Generating approximate concepts for the UAV

Marcin S. Szczuka
Institute of Mathematics, Warsaw University
Banacha 2, 02-097 Warsaw, Poland
szczuka@mimuw.edu.pl

Abstract

In this paper we describe the issue of generating approximate descriptions of objects for further use with precise (crisp) reasoning methods. The reasoning methods are devised in such a way, that they take into account impreciseness of underlying rough-set-based descriptions. The knowledge is represented in the form of rules. The idea is exemplified with problems coming from WITAS UAV project.

Keywords: Approximations, Rough Sets, decision rules, transducers, UAV.

1 Introduction

The goal of the WITAS[1] project (see [1, 9]) is to construct methods that allow for autonomous control of intelligent systems. In the present phase the project encompass, by the end of 2003, construction of autonomous navigation system for Unmanned Aerial Vehicle (UAV). This airborne vehicle (mini-helicopter) will be equipped with various sensors such as video camera, inertional and satellite positioning systems that allow it to gather knowledge about environment it operates in. It will also have access to pre-stored sources of knowledge such as Geographical Information System (GIS) and it will be able to incorporate knowledge communicated remotely by operator (via radio).

Needless to say, construction of such system is a multi-fold and complicated task. In the paper we address only a small piece of the puzzle. We are concerned with the methods for extracting elements of knowledge from data in a way that permits their further storage in knowledge representation structure as well as utilisation as a building blocks for higher level concepts (as described in [2]).

The overall process presented in this study comprises of several steps leading to recognition of situation underneath by the UAV. It starts with assessment of measurements using sensors. These measurements undergo preprocessing resulting in formation of information system (or decision table) that is further investigated using rough set techniques. The result of rough set phase is a set of rules depicting some basic properties of data objects.

From the point of view of rough set techniques the task of rule generation is a standard one. However, in this particular problem the rule-generating mechanism have to be prepared to fulfill some specific demands including ability to cope with relations defined for collections of objects and robustness.

The paper starts with recall of some basic notions from rough set theory that are further used. Then the general outline of knowledge representation and processing structure is presented. The requirements for rough set techniques are formulated. Some examples are provided to extend intuition.

[1] Wallenberg laboratory for research on Information Technology and Autonomous Systems located at Linköping University, Sweden

2 Basic Notions

We will further use few basic notions from Rough Set theory so, we briefly recall them here (see [5, 4]). Given an information system $\mathcal{A} = \langle U, A \rangle$ and subset of attributes $B \subset A$ for arbitrary $X \subset U$ we have:

- $\underline{B}(X)$ is a B-*lower approximation* of X,
- $\overline{B}(X)$ is a B-*upper approximation* of X,
- $BN_B(X)$ is a B-*boundary region* of X consisting of objects belonging to B-upper, but not to B-lower approximation of X,
- $U - \overline{B}(X)$ is an *outside region* of X relative to B.

The *accuracy of approximation* is defined in terms of the coefficient:

$$\alpha_B(X) = \frac{|\underline{B}(X)|}{|\overline{B}(X)|}.$$

We will also reference to other fundamental rough set notions as: decision table, reduct, indiscernibility etc. Further in the paper we will consider only the decision tables with binary decisions.

We will frequently make reference to minimal decision rules. A decision rule is a formula r_i of the form:

$$(a_{i_1} = v_1) \wedge \ldots \wedge (a_{i_k} = v_k) \Rightarrow d = v_d$$

where $a_{i_j} \in A$ for $j = 1, \ldots, k$ and $v_d \in \{0, 1\}$. The rule is said to be minimal with respect to the set of labelled examples (decision table), if removal of any condition in antecedent decreases ratio of cases correctly classified by the rule. In other words, a minimal rule cannot be generalised without loss of prediction quality.

3 Knowledge representation and processing

The main motivation for the approach presented in this paper is the type of knowledge representation and processing infrastructure that is currently being developed in the context of WITAS project. This methodology is in the state of investigation and development. Interested reader is kindly referenced to [2] and [3] for detailed descriptions.

