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Rough Set Approach to Behavioral Pattern Identification

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Abstract. The problem considered is how to model perception and identify behavioral patterns of objects changing over time in complex dynamical systems. An approach to solving this problem has been found in the context of rough set theory and methods. Rough set theory introduced by Zdzisław Pawlak during the early 1980s provides the foundation for the construction of classifiers, relative to what are known as temporal pattern tables. Temporal patterns can be treated as features that make it possible to approximate complex concepts. This article introduces some rough set tools for perception modeling that are developed for a system for modeling networks of classifiers. Such networks make it possible to identify behavioral patterns of objects changing over time. They are constructed using an ontology of concepts delivered by experts that engage in approximate reasoning about concepts embedded in such an ontology. We also present a method that we call *a method for on-line elimination of non-relevant parts* (ENP). This method was developed for on-line elimination of complex object parts that are irrelevant for identifying a given behavioral pattern. The article includes results of experiments that have been performed on data from a vehicular traffic simulator and on medical data obtained from Neonatal Intensive Care Unit in the Department of Pediatrics, Collegium Medicum, Jagiellonian University. The contribution of this article is the introduction of a network of classifiers that make it possible to identify the behavioral patterns of objects that change over time.

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1. Introduction

This article considers the problem of perception modeling and identifying behavioral patterns of objects changing over time in complex dynamical systems. An approach to solving this problem has been found in the context of rough set theory and methods. A *complex dynamical system* [6, 3, 27] (also called as an *autonomous multiagent system* [6, 16, 21, 23, 27] or $swarm$ [21]) 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 dynamical system represented by a road simulator (see, e.g. [31, 6]). A driving simulation takes place on a board (see Figure 1) which presents a crossroads together with access roads. While driving on a road each vehicle can be treated as *an intelligent autonomous agent*. Each agent is "observing" the surrounding situation on the road, keeping in mind its destination and its own parameters, and makes an independent decision about further steps by performing some maneuver such as passing, overtaking, changing lane, or stopping. 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 [7] and Section 7.1).

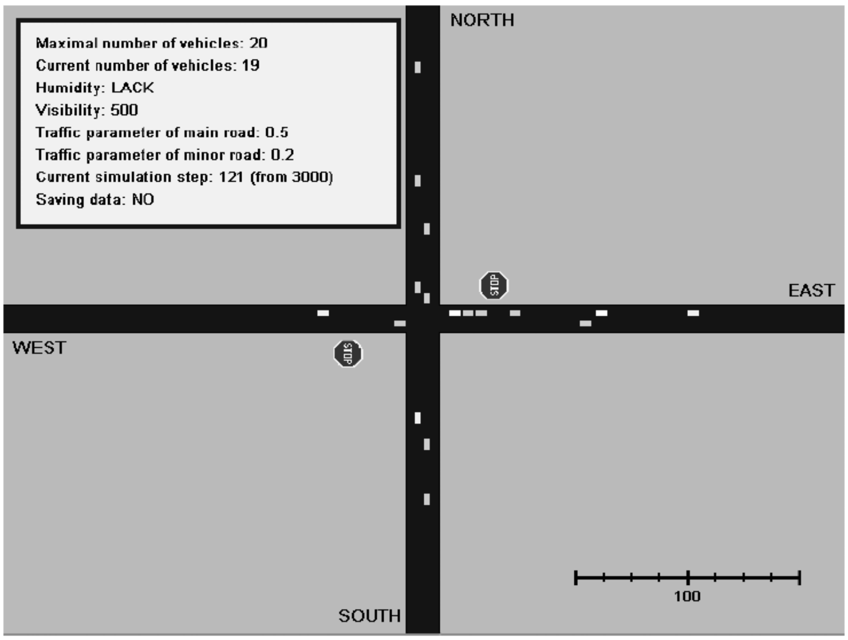

Figure 1. The board of simulation

An efficient monitoring of a complex dynamic system can be made using so called behavioral patterns (see Figure 2). Any behavioral pattern can be understood as a way to represent some behavior of complex objects and their parts changing over time. Identification of some behavioral patterns can be very important for recognition or prediction of behavior of a dynamical system, e.g., some behavioral patterns correspond to undesirable behaviors of complex objects. In this case, we call such behavioral patterns as *risk patterns* and we need some tools for identifying them. If in the current situation some risk patterns are identified, then the control object (a driver of the vehicle, a medicine doctor, a pilot of the aircraft, etc.) can use this information to adjust selected parameters to obtain the desirable behavior of the complex dynamical system. This can make it possible to overcome dangerous or uncomfortable situations. For example, if some behavior of a vehicle that cause a danger on the road is identified, we can try to change its behavior by using some suitable means such as road traffic signalling, radio message or police patrol intervention. Another example can be taken from medical practice. A very important element of the treatment of the infants with respiratory failure is the appropriate assessment of the risk of death. The appropriate assessment of this risk leads to the decision of particular method and level of treatment. Therefore, if some complex behavior of an infant that causes a danger of death is identified, we can try to change his/her behavior by using some other methods of treatment (may be more radical) in order to avoid the infant's death.

Note also that the study of collective behavior in intelligent systems is now one of the more challenging research problems (see, e.g., [21, 9, 22, 23]), especially if one considers the introduction of some form of learning by cooperating agents (see, e.g., [10, 24, 25, 18, 8, 26]).

The prediction of behavioral patterns of a complex object evaluated over time is usually based on some historical knowledge representation used to store information about changes in relevant futures 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 road traffic, we associate the object-vehicle parameters with the readouts of different measuring devices or technical equipment placed inside the vehicle or in the outside environment (e.g., alongside the road, in a helicopter observing the situation on the road, in a traffic patrol vehicle). Many monitoring devices play serve as informative sensors such as GPS, laser scanners, thermometers, range finders, digital cameras, radar, image and sound converters (see, e.g., [27]). Hence, many vehicle features serve as models of physical sensors. Here are some exemplary sensors: location, speed, current acceleration or deceleration, visibility, humidity (slipperiness) of the road. By analogy to this example, many features of complex objects are often dubbed sensors. It is worth to mention, that in case of the treatment of infants with respiratory failure, we associate the object parameters (sensors) mainly with values of arterial blood gases measurements and the X-ray lung examination.

