Automatic Planning of Treatment of Infants with Respiratory Failure Through Rough Set Modeling

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Abstract. We discuss an application of rough set tools for modeling networks of classifiers induced from data and ontology of concepts delivered by experts. Such networks allow us to develop strategies for automated planning of a treatment of infants with respiratory illness. We report results of experiments with the networks of classifiers used in automated planning of the treatment of newborn infants with respiratory failure. The reported experiments were performed on medical data obtained from the Neonatal Intensive Care Unit in the Department of Pediatrics, Collegium Medicum, Jagiellonian University.

Keywords: Automated planning, concept approximation, dynamical system, ontology of concepts, respiratory failure, rough sets.

1 Introduction

This paper investigates medical planning in the context of a complex dynamical system (see, e.g., [1,3,6,2,4]). A *complex dynamical system* (also called as an *autonomous multiagent system* [2] or *swarm* [9]) is a system of complex objects that are changing (adapting), interacting, and learning over time. Such objects are usually linked by some dependencies, sometimes can cooperate between themselves and are able to perform flexible autonomous complex actions (operations, changes). For example, one can consider *road traffic* as a complex dynamical system represented by a road simulator (see e.g. [2]). Another example can be taken from medical practice. This second example concerns the treatment of infants with respiratory failure, where a given patient is treated as a complex dynamical system, while diseases of a patient are treated as complex objects changing and interacting over time (see [4] and Section 2).

S. Greco et al. (Eds.): RSCTC 2006, LNAI 4259, pp. 418–427, 2006.

The prediction of behaviors of a complex object evaluated over time is usually based on some historical knowledge representation used to store information about changes in relevant features or parameters. This information is usually represented as a data set and has to be collected during long-term observation of a complex dynamic system. For example, in case of the treatment of the infants with respiratory failure, we associate the object parameters mainly with values of arterial blood gases measurements and the X-ray lung examination. A single action is often not sufficient for changing the complex object in the expected direction. Therefore a sequence of actions need to be used instead of a single action during medical treatment. Hence, methods of automated planning are necessary during monitoring of a given complex dynamic system (see [7,10]).

This paper is organized as follows. In Section 2, some medical knowledge about the treatment of the infants with respiratory failure is given. The basic concept of a planning rule is given in Section 3. The automated planning of actions for groups of complex objects realized using *planning graphs for a group of objects* is considered in Section 4. Experimental results using the proposed tools for automated planning, are presented in Section 5.

2 Neonatal Respiratory Failure

The new possibilities in medical intensive care have appeared during last decades thanks to the progress in medical and technical sciences. This progress allowed us to save the live of prematurely born infants including the smallest born between 20th and 24th week of gestation with the birth weight above 500g.

Prematurely born infants demonstrate numerous abnormalities in their first weeks of life. Their survival, especially without severe multiorgan complications is possible with appropriate treatment. Prematurity can be characterized as inappropriate maturity of systems and organs leading to their dysfunction after birth.

The respiratory system dysfunction appearing in the first hours of life and leading to respiratory failure is the most important single factor limiting survival of our smallest patients. The respiratory failure is defined as inappropriate blood oxygenation and accumulation of carbon dioxide and is diagnosed based on arterial blood gases measurements. Clinical symptoms - increased rate of breathing, accessory respiratory muscles use as well as X-ray lung examination are also included in assessment of the severity of respiratory failure.

The most important cause of respiratory failure in prematurely born infants is RDS (respiratory distress syndrome). RDS results from lung immaturity and surfactant deficiency. The other co-existing abnormalities such as PDA (patent ductus arteriosus), sepsis (generalized reaction on infection leading to multiorgan failure) and Ureaplasma lung infection (acquired during pregnancy or birth) may exacerbate the course of respiratory failure. Each of these conditions can be treated as an unrelated disease requiring separate treatment. However, these abnormalities very often co-exist, so it is sometimes necessary to treat combinations such as RDS + PDA + sepsis. In a holistic, therapeutic approach, it is important to synchronize the treatment of co-existing abnormalities in an effort to combat respiratory failure.

