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A Case-Based Reasoning for Regulation of an Urban Transportation Network

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Abstract

This paper presents a classification-based approach to case-based reasoning. This approach has been implemented in a decision-making system for regulating an urban transportation network. Planning relies on two classification processes: strong classification to retrieve a similar planning perturbation and smooth classification when the former fails. Smooth classification is an original mechanism that can become of general use in case-based reasoning. We discuss in this paper the two processes from general and applicative point of view.

Key words: Case-Based Reasoning, regulation, transportation network, strong classification, smooth classification.

1 Introduction

The principle of Case-Based Reasoning (CBR) is based on an analogical reasoning [3][5], where previous experiences are used to define a solution to the present problem. This artificial reasoning proposes solutions to a problem which belongs to a class of problems frequently, encountered by the decision-maker. It rests on a case bases where are recorded the situations already met and on a measure of similarity between the situations which allow, for a given situation, to find the nearest cases in the case bases. The present case is composed of a problem (disturbance in our case), in need of a solution, it is taken by the Automatic Vehicle Monitoring (AVM) system or telephone (figure 1). This case is compared to former ones in the cases-base. A disturbance and its solution compose each one of them.

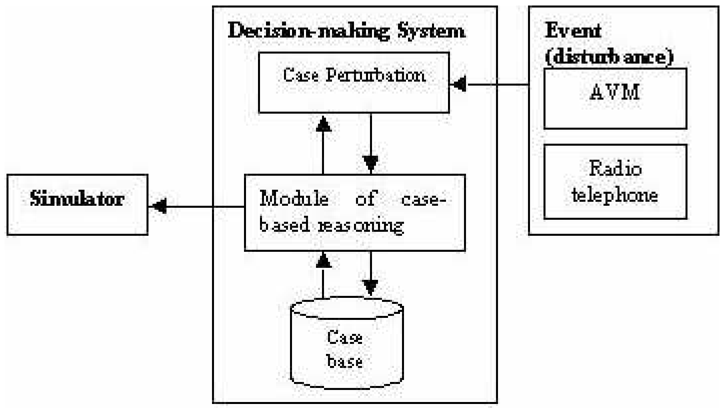

Figure 1. Global Architecture

The execution of the cycle allows to create a knowledge base for the resolution of real problems and reuse this knowledge to solve future problems. This reasoning is used by man in various environments and plays an important role in the expertise.

2 Presentation of the CBR

In our Decision-making system for regulation, this module contains a case-base reasoning organized in the form of databases. The disturbances which occur are compared thanks to a partial order < such as if db1<db2. We can say that the disturbance db1 is more specific than db2. With each recorded disturbance noted source an index idx(source) is associated such as idx(source)>source : an index is a generalization of a disturbance source. The index is organized in a hierarchy Hidx for the order <. To remind a scenario (recorded disturbance) by the means of Hidx. We use two processes of classification. Strong classification seeks the index of the sources problems, which are more general than the target problem. More precisely, given that a target problem "noted target", our CBR seeks a disturbance source such as idx(source)>target.

The source<idx(source) is a strong classification characterized by the equation:

$$\text{Source}<\text{idx(source)}>\text{target} \qquad (1)$$

In the event of failure of strong classification, when there is not treated disturbance source such as idx(source)>target, smooth classification is activated. The latter is based on an "approximate" pairing. In other words, the CBR module seeks functions of modification φ and ψ such as:

$$\text{Source}<\text{idx(source)}\cong \varphi(\text{idx(source)})>\text{ target} \qquad (2)$$

Such that $\cong$ is read "similar to" and means intuitively "equal to near modification". The function of modification φ checks the following property: if a treatment treatment(idx(source) is known, then we can build a treatment(φ(idx(source))). Unlike the function of modification, ψ is such, that if a treatment treatment(ψ(target)) is known, then a treatment treatment(target) can be built. Reminder in the CBR model seeks a similar treatment to the target disturbance and establishes how they are similar. Source is similar to target if one of the sequences of relations (1) and (2) between source and target is checked. These sequences of relation (1) and (2) are called "ways of similarity". The similarity in our case is based on six data:

- name of the nearest stop where the dysfunction is located,
- distance to the next stop
- distance to the next terminus
- Source<idx(source)>target
- Source<idx(source)>target
- Mode of transportation (bus or tramway)

Given a target target disturbance, the case source which is the nearest to target is calculated with a distance. This distance is based on a cost function which, with a way of similarity Sim(source, target), associates a numerical value cost(Sim(source, target)). Given two disturbances, source and target, the distance from source to target is defined as:

$$\text{d(source, target)} = \min\{\text{cost(Sim(source, target))}\} \qquad (3)$$

The minimum being taken on the whole of the ways of similarity Sim(source, target) from source to target. This distance is similar to an edition distance [3]. In the resolution of our disturbance, the cost is evaluated by using three criteria: regularity, punctuality and transfer

3 Planning starting from case

There are two principal stages in the process of planning in our decision-making system for regulation. Knowing that the regulator builds the solution of regulation to leave basic actions such as (injects a vehicle, delay a vehicle or advances a vehicle): the remind processes lean on the strong classification, followed if necessary by a smooth classification. Initially, the target disturbance is classified in the database of the disturbances with the identified parameters of the urban transportation network (strong classification). Two cases are possible

(1) there is an analogy of the target disturbance with which a source plan Plan is associated (in this case, Plan can be adapted in a plan for the target disturbance);

(2) it does not have an obvious analogy (in this case, the system must modify the target disturbance p and a quite selected disturbance P from database in order to find a relation of compatibility between P and p) (smooth classification).

The result of the remind is a couple (Plan(pk), Sim(pk, p)), where Plan (pk) is a source plan associated with P and where Sim(pk, p) is a way of similarity between pk and p, that is to say a way of the form $pk{<}P{>}p$ for strong classification and $pk{<}P \cong \varphi(P){>}\ \psi\ (p) \cong p$ for smooth classification. The fact that a couple (Plan(pk), Sim(pk, p)) goes back by the reminding process assures that the system will be able to adapting a plan Plan(pk) in a plan Plan(p) for the disturbance p.

4 Discussion

The principal objective of our system of regulation which is based on a CBR approach is to propose to the regulator in a tiny time a solution nearest possible to the disturbance in progress. This is so that it could be discharged from this task given that it passes more than 50% of time with the radiotelephone. This approach is applicable insofar as the consultation of the incident sheets carried out by the services of the maintenance and regulation raises thousands of incidents per year, whose majority is similar, as much on the context that on the strategies applied to solve them.

Many works in the context of regulation were done. Besma [2] uses a multi-agent approach integrating a genetic algorithm. The genetic algorithm makes it possible to give an optimal solution. But it is not the purpose of the regulator, which needs instantaneous answers taking into account the workload of regulation of a transportation system. The latter on average includes more than one hundred of vehicles. Optimising a solution of regulation is interesting during the off-peak hours. At this period, the regulator can be allowed to await the response of an advanced algorithm beyond a response time necessary for the correct operation of the network. Laichour [5] uses a multi-agent approach, but he is interested only in the regulation of connections. On the other hand, Chihaib [4] uses techniques of the artificial intelligence and in particular the propagation of constraints and fuzzy logic. All this works are available but not complete.

5 Conclusion

In this article, we presented a Case-based approach starting from a case which is based on classification. This approach was established in a Decision-making system for regulation of an urban transportation network and shows the following characteristics: (1) the cases are indexed by structures of graphs [9], and are organized in a hierarchy according to an analogy relation; (2) the remind and adaptation are interdependent processes: if the remind succeeds, the adaptability is assured; (3) the objective of the system is in record time to propose plans of solution for the occurring disturbances. Work on the regulation was undertaken and is always in hand with reference to the proposal for a computerized decision-making system for regulation. The approach that we dealt with is a step to increase the number of choices concerning approaches used in such systems.

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