Rough set theory introduced by Zdzisław Pawlak during the early 1980s provides the foundation for the construction of classifiers, i.e., algorithms which permits us to repeatedly make a forecast on the basis of accumulated knowledge in new situations. In this paper, we discuss some rough set [20] tools for perception modeling that have been developed in our project as part of a system for modeling networks of classifiers (see also Figure 2). Such networks make it possible to identify behavioral patterns of objects and their parts changing over time. Such networks are constructed using an ontology of concepts delivered by experts aiming to reason approximately about concepts embedded in such an ontology.

In our approach, we use the notion of *temporal pattern* (see Section 2) that express simple temporal features of objects or groups of objects in a given complex dynamic system. Temporal patterns can be used to approximate *temporal concepts* (see Section 3), that represent more complex features of complex

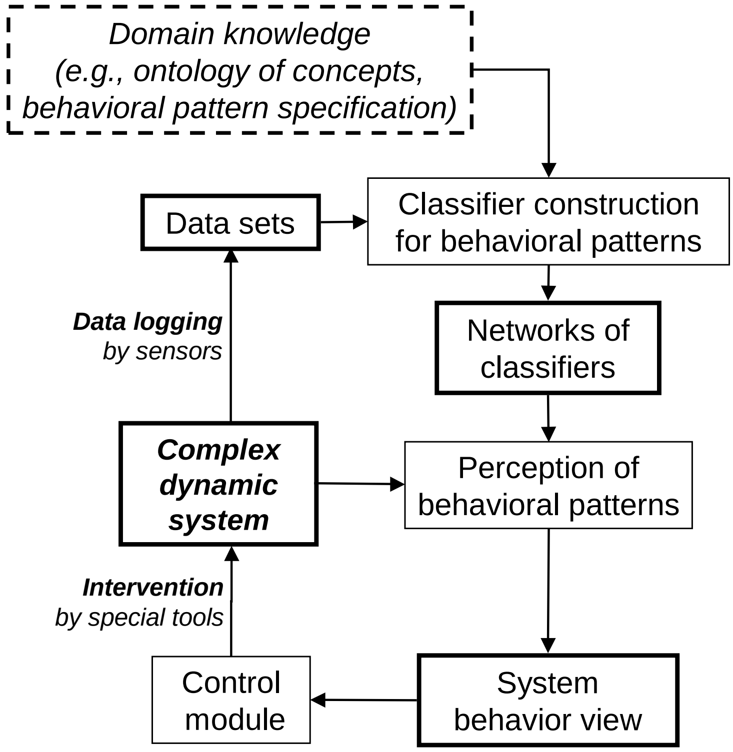

Figure 2. Monitoring of complex dynamic systems using behavioral patterns

objects. More complex behavior of complex objects or groups of complex objects can be presented in the form of *behavioral graphs* (see Section 4 and Section 5). Any behavioral graph can be interpreted as a *behavioral pattern* and can be used as a complex classifier for identification of complex behaviors (see Section 6).

In Section 7, we apply the method of complex classifier construction for identification of complex behaviors for medical data sets obtained from Neonatal Intensive Care Unit in Department of Pediatrics, Collegium Medicum, Jagiellonian University, Cracow. This application is concerned with the identification of the infants' death risk caused by respiratory failure.

Behavioral pattern identification for a part of complex object is performed by testing properties of registered behavior of this part, often during a quite long period of time. However, in many applications, faster (often in real-time) testing if parts of complex objects are matching the given behavioral pattern is necessary. Hence, we have developed the ENP method for on-line elimination of non-relevant parts of a behavioral pattern for a complex object in a short observational period. In analysis of complex dynamical systems, we usually have to investigate very many parts of complex objects. Therefore, the fast verification of parts of complex objects can save time necessary for searching among parts matching the given behavioral pattern. In Section 8, we show that the testing of parts of complex objects can be speeded up by using some special decision rules. The new ENP method makes it possible to achieve very fast elimination of many irrelevant parts of a given complex object in identification of a given behavioral pattern.

To illustrate the method and to verify the effectiveness of classifiers based on behavioral patterns and the ENP method, we have performed several experiments with the data sets recorded in the road simulator [31]. We present results of these experiments in Section 9.1. Additionally, we also present results of experiments, that have been performed on medical data sets obtained from Neonatal Intensive Care Unit in Department of Pediatrics, Collegium Medicum, Jagiellonian University, Cracow (see Section 9.2).

This paper is a continuation of a research project in which we investigate methods for complex concept approximation using a hierarchical approach (see, e.g., [5, 18, 4, 6]), and is related to companion research on interactive behavior and learning by swarms of cooperating agents (see, e.g., [21, 22, 23, 24, 25].

This paper is organized as follows. Section 2 briefly introduces temporal patterns. In Section 3, we discuss temporal concepts and methods of their approximation. In Sections 4 and 5 we present behavioral graphs for an object and for a group of objects. Behavioral patterns are defined in Section 6. Section 7 describes an application of behavioral patterns to the identification of the infants' death risk caused by respiratory failure. In Section 8, we present the ENP method for on-line elimination of non-relevant parts of a complex object in a short observational period of behavioral pattern identification. Finally, in Section 9, we report results of experiments performed on two data sets, i.e., data recorded in the road simulator and medical data.