Effective care of prematurely born infants entails consideration of all co-existing abnormalities such as infections (both congenital and acquired), water-electrolyte and acid-base imbalance, circulatory, kidney problems. All of these factors are related and influence one another. The care of prematurely born infants during their first days of life requires continuous analysis of many parameters. These parameters can be divided into stationary (e.g., gestational age, birth weight, Apgar score) and continuous (changing over time). Parameter values can be obtained from various monitoring devices (e.g., oxygen hemoglobin saturation (SAT), blood pressure, temperature, lung mechanics) either on a discrete (e.g. blood gases) or continuous basis. Neonatal care includes assessment of a number of sources of information such as ultrasound scans of the brain, echocardiography and chest X-ray. Global analysis should also include current methods of treatment used for particular patients. These methods may have qualitative (e.g., administration of medication) or quantitative (e.g., respiratory settings) characteristics. It should also be observed that assessment of a patient's state is very often performed hurriedly under stress conditions.

Computerized data analysis may provide support for a physician during daily diagnostic-therapeutic processes both in collecting and storing patient data using a number of tools (e.g., Neonatal Information System) and as a means of quick, automatic and intelligent analysis of patient data. This approach might allow for computer presentation of some information based on the observed patterns, which might be helpful in automating the planning of treatment.

The aim of this paper is to present some computer tools for automated planning of the treatment (see, e.g., [7,10]). In this approach, a given patient is treated as a complex dynamical system, while patient diseases (e.g., RDS, PDA, sepsis, Ureaplasma and respiratory failure) are treated as complex objects changing and interacting over time (see Section 4). Respiratory failure is very complex because it is a consequence of RDS, PDA, sepsis or Ureaplasma. Our task is to facilitate automatic planning for sequences of medical actions required to treat a given patient.

3 The Automatic Planning for Complex Objects

In this research, we discuss some rough set [8] tools for automated planning as part of a system for modeling networks of classifiers. Such networks are constructed using an ontology of concepts delivered by experts[1].

The basic concept we use is a *planning rule*. Let $s_l, s_{r_1} \dots s_{r_k}$ denote states of a complex object and a denotes an action that causes a transition to some another state. A planning rule proposed by a human expert such as a medical doctor has the following simplified form: $(s_l, a) \rightarrow s_{r_1} | s_{r_2} \dots | s_{r_k}$. Such rule can be used to change the state s_l of a complex object, using the action a to some state from the right hand side of a rule. But the result of applying such a rule is

[1] The ontology focuses on bases for concept approximation (see, e.g., [5]).

nondeterministic, because there are usually many states on the right hand side of a planning rule.

A set of planning rules can be represented by a *planning graph*. There are two kinds of nodes in planning graphs: *state nodes* represented by ovals and *action nodes* represented by rectangles (see, e.g., Figure 1). The connections between nodes represent temporal dependencies, e.g., the connection between the state node s_1 and the action node a_1 says that in state s_1 of a complex object, action a_1 can be performed while the connection between a_1 and state node s_2 means that after performing action a_1 in s_1 the status of the complex object can be changed from s_1 to s_2. Figure 1 shows how planning rules can be joined to obtain a planning graph.

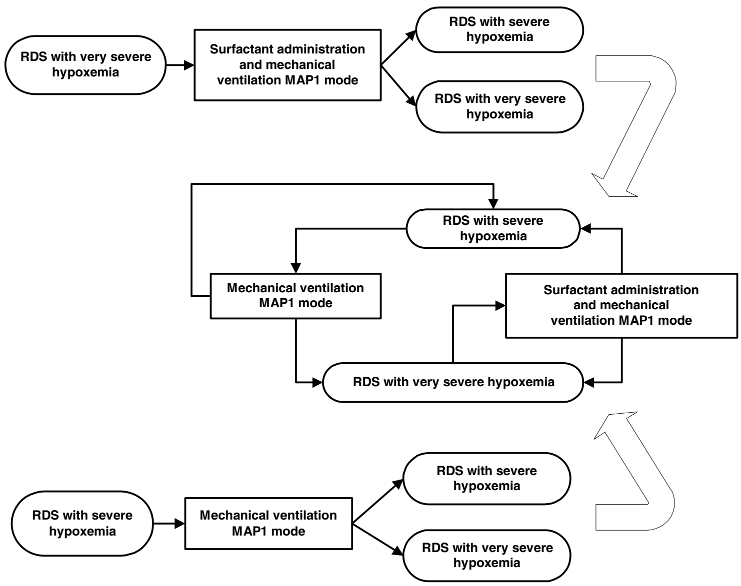

Fig. 1. Planning Rules in a Planning Graph

Notice, that any state from the planning graph can be treated as a complex concept specified by a human expert in natural language. Such concepts can be approximated by approximate reasoning schemes (AR-schemes, for short) using data sets and domain knowledge accumulated for a given complex dynamical system (see [1,2,4]). Hence, it is possible to identify the initial state at the beginning of planning for a particular complex object.

