligent statement may be made i.e. very shallow water, patchy snow for roads etc.. As was discussed in section 2, manipulation of this list can be a significant action in and of itself and may also serve as an ideal place for changing context. For example, if we know that an area had recently been flooded, we would move shallow water to the characteristic error set for all km lying classes.

The explicit designation of the classes expected to occur in the environment has a very useful side effect: It is now possible to determine that a knowledge source is operating outside of its area of expertise. For example, an airport hangar area grower would expect fuel storage tanks appearing next to it as a hard boundary. The highway expert, on the other hand, would not expect such a structure in any immediately adjacent pixel*. Fuel storage tanks would therefore not appear anywhere on a highway grower's, list of error classes; not in •characteristic" "uncharacteristic" nor in 'neutral". Therefore if the conflict resolution process retained the storage tank classification, the conflict resolver would disregard the results of the highway finder in the abutting region. It would then try to find alternate explanations of the region/pixel which it had designated as "highway*, by eliminating the highway designation and asking for alternate opinions.

* All error classes pertain to the characteristics of immediately adjacent pixels/regions.

4. CONCLUSIONS/FUTURE WORK

The characteristic error paradigm allows for other types of contextural and programmatic information to be easily added to the system. For example, if it were very important to catch the existence of highways in a particular application, we would move more classes into the highway grower's •characteristic* list. These actions alter the relative "push" given to a particular classfication and can substantially alter the final characteristics of the classified image.

This paper presents a unique means of combining the opinions of divergent experts in a uniform manner using only their own a priori knowledge about their own characteristics. The characteristic error method is a planned enhancement to the MSIAS system. It is planned that the upgraded MSIAS will serve as the testbed for this technique, after it is given the ability to evaluate structural information.

ACKNOWLEDGEMENTS

The author wishes to thank M. J. Carlotto, J-M Pomarede, and V. T. Tom for comments on earlier drafts of this paper. Discussions with L. A. Staub and RA. Upton were invaluable in refining the concept of characteristic error.

5. REFERENCES

1. Clancy, WJ., "Clarification Problem Solving" *Proceedings of the National Conference on Artificial Intelligence* 1984.

2. Cohen. P.R "Heuristic Reasoning About Uncertainty: An Artificial Intelligence Approach" *PhD. Thesis Stanford University,* Stanford Ca. 1983.

3. Ferrante, R.D ., Carlotto, M J . , Poauurede, J.M Balm, P.W., "Multi-Spectral Image Analysis System" *IEEE Conference on Applications of Artificial Intelligence* December 1984*

4 Garvey, T. et al "An Inference Technique For Integrating Knowledge From Disparate Sources* *Proceedings Of The Seventh International Joint Conference On Artificial Intelligence.* Vancouver, British Columbia, Canada.

5. Shafer, G. *A Mathematical Theory of Evidence* Princeton University Press, Princeton, New Jersey. 1976.

6. Tenenbaum, J.M., and Barrow, HG.,, "Experiments in Interpretation-Guided Segmentation" *Artificial Intelligenet* Vel s pp. 241- 274 1977.