2. Temporal patterns

In many complex dynamic systems, there are some *elementary actions* (performed by complex objects) that are easily expressed by a local change of object parameters, measured in a very short but a registerable period. So, an elementary action should be understood as a very small but meaningful change of some sensor values such as location, distance, speed. In case of the road traffic example, we distinguish elementary actions such as increase in speed, decrease in speed, lane change.

However, a perception of composite actions requires analysis of elementary actions performed over a longer period called a *time window*. Therefore, if we want to predict composite actions or identify a behavioral pattern, we have to investigate all elementary actions that have been performed in the current time window. Hence, one can consider, e.g., the frequency of elementary actions within a given time window and temporal dependencies between them. These properties can be expressed using so called *temporal patterns*. We define a temporal pattern as a function of parameters of an object observed over a time window. In this paper, we consider temporal patterns of the following types:

- *sensory pattern*: a numerical characterization of values of selected sensor from a time window (e.g., the minimal, maximal or mean value of a selected sensor, initial and final values of selected sensor, deviation of selected sensor values);

- *local pattern*: a crisp (binary) characterization of occurrences of elementary actions in a given time window (e.g., action A occurs within a time window, the action B occurs at the beginning of a time window, the action C does not occur within a time window);

- *sequential pattern*: a binary characterization of temporal dependencies between elementary actions inside a time window (e.g., action A persists throughout a time window or action A begins before action B, action C occurs after action D).

One can see that any sensory pattern is determined directly by values of some sensors. For example, in case of the road traffic one can consider sensory patters such as minimal speed and estimated speed within a time window. The value of a local or sequential pattern is determined by elementary actions registered in a time window. Local or sequential patterns are often used in queries with binary answers such as Yes or No. For example, in case of road traffic we have exemplary local patterns such as “Did vehicle speed increase in the time window?” or “Was the speed stable in the time window?” and sequential patterns such as “Did the speed increase before a move to the left lane occurred?” or “Did the speed increase before a speed decrease occurred?”. We assume that any temporal pattern ought to be defined by a human expert using domain knowledge accumulated for the given complex dynamical system.

3. Approximation of temporal concepts

The temporal patterns mentioned in Section 2 can be treated as new features that can be used to approximate complex concepts. In this paper, we call them *temporal concepts*. We assume that temporal concepts are specified by a human expert. Temporal concepts are usually used in queries about the status of some objects in a particular temporal window. Answers to such queries can be of the form Yes, No or *Does not concern*.

For example, in case of road traffic one can define complex concepts such as “Is a vehicle accelerating in the right lane?”, “Is a vehicle speed stable while changing lanes?”, or ”Is the speed of a vehicle in the left lane stable?”.

The approximation of temporal concepts is defined by classifiers, which are usually constructed on the basis of decision tables. Hence, if we want to apply classifiers for approximation of temporal concepts, we have to construct a suitable decision table called a *temporal pattern table* (PT) (see Figure 3).

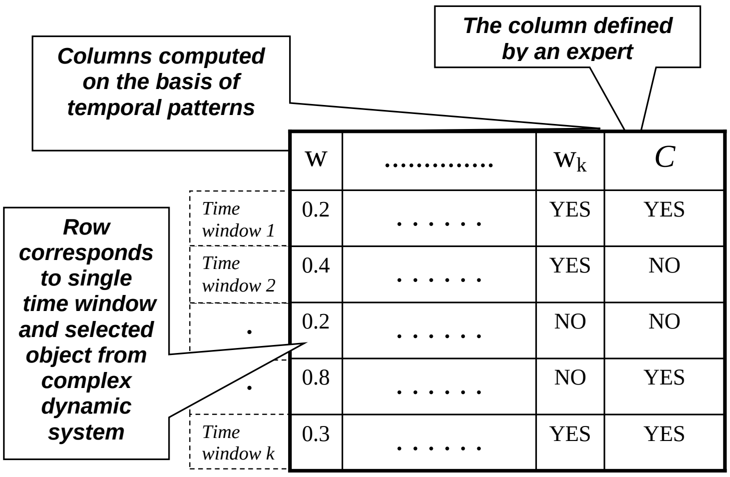

Figure 3. The scheme of the temporal pattern table (PT)

A temporal pattern table is constructed from a table T consisting of registered information about objects occurring in a complex dynamical system. Any row of table T represents information about parameters of a single object registered in a time window. Such a table can be treated as a data set accumulated from observations of the behavior of a complex dynamical system. Assume, for example, that we want to approximate a temporal concept C using table T. Initially, we construct a temporal pattern table PT as follows.

- Construct table PT with the same objects as contained in table T.
- Any condition attribute of table PT is computed using temporal patterns defined by a human expert for the approximation of concept C.
- Values of the decision attribute (the characteristic function of concept C) are proposed by the human expert.

We assume that for any temporal pattern a formula for computing its value is given by an expert. In more advanced approach the classifiers for the temporal patterns represented by condition attributes should be constructed.

Next, we construct a classifier for table PT that can approximate temporal concept C. Notice that many temporal concepts should be approximated using this approach. Some of these concepts are in some sense more complex than others. Therefore, usually a concept ontology for particular temporal concepts should be provided. The resulting ontology makes it possible to construct approximate reasoning schemes (AR schemes) that can be used to approximate temporal concepts (see e.g. [4]).

4. Behavioral graph for an object

Temporal concepts defined for objects from a complex dynamical system and approximated by AR schemes, can be treated as nodes of a graph called a *behavioral graph*, where connections between nodes represent temporal dependencies. Such connections between nodes can be defined by an expert or read from data accumulated for a given complex dynamical system.

Figure 4 presents a behavioral graph for a single object-vehicle exhibiting a behavioral pattern of vehicle while driving on a road.