The output for the planing problem for a single complex object is a path in the planning graph from the initial node-state to the *expected (target) node-state*. Such a path can be treated as a plan of action that should be performed beginning from the given complex object in order to change its state to the expected status.

In practice, it is often the case that a generated plan must be compatible with the plan proposed by a human expert (e.g., the treatment plan should be compatible with the plan suggested by human experts from a medical clinic). It is strongly recommended that the method of the verification and evaluation of generated plans should be based on the similarity between the generated plan and the plan proposed by human experts (see Section 5). Hence, the usage of special tools that make it possible to resolve conflicts (nondeterminism) of actions in planning rules is needed. Therefore, in this paper we propose a family of classifiers constructed for all state-nodes from a planning graph. These classifiers are constructed on the basis of decision rules computed for a special decision table called a *resolving table*. The resolving table is constructed for any state-nodes from the planning graph and stores information about objects of a given complex dynamical system satisfying the concept from the current state-node. Any row of this table represents information about parameters of a single object registered at a given time. Condition attributes (features) from this table are defined by human experts and have to be computed on the basis of information included in the description of the current state of a complex object as well on some previous states or actions obtained from the near or far history of an object. It should be emphasized that the definition of such condition attributes should facilitate easy update of attribute values during the construction of a given plan according to performed actions and new states of a complex object. The proposed approach should be accompanied by some kind of simulation during plan construction. The decision attribute of the resolving table is defined as the action that has been performed for a given training object combined with the real effect of this action for an object. Next, we construct rule based classifiers for all states, i.e., for all associated resolving tables. In addition, these classifiers make it possible to obtain a list of actions and states after usage of actions with their weights in descending order. This is very important in generating plans for groups of objects (see Section 4).

4 Automatic Planning for Groups of Complex Objects

In this section, we present a generalization of the method for automated planning described in Section 3. For a group of objects, we define a graph that we call a *planning graph for a group of objects*. This new graph is similar to a planning graph for a single object (see Section 3). There are two kinds of nodes in this graph, namely, *states nodes* (denoted by ovals) that represent the current state of a group of objects specified as complex concepts by a human expert in natural language, and *action nodes* (denoted by rectangles) that represent so-called *meta actions* defined for groups of objects by a human expert. Meta actions are performed over a longer period called a *time window* [2].

In Figure 2, we present an exemplary planning graph for a group of four diseases: sepsis, Ureaplasma, RDS and PDA, related to the planning of the treatment of the infant during the respiratory failure. This graph was created on

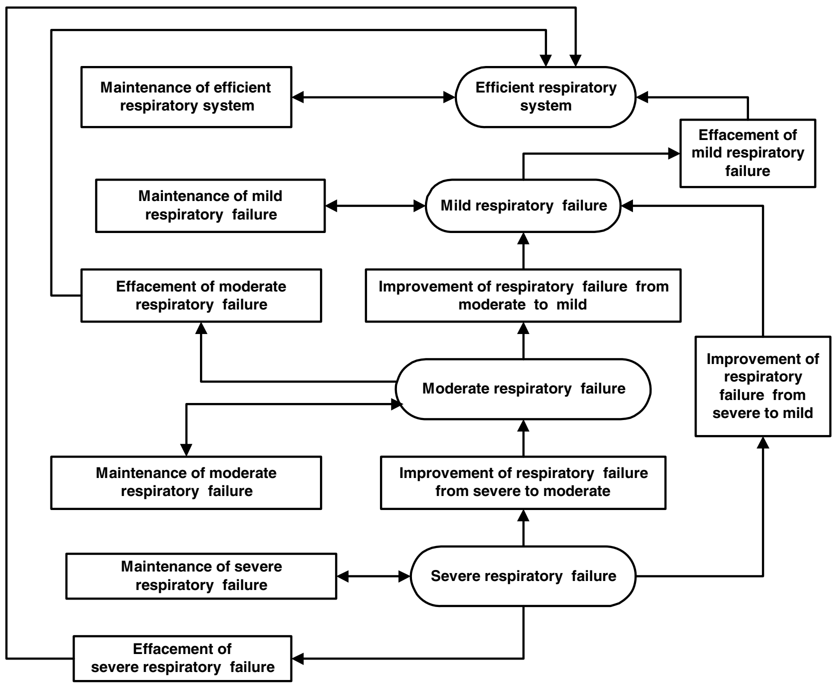

Fig. 2. A planning graph for the treatment of infants during the respiratory failure

the basis of observation of medical data sets (see Section 5) and with support of human experts.