To briefly sketch the idea behind considered approach let us bring a simple example. Assume we are able to identify moving objects, in particular cars, with corresponding speed and direction, in the video stream coming from UAV's onboard camera. In some part of the frames we notice objects (cars) being close to each other. Given a sets of attribute measurements for these frames we may construct a decision table that stores positive and negative examples (pairs of objects) for the concept of *close*. From this set of positive and negative examples we construct lower and upper approximations of our concepts of being *close* and *not close* with respect to different subsets of attributes. To express these approximations we use corresponding sets of certain and uncertain minimal decision rules. For example we may have decision rules:

- *if distance is less than 5 meters then they are close* - a certain rule describing lower approximation.
- *if distance is more than 5 and less than 9 meters then they are close* - an uncertain rule describing upper approximation.
- *if distance is more than 9 meters then they are not close* - a certain rule describing outside region.

The knowledge representation with use of so called *Rough Knowledge Databases*(RKDB) is proposed in [3]. RKDB extends the notion of deductive database to the case where relations in the database are defined with use of rough sets. The problem of querying such database is in generic case overly complex but, fortunately, a sufficiently large subset of queries can be catered efficiently. The RKDB is able to store approximate concepts and provide on-demand description of approximations.

The main use of RKDB described above is as a knowledge repository and *engine* for constructing a higher level knowledge out of basic components. Following our previous simple example, we may be for instance interested in constructing a conditional formula (rule) describing more compound concept of *overtake*. Such a formula may look as follows:

if two cars are close and driving side-by-side and one have higher speed then there is overtake

If we assume, as previously discussed, that it is possible to extract the approximations of *close*, *side-by-side* and *higher speed* then we may attempt to generate approximations of higher-level concept of *overtake*. To perform such a composition the idea of *approximation transducer* was introduced in [2]. Such a transducer takes as inputs upper and lower approximations of basic (simple) concepts and produces higher level concept expressed as a pair of approximations. The mechanism for inference with use of approximation transducers and RKDB's is tractable as shown in [2]. Such transducers may be combined into approximation providing means for construction of high-level knowledge.

It is worth mentioning that the idea of using approximate description of basic concepts to create more compound ones is closely related to investigations in granular computing and to ideas present in rough mereology (see [6, 7]). We should, however, stress the fact that in the presented stage only the concepts are described approximately, while inference mechanism is defined in strict, logical way. Therefore, there is no "quality assurance" in inference mechanism as postulated in rough mereological approach. The present state may be viewed as a combination of approximate/rough and crisp knowledge.

4 Rule retrieval

As stated before, the mechanism for constructing approximations of higher level concepts from basic ones is crisp. This feature impose several possible restrictions when it comes to induction of rules describing those basic concepts. First off, the set of attributes used to describe approximations of a given concept should be uniquely defined, since transducer inference mechanism does not allow for ambiguity in this respect. Secondly, the size of description (number of rules) should not be excessive. The requirement of compactness is important and possibly hard since most of the attributes in the data is expected to have numerical values. Therefore, unavoidably, the rule generation algorithms will have to coupled with efficient discretization/grouping methods (see [4]).

The general requirements for approximations (rules describing them) may be formulated as follows:

- **Quality of approximation**. The relative quality of approximation may be important factor. If the concepts are defined in the crisp way then their derivatives obtained with use of transducers are crisp as well, which may cause the whole construction to collapse in presence of noise. The desired situation is that of having relatively small but not empty boundary region. That allows for, on one hand, flexibility and fault-tolerance, on the other hand, sufficient precision and validity of the learned concepts. One may think of applying the measures such us approximation accuracy in the process of rule generation. Other approach to keeping control over the shape of boundary region is by using parameterised approach such as *variable precision rough set* concept (see [8]).