In this behavioral graph, for example, connections between node "Acceleration on the right lane" and node "Acceleration and changing lanes lanes from right to left" indicates that after an acceleration in the right lane, a vehicle can change to the left lane (maintaining its acceleration during both time windows). In addition, a behavioral graph can be constructed for different kinds of objects such as single vehicles or groups of vehicles and defined for behaviors such as driving on the strength road, driving through crossroads, overtaking, and passing. We consider behavioral graphs as models for behavioral patterns (see Section 6).

5. Behavioral graph for a group of objects

In this paper, we introduce a method for approximation of temporal concepts for a group of objects based on what is known as a *group temporal pattern table* (GT - see Figure 5), which is constructed using the methodology presented in the Section 3 for the construction of the temporal pattern table, but with some important differences. To construct such a table, assume that behavioral graphs for all objects belonging to a group of objects have been constructed. For example, we construct behavioral graphs for all vehicles belonging to the investigated group of vehicles.

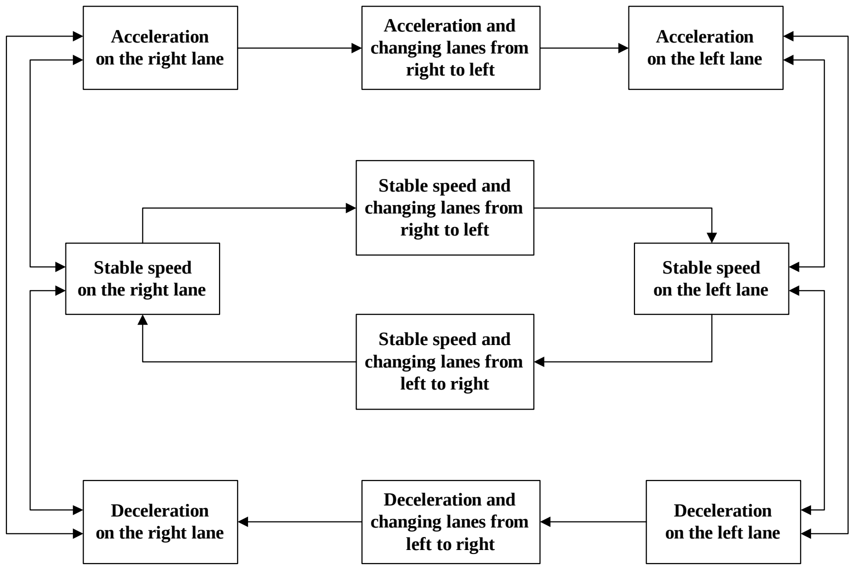

Figure 4. A behavioral graph for a single object-vehicle

Apart the behavioral graph for any object belonging to the investigated group, we usually consider some new behavioral graphs. These behavioral graphs describe temporal relations between objects in the group. For example, one can define a behavioral graph describing changes of distances between vehicles from the investigated group of vehicles.

For each behavioral graph, we define new temporal patterns using only two kinds of temporal patterns, namely, local patterns and sequential patterns. Sensory patterns are not used since information about sensors is not directly available on this abstraction level (see Section 2).

Any row in GT represents information about all complex objects (from the investigated group). This information is given as paths of nodes from behavioral graphs of complex objects belonging to this group. Any path in a behavioral graph is understood as a sequence of graph nodes (temporal concepts) registered over some period (over a number of time windows) for a complex object.

More precisely, GT is constructed in the following way (see also Figure 5):

- Table GT is created from training data for approximation of a given temporal concept C.
- Any object of GT represents information for all objects from the considered group. This information is based on behavioral graphs and for any such object is given by a sequence of graph nodes from behavioral graphs registered over some period.
- Any condition attribute of GT is computed using temporal patterns provided by the expert for the approximation of a concept C. There are two types of condition attributes:
  - Condition attributes of the first type are defined for any pair selected by expert consisting of: a temporal pattern and a sequence of graph nodes from behavioral graph constructed for a considered complex object belonging to the investigated group. The condition attribute value is computed using the selected temporal pattern (local or sequential) on the selected path.

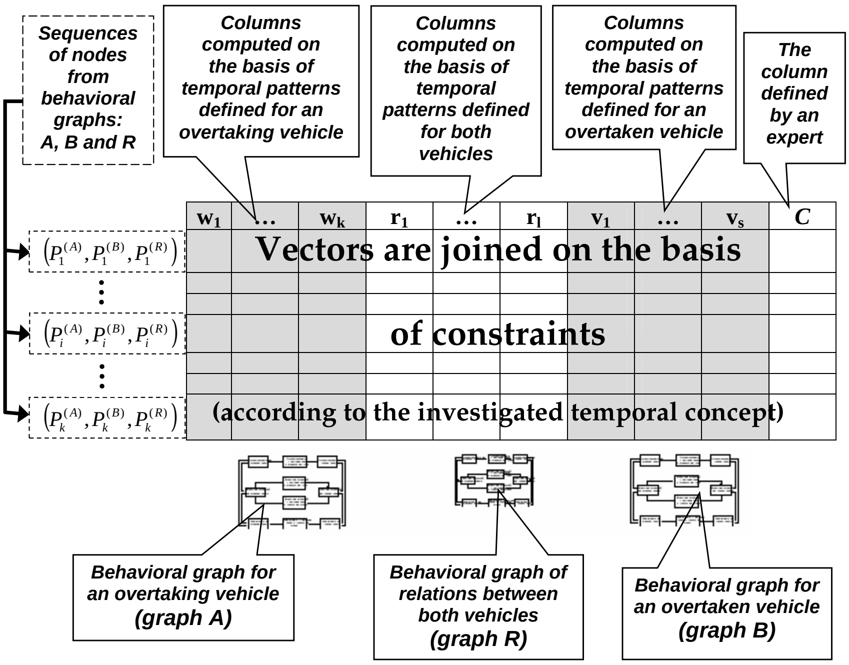

Figure 5. The scheme of the group temporal pattern table (GT) constructed for group of two vehicles

- Condition attributes of the second type are defined for selected by expert pairs consisting of: a temporal pattern and all paths in the row. These attributes describe temporal relations between objects in the investigated group of complex objects.

- Values of the decision attribute (the characteristic function of concept C) for any object in GT are given by the human expert.

It is very important, that during construction of GT, we insert into this table objects representing information about groups of objects which are relevant for the investigated temporal concept from the given behavioral pattern (see Figure 6). For example, if we are interested in the overtaking maneuver, we compose only vehicle pairs that are close to each other. It means that during construction of GT vehicles are joined on the basis of constraints according to the investigated temporal concept.

Figure 5 presents a scheme used for construction of GT for group of two objects (vehicles). Any object is represented by a triple $(P_i^{(A)}, P_i^{(B)}, P_i^{(R)})$, where $P_i^{(j)}$ denotes the j-th path in the i-th row ($j \in \{A, B, R\}$ and $i \in \{1, ..., k\}$).

The temporal concepts defined for a group of objects and approximated by AR schemes (see [4]) are nodes of a new graph, that we call as *a behavioral graph for a group of objects*. One can observe, that the behavioral graph for a group of objects expresses temporal dependencies on a higher level of generalization. On lower level behavioral graphs are expressing temporal dependencies between single objects (or simpler groups of objects).

In Figure 6, we present exemplary behavioral graph for two vehicles: vehicle A and vehicle B, related to the standard overtaking pattern. There are 6 nodes in this graph representing the following temporal concepts: vehicle A is driving behind B on the right lane, vehicle A is changing lanes from right to left, vehicle A is moving back to the right lane, vehicle A is passing B (when A is on the left lane and B is on the right lane), vehicle A is changing lanes from left to right and vehicle A is before B on the right lane. There are 7 connections representing spatio-temporal dependencies between behavioral patterns from nodes. For example, after the node "Vehicle A is driving behind B on the right lane" the behavior of these two vehicles matches to the pattern "Vehicle A is changing lanes from right to left and B is driving on the right lane".

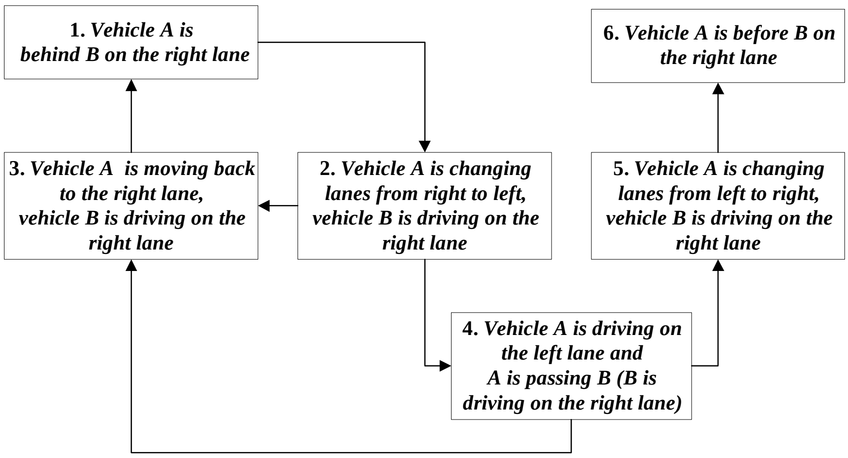

Figure 6. A behavioral graph for the maneuver of overtaking

6. Behavioral patterns

In perceiving complex behavior by individual objects or by a group of objects over a long period of time, it is possible to construct behavioral graphs to codify our observations. Such graphs facilitate observations about transitions between nodes of behavioral graph and registering a sequence of nodes that form paths in temporal patterns. If the path of temporal patterns matches a path in a behavioral graph, we conclude that the observed behavior is compatible with the behavioral graph. In effect, we can use a behavioral graph as a complex classifier for perception of the complex behavior of individual objects or groups of objects. For this reason, a behavioral graph constructed for some complex behavior is called a *behavioral pattern*.

As an example, let us study the behavioral graph presented in Figure 6 for a group of two objects-vehicles (vehicle A and vehicle B) related to the standard overtaking pattern. We can see that the path of temporal patterns with indexes "1, 2, 3, 1, 2, 4" is matching a path from this behavioral graph, while the path with indexes: "6, 5, 4" is not matching any path from this behavioral graph (this path can match some other behavioral patterns).

A path of temporal patterns (that makes it possible to identify behavioral patterns) should have a suitable length. In the case where the length is too short, it may be impossible to discern one behavioral pattern from another pattern. For example, we can make a mistake between an overtaking and a passing by a vehicle in traffic.

7. Risk pattern identification in medical data: case study

An identification of some behavioral patterns can be very important for identification or prediction of behavior of a dynamical system, especially when behavioral patterns describe some dangerous situations. In this case, we call such behavioral patterns as *risk patterns* and we need some tools for identifying them. If in the current situation some risk patterns are identified, then the control object (a driver of the vehicle, a medicine doctor, a pilot of the aircraft, etc.) can use this information to adjust selected parameters to obtain the desirable behavior of the complex dynamical system. This can make it possible to overcome dangerous or uncomfortable situations. For example, a very important element of the treatment of the infants with respiratory failure is the appropriate assessment of the risk of death. The appropriate assessment of this risk leads to the decision of particular method and level of treatment. Therefore, if some complex behavior of an infant that causes a danger of death is identified, we can try to change her/his behavior by using some other methods of treatment (may be more radical) in order to avoid the infant's death. In this section we describe how the presented approach in previous sections can be applied to identification of the infants' death risk caused by respiratory failure.

7.1. 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 is evoked by lung immaturity and surfactant deficiency. The other co-existing abnormalities - 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 a unrelated disease requiring separate treatment. But they co-exist patient very often, so in a single patient we may deal with their combination, for example: RDS + PDA + sepsis. In the holistic therapeutic approach, it is important to synchronize the treatment of the co-existing abnormalities, what finally can lead to cure from respiratory failure.

The respiratory failure dominates in clinical course of prematurity, but is not the only factor limiting the success of treatment. Effective care of the prematurely born infant should include all co-existing abnormalities, such as infections, both congenital and acquired, water-electrolyte and acid-base imbalance, circulatory, kidney and other problems. All these factors are related and their influence one another. The care of the prematurely born infants in their first days of life requires continuous analysis of plenty of the parameters including vital sings and the results of the additional tests. These parameters can be divided into stationary (e.g. gestational age, birth weight, Apgar score) and continuous - changing in time. The continuous values can be examined on discrete (e.g. blood gases) or continuous basis, e.g., with the monitoring devices (oxygen hemoglobin saturation - SAT, hear rate, blood pressure, temperature, lung mechanics). The neonatal care includes assessment of imagine techniques results (ultrasound of the brain, echocardiography, chest X-ray). The global analysis should also include current methods of treatment applied in the particular patients. They may have qualitative (e.g., administration of medication) or quantitative (e.g., respiratory settings) characteristics.

Everyday analysis of numerous parameters requires great theoretical knowledge and practical experience. It is worth to mention that this analysis should be quick and precise. Assessment of the patient's state is performed very often under rush and stress conditions.

A very important element of this analysis is appropriate assessment of the risk of death of the small patient caused by respiratory failure during next hours or days. The appropriate assessment of this risk leads to the decision of particular method and level of treatment. The life of a sick child depends on this quick and correct decision. It should be emphasized, that correct risk of death assessment depends not only on analysis of the current clinical status, lab tests and imagine techniques results but also on the observed lately dynamics and the character of changes (e.g., progression of the blood gases indices of respiratory failure). The additional risk parameters, such as birth weight are also important.

Computer techniques can be very useful in the face of difficulties in effective data analysis. They may provide support for the physician in everyday diagnostic-therapeutic process both as a collecting, storing and patient's data presenting tools (e.g., Neonatal Information System - NIS) and as a tool of quick, automatic and intelligent analysis of this data. This approach might allow for computer presentation of some information based on the observed patterns, which might be helpful in planning the treatment. The example of such a tool is the system for detecting patterns of changes in the newborn clinical status, which with high probability are leading to death. This kind of patterns is called the risk patterns (see Section 6). In this approach, a given patient is treated as an investigated complex dynamical system, whilst diseases of this patient (RDS, PDA, sepsis, Ureaplasma and respiratory failure) are treated as complex objects changing and interacting over time (see Section 5).

7.2. Medical temporal patterns

As we told before (see Section 2), any elementary action should be understood as a very small but meaningful change of some sensor values such as location, distance, speed, temperature, weight, etc. In case of our medical example (the treatment of the infants with respiratory failure), we can distinguish the following elementary actions such as increase in FiO2 (the percent concentration of oxygen in the gas entering the lungs), decrease in PaO2 (the arterial oxygen tension), decrease in PaO2/FiO2, stable creatinine serum (blood) level etc. However, a perception of composite actions requires analysis of elementary actions performed over a longer period called a *time window* (see Section 2). Therefore, if we want to predict composite actions or discover a behavioral pattern, we have to investigate all elementary actions that have been performed in the current time window. Hence, one can consider, e.g., the frequency of elementary actions within a given time window and temporal dependencies between them. These properties can be expressed using temporal patterns. We consider temporal patterns of the following types: sensory pattern, local pattern and sequential pattern (see Section 2). For example, in the case of the medical example one can consider sensory patters such as minimal PaO2/FiO2, first PaO2/FiO2 or last creatinine in the given time window, local patterns such as “Did PaO2/FiO2 increase in the time window?” or “Was PaO2/FiO2 stable in the time window?” and sequential patterns such as “Did the PaO2/FiO2 increase before the closing of PDA?” or “Did the PaO2/FiO2 increase before a PaO2/FiO2 decrease occurred?”. Notice that all such patterns ought to be defined by a human, medical expert using domain knowledge accumulated for the respiratory failure disease.

7.3. Behavioral graph for a disease

The temporal patterns can be treated as new features that can be used to approximate temporal concepts (see Section 2). In the case of the treatment of infants with respiratory failure one can define complex concepts such as “Is the infant suffering from the RDS on level 1?”, “Was an multi-organ failure detected?”, or “Is the progressing of multi-organ failure in sepsis on level 4?”.

Temporal concepts defined for objects from a complex dynamical system and approximated by AR schemes, can be treated as nodes of a graph called a *behavioral graph* (see Section 4), where connections between nodes represent temporal dependencies. Figure 7 presents a behavioral graph for a single patient exhibiting a behavioral pattern of patient by analysing of the organ failure caused by sepsis. This graph has been created on the basis of observation of medical data sets (see Section 9.2) and the SOFA scale (Sepsis-related Organ Failure Assessment - see [29] for more details).

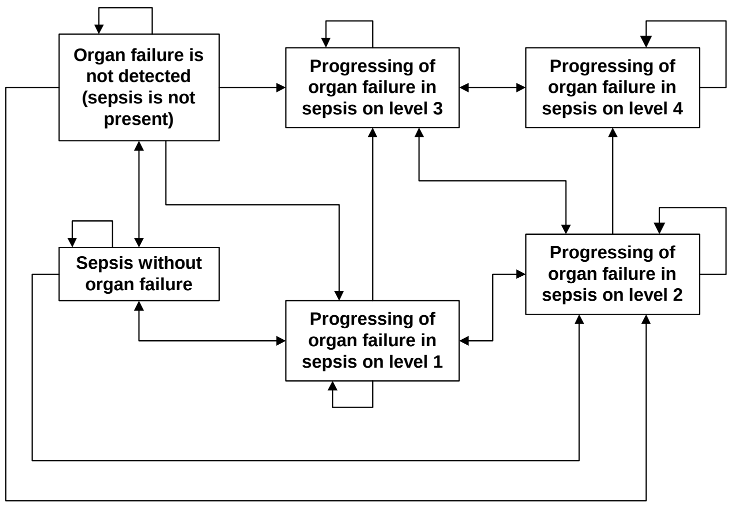

Figure 7. A behavioral graph of sepsis by analysing of the organ failure

In this behavioral graph, for example, connections between node “Progressing of organ failure in sepsis on level 1” and node “Progressing of organ failure in sepsis on level 3” indicates that after some period of progressing of organ failure in sepsis on level 1 (rather low progressing), a patient can change his behavior to the period, when progressing of organ failure is high. In addition, a behavioral graph can be constructed for different kinds of diseases (like RDS, PDA, ureaplasma - see Section 7.1) or groups of diseases represented for example by the respiratory failure (see Section 7.1 and 5).

7.4. Medical risk pattern

The temporal concepts defined for group of objects and approximated by AR schemes, are nodes of a new graph, that we call as *a behavioral graph for a group of objects* (see Section 5). In Figure 8, we present an exemplary behavioral graph for group of four diseases: sepsis, ureaplasma, RDS and PDA, related to the behavior of the infant during high death risk period due to respiratory failure. This graph has been created on the basis of observation of medical data sets (see Section 9.2) and with support of medical experts. There are 16 nodes in this graph and 21 connections represented spatio-temporal dependencies between temporal concepts from nodes. For example, after the node "Stabile and mild respiratory failure in sepsis" the behavior of patient can match to the node "Exacerbation of respiratory failure from mild to moderate in sepsis".

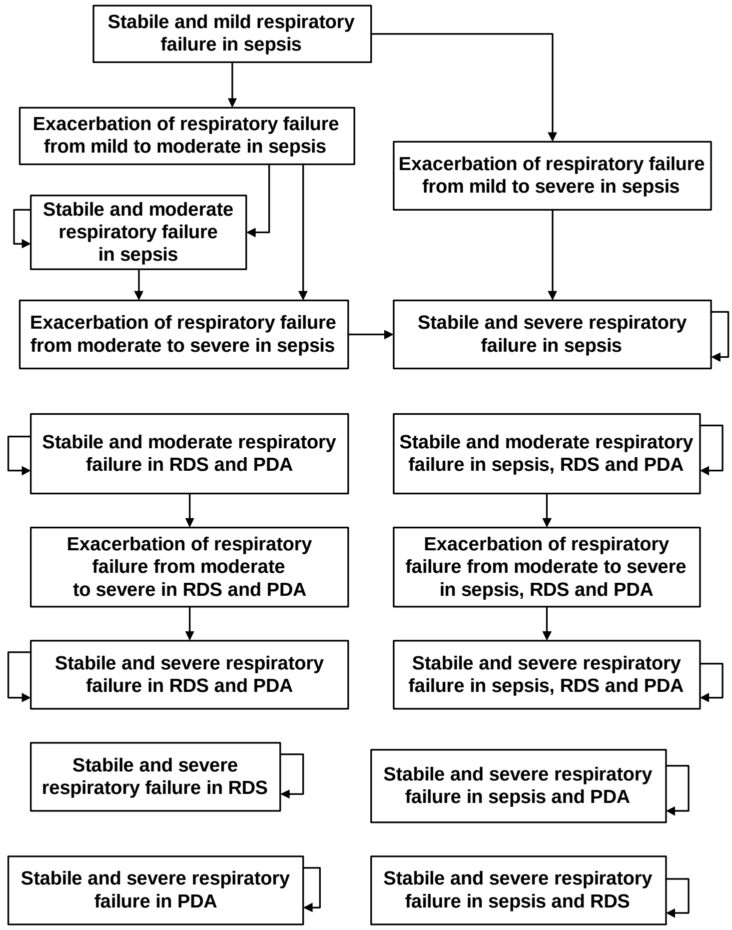

Figure 8. A behavior graph of the infant during high death risk period due to respiratory failure

This behavioral graph is an example of risk pattern. We can see that the path of temporal patterns: ("Stable and mild respiratory failure in sepsis", "Exacerbation of respiratory failure from mild to severe in sepsis", "Stable and severe respiratory failure in sepsis") is matching a path from this behavioral graph, while the path: ("Stable and severe respiratory failure in sepsis", "Exacerbation of respiratory failure from moderate to severe in sepsis", "Stable and moderate respiratory failure in sepsis") is not matching any path from this behavioral graph.

8. Discovering perception rules for fast identification of behavioral patterns

Let us assume that we have a family of behavioral patterns $BP = \{b_1, ..., b_n\}$ defined for groups of objects (or parts of a given object). For any pattern b_i from the family BP one can construct a complex classifier based on a suitable behavioral graph (see Section 6) that makes it possible to answer the question: "Does the behavior of the investigated group (or the part of a complex object) match the pattern b_i?". The identification of behavioral patterns of any group is performed by investigation of a time window sequence registered for this group during some period (sometimes quite long). This registration of time windows is necessary if we want to avoid mistakes in identification of the investigated object group. However, in many applications, we are forced to make a faster (often in real-time) decision if some group of objects is matching the given behavioral pattern. In other words, we would like to check the investigated group of objects at once, that is, using the first or second temporal window of our observation only. This is very important from the computational complexity point of view, because if we investigate complex dynamic systems, we usually have to investigate very many groups of objects. Hence, the faster verification of groups can help us to optimise the process of searching among groups matching the given behavioral pattern.

The verification of complex objects consisting of some groups of objects can be speeded up by using some special decision rules. Such rules can make it possible to exclude very fast many parts (groups of objects) of a given complex object as irrelevant for identification of a given behavioral pattern. This is possible because these rules can be often applied at once, that is after only one temporal window of our observation.

Temporal patterns are constructed over temporal windows. At the beginning we define a family of temporal patterns $TP = \{t_1, ..., t_m\}$ that have influence on matching of investigated groups to behavioral patterns from family BP. These temporal patterns should be defined on the basis of information from temporal windows (for the verification of single object) or from information in behavioral graphs (for the verification of group of objects). Next, we construct classifiers for all defined temporal patterns (see [6] for more details).

For any temporal pattern t_i from the family TP we create a decision table DT_i with only two attributes (see Figure 9). Any object of the table DT_i is constructed on the basis of information registered during a period that is typical for the given temporal pattern t_i. The decision attribute of the table DT_i (the decision attribute of this table) is computed using the classifier for t_i for a given temporal window. The condition attribute b registers the index of behavioral pattern from the family BP. The index computation is based on observation that any complex classifier from BP can check for the investigated group of objects if there is a sequence of temporal windows matching the given behavioral pattern and starting from a given temporal window.

Next, we compute decision rules for DT_i using methods of attribute values grouping that have been developed in the RSES system [32]. Any computed decision rule expresses a dependency between a temporal pattern and the set of behavioral patterns that are not matching this temporal pattern. Let us consider a very simple illustrative example. Assume we are interested in the recognition of overtaking that can

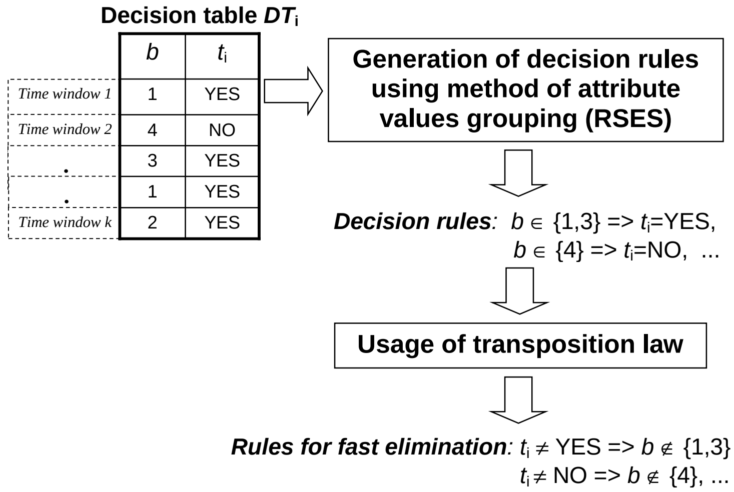

Figure 9. The scheme of rules extraction for the fast elimination of behavioral patterns from data tables

be understood as a behavioral pattern, defined for the group of two vehicles. Using the methodology presented above, we can obtain the following decision rule: `If the vehicle A is overtaking B then the vehicle B is driving on the right lane`. After applying the transposition law, we obtain the following rule: `If the vehicle B is not driving on the right lane then the vehicle A is not overtaking B`. The last rule (see also Figure 10) allows us for fast verification whether the investigated group of objects (two vehicle: A and B) is matching the behavioral pattern of overtaking.

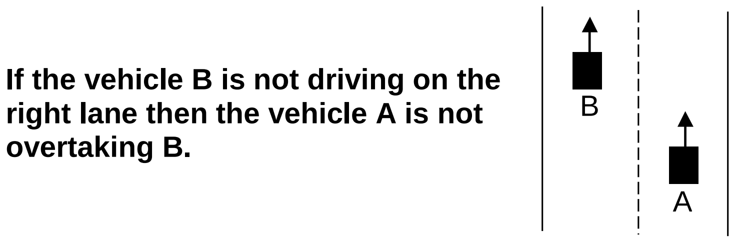

Figure 10. The illustration of the perception rule for fast elimination of behavioral pattern

Of course, in the considered complex dynamic system, there are many other rules that can help us in the fast verification of groups of objects related to the overtaking behavioral pattern. Besides, there are many other behavioral patterns in this complex dynamic system and we have to calculate rules for them using the methodology presented above.

The presented method (called the ENP method) is not a method for behavioral pattern identification. However, this method allows us to eliminate some parts of a given complex object that are not relevant for checking if this object is matching a given behavioral pattern. After such elimination the complex classifiers based on a suitable behavioral graphs should be applied to the remaining parts of the complex object.

Table 1. Results of experiments for the overtaking pattern

Decision class	Method	Accuracy	Coverage	Real accuracy
Yes (overtaking)	RS-D	0.800	0.757	0.606
	BP	0.923	1.0	0.923
	BP-E	0.883	1.0	0.883
No (no overtaking)	RS-D	0.998	0.977	0.975
	BP	0.993	1.0	0.993
	BP-E	0.998	1.0	0.998
All classes (Yes + No)	RS-D	0.990	0.966	0.956
	BP	0.989	1.0	0.989
	BP-E	0.992	1.0	0.992

9. Experimental results

To verify the effectiveness of classifiers based on behavioral patterns, we have implemented the algorithms from the *Behavioral Patterns* library (BP-lib), which is an extension of the RSES-lib 2.1 library forming the computational kernel of the RSES system [32].

Our experiments have been performed on the data sets obtained from the road simulator (see [31]) and on the medical data sets obtained from Neonatal Intensive Care Unit in Department of Pediatrics, Collegium Medicum, Jagiellonian University, Cracow.

9.1. Results for the road simulator data

In case of experiments on the data sets obtained from the road simulator, we have applied the "train and test" method for estimating accuracy. A training set consisted of 17553 objects generated by the road simulator during one thousand of simulation steps. Whereas, a testing set consisted of 17765 objects collected