Notice that any state-node from a planning graph for groups of objects can be treated as a complex concept that is specified by a human expert in natural language. Such concepts can be approximated by AR-schemes using data sets and the domain knowledge accumulated for a given complex dynamical system (see [1,2,4]). As a result, it is possibly to recognize an initial state at the beginning of planning for a particular group of complex objects.

At the beginning of planning for a group of objects, we assign the current state of a group of objects. As mentioned earlier, this can be done by AR-schemes that have been constructed for all states from the planning graph. Next, we plan a sequence of actions that can transform a group of objects from the current state to the target state (more expected, safer or more comfortable). For example, in the case of the treatment of infants with respiratory failure, if the infant is suffering from severe respiratory failure, we try to change the patient status using some methods of treatment to change its status to moderate or mild respiratory failure (see Figure 2).

So, our system can propose many plans on the basis of connections in a planning graph for groups of objects starting from the current state. Next, the proposed system chooses a plan that seems to be the most effective. However, it is necessary to make sure that the proposed plan can be realized on the level of any object belonging to a group. In other words, for any object from the group a specific plan should be constructed that leads to a given meta action from the level of the group. Besides, all constructed plans for objects belonging to a group should be compatible.

Therefore, during planning a meta action for a group of objects, we use a special tool for verifying the compatibility of plans generated for all members of a group. This verification can be performed by using some special decision rules that we call *elimination rules*. Such rules make it possible to eliminate combination of plans that are not compatible relative to domain knowledge. This is possible because elimination rules describe all important dependencies between plans that are joined together. If any combination of plans is not consistent with any elimination rule, then it is eliminated. A set of elimination rules can be specified by human experts or can be computed from data sets. In both of these cases, we need a set of attributes (features) defined for a single plan that are used for the explaining elimination rules. Such attributes are specified by human experts on the basis of domain knowledge and they describe some important features of the plan (generated for single complex object) with respect to proper joining a plan with plans generated for other members of a group.

These features are used as a set of attributes in the special table that we call *an elimination table*. Any row of an elimination table represents information about features of plans assigned for complex objects belonging to an exemplary group of objects from the training data. We propose the following method of calculation the set of elimination rules on the basis of the elimination table.

For any attribute from an elimination table, we compute the set of rules treating this attribute as a decision attribute. In this way, we obtain a set of dependencies in the elimination table explained by decision rules. In practice, it is necessary to filter elimination rules to remove the rules with low support because such rules can be too strongly matched to the training data. The resulting set of elimination rules can be used as a filter of inconsistent combinations of plans generated for members of groups. Any combination of plans is eliminated when there exists an elimination rule that is not supported by features of a combination while the combination matches a predecessor of this rule. In other words, a combination of plans is eliminated when the combination matches to the predecessor of some elimination rule and does not match the successor of a rule.

If the combination of plans for members of the group is consistent (it was not eliminated by elimination rules), we should check if the execution of this combination allow us to achieve the expected meta action from the level of group of objects. This can be done by a special classifier constructed for a table called as an *action table*. The structure of an action table is similar to the structure of an elimination table, i.e., attributes are defined by human experts, where rows represent information about features of plans assigned for complex objects belonging to exemplary groups of objects from the training data. In addition, we add to this table a decision attribute. Values of decision attributes represent names of meta actions which will be realized as an effect of the execution of plans described in the current row of a training table. The classifier computed for an action table makes it possible to predict the name of a meta action for a given combination of plans from the level of members of a group. The last step is the selection of combinations of plans that makes it possible to obtain a target meta action with respect to a group of objects.

It was mentioned in Section 3 that the resolving classifier used for the generation of a next action during the planning for a single object, gives us the list of actions (and states after usage of action) with their weights in descending order. This makes it possible to generate many alternative plans for any single object and many alternative combinations of plans for a group of objects. Therefore, the chance of finding an expected combination of plans from a lower level to realize a given meta action (from the higher level) is relatively high.

After planning the selected meta action from the path of action from the planning graph (for a group of objects), the system begins the planning of the next meta action from this path. The planning is stopped, when the planning of the last meta action from this path is finished.

5 Experimental Results

To verify the effectiveness of the proposed methods of automated planning, we have implemented algorithms in a *Automated Planning* library (AP-lib), which is an extension of the RSES-lib 2.1 library forming the computational kernel of the RSES system[2].

Experiments have been performed on medical data sets obtained from Neonatal Intensive Care Unit in Department of Pediatrics, Collegium Medicum, Jagiellonian University, Cracow. The data were collected between 2002 and 2004 using computer database NIS (Neonatal Information System). Detailed information about treatment of 340 newborns are available in the data set that includes perinatal history, birth weight, gestational age, lab tests results, imagine techniques results, detailed diagnoses during hospitalization, procedures and medication were recorded for the each patient. The study group included prematurely born infants with the birth weight $\leq 1500g$, admitted to the hospital before the end of 2 days of life. Additionally, children suffering from respiratory failure but without diagnosis of RDS, PDA, sepsis or ureaplasma infection during their entire clinical course, were excluded from the study group.

In our experiments we used one data table extracted from the NIS system, that consists of 11099 objects. Each object of this table describes parameters of one patient in single time point. There were prepared 7022 situations on the basis of this data table, when the plan of treatment has been proposed be human experts during the realistic clinical treatment.

As a measure of planning success (or failure) in our experiments, we use a special hierarchical classifier that can predict the similarity between two plans as a number between 0.0 and 1.0. This classifier has been constructed on the basis of a special ontology specified by human experts (see Figure 3) and data

[2] See RSES Homepage at `logic.mimuw.edu.pl/~rses`

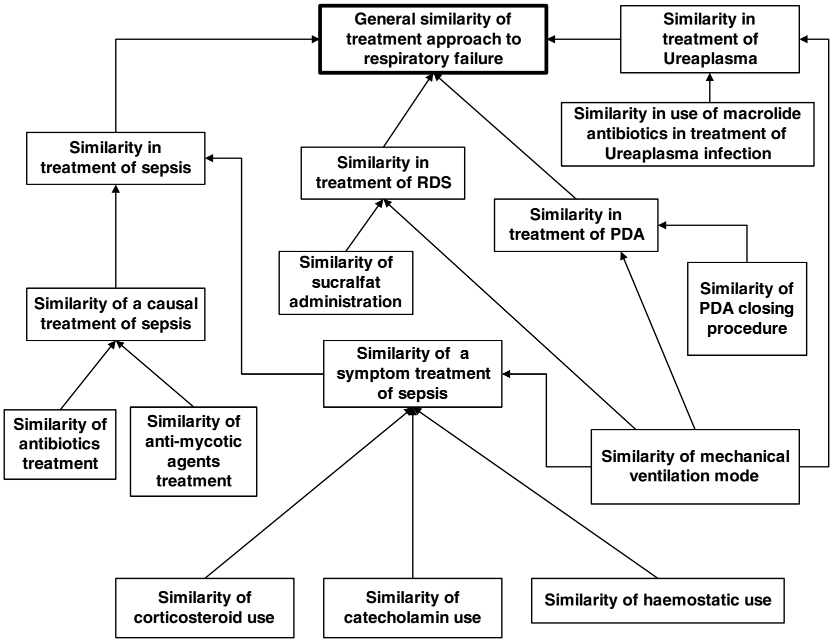

Fig. 3. An Ontology of Similarity between Plans

sets. It is important to mention that besides the ontology, experts provided exemplary data (values of attributes) for the purpose of concept approximation from the ontology. The methods of construction of such classifiers are based on AR schemes and were described in [1]. We use this classifier to determine the similarity between plans generated by our methods of automated planning and plans proposed be human experts during realistic clinical treatment. A training set consists of 4052 situations (when plans of treatment have been assigned), whereas a testing set consists of 2970 situations when plans have been generated by an automated method and comparable expert plans were known. The average similarity between plans for all tested situations was about 0.82, while the coverage of tested situations by generated plans was about 88 percent.

6 Conclusion

In this paper, we discussed some rough set tools for automated planning that are developed for a system for modeling networks of classifiers. The performed experiments show that the similarity between the plan of treatment generated automatically and the plan proposed by human experts during the real clinical treatment is sufficiently high. Therefore, we conclude that our methods have promise as useful tools in medical practice. In our further work, we would like to increase the recognition of similarity between plans of the treatment (generated automatically and proposed by human experts) and to improve the coverage of tested situations by the generated plans.

Acknowledgement

The authors wish to thank professor James Peters for his insights and many helpful comments and corrections for this article. The research has been supported by the grant 3 T11C 002 26 from Ministry of Scientific Research and Information Technology of the Republic of Poland.

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