- **Robustness**. The produced rules should be, to the largest possible extent, invariant to noise and distortion. It means that we should take care of their generality during generation process. This is a strong motivation for using several techniques to avoid overfitting. Train-and-test, bootstrap or cross-validation, to name just a few, may be used for that purpose.

- **Compactness**. The call for a proper choice of attributes to be use in approximation calculation sounds quite natural in rough set context. The number of attributes used should be possibly small and the attributes themselves should have simple structure (e.g. few possible values).

The importance of proper choice of attributes appears in one more context when it comes to processing of data from video stream. The active vision platform of UAV processes raw image data producing higher level features (attributes). The vision subsystem is capable of performing a number of different operations aimed at e.g. object detection, velocity estimation or filtering. However, it is not possible to perform all of them in the real-time system. Also, some of the image processing methods are constrained by results of previously applied ones. Since the learning of rules is done off-line, we may use computation-intensive methods to retrieve best possible set of attributes. However, at the same time, we should retain the information about attribute availability. Classical rough set methods, since they are concerned with discernibility, tend to treat attributes uniformly. In the practical case of UAV we will have to incorporate knowledge about cost of attribute retrieval. This can be done, in the simplest case, by attaching the weights to attributes and using weighted performance measures during rule generation. In general case, one will also have to consider various constraints bounding the attributes obtained by means of vision library functions. Some of the operations, for instance, are changing significantly the original image so, they should not be performed before some other that are meant for raw data.

5 Examples

We have started initial experiments utilising the presented approach. We bring here two basic examples that are meant to illustrate the kinds of tasks we are dealing with. First of them is based on simulation data, the other, on data coming from actual video stream.

One of initial tasks in WITAS project was to construct a simulation environment for experiments. Since the work on UAV prototype runs in parallel with development of methods for its control, the working experimentation framework was an imperative to avoid chicken-and-egg situation. At the current stage we are able to collect large amounts of data from simulations. In figure 1 we show a simple representation of simulation involving five cars moving in the road system. The underlying road system represents a fragment of actual road system of the area, where UAV prototype is being tested. In this example we use attributes such us car (centre) position and velocity vector (2 dimensional) are taken into account. Notice, that if we want to approximate concepts such as closeness of two objects (cars) we have to consider pairs. This increases significantly the size of data. Even for a simple example of five simulated cars we have to consider 10 objects having 8 continuous attributes at each time step (each 0.1 sec.). That fact justify the call for efficiency of rule generation formulated earlier. In this example all measurements (attributes) used are instantly available and there is no additional cost connected with their gathering. Therefore, this example is well suited for testing the behaviours of essential approximation construction mechanisms in clean-room-like conditions.

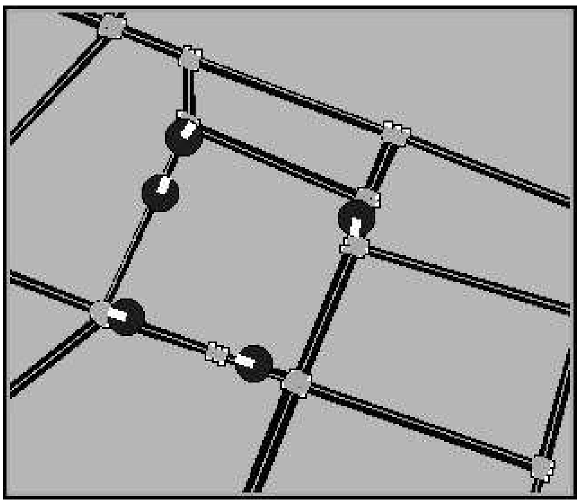

Figure 1: Example of simulated environment.

The second example is meant to provide general idea of the quality, or rather a lack of quality, in actual data. Figure 2 shows a fragment of image from camera. The magnified fragment in top-left is a part of image which is interpreted as an upper approximation of moving object (car). Obviously in the UAV system such an image will not be feeded to learning module "as is". It will undergo image processing phase first. The idea is to identify the set of attributes that will be at the same time easy to calculate and effective in classification/recognition tasks.

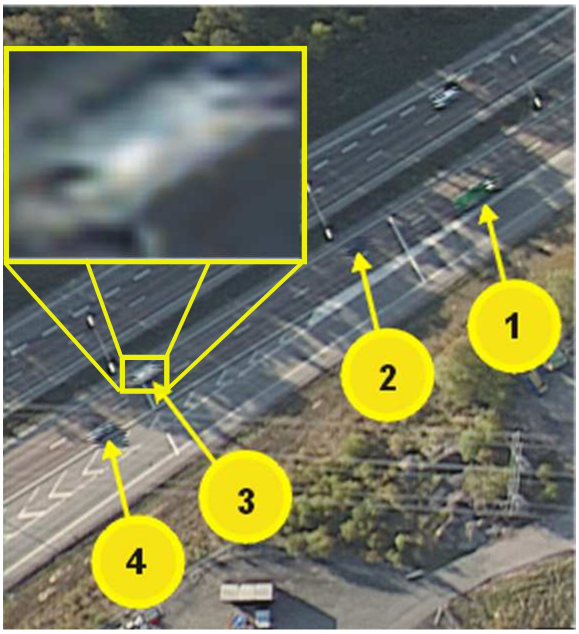

Figure 2: Example from video stream.

6 Conclusions

Described approach is in early stage of development and experimental verification. As more data is coming from real-life experiments we expect that new functionalities will be added to the model. Also, the real-life application will certainly verify some of current ideas and bring new demands. The general framework as partly presented here has some potential, notably thanks to well defined inference (approximation construction) mechanisms. There is still a need for more fundamental investigation leading to construction of methods for rule learning with attribute weights and constraints.

Acknowledgements

This work was supported by the Wallenberg Foundation in frame of the WITAS project and by KBN grant 8T11C 025 19.

References

[1] Doherty P. The WITAS Integrated System Architecture, Linköping Electronic Articles in Computer and Information Science, Vol. 4 No. 17, Linköping University Electronic Press, Linköping, 1999 `http://www.ep.liu.se/ea/cis/1999/017/`

[2] Doherty P., Łukaszewicz W., Skowron A., Szałas A., Approximation Transducers and Trees: A Technique for Combining Rough and Crisp Knowledge, In: Polkowski L., Skowron A., Pal S.K.(eds.), *Rough-Neuro Computing*, Springer Verlag, Berlin, 2002.

[3] Doherty P., Kachniarz J., Szałas A., Using Contextually Closed Queries for Local Closed-World Reasoning in Rough Knowledge Databases, In: Polkowski L., Skowron A., Pal S.K. (eds.), *Rough-Neuro Computing*, Springer Verlag, Berlin, 2002.

[4] Komorowski J., Pawlak Z., Polkowski L., Skowron A., Rough sets: A tutorial., In: S.K. Pal and A. Skowron (eds.), *Rough fuzzy hybridization: A new trend in decision-making*, Springer-Verlag, Singapore, 1999, pp. 3–98.

[5] Pawlak Z., Rough Sets: Theoretical Aspects of Reasoning about Data, Kluwer, Dordrecht, 1991

[6] Polkowski L., Skowron A., Rough Mereology: A New Paradigm for Approximate Reasoning, In: *International Journal of Approximate Reasoning*, 15(4), 1996, pp. 333–365

[7] Polkowski L., Skowron A., Towards Adaptive Calculus of Granules, In: Zadeh L.A., Kacprzyk J. (eds.), *Computing with Words in Information/Intelligent Systems*, Physica Verlag, Heidelberg, 1999, pp. 201–227

[8] Ziarko W., Variable Precison Rough Set Model, In *Journal of Computer and System Sciences*, vol. 46, 1993, pp. 39-59

[9] The WITAS project Homepage at `http://www.ida.liu.se/ext/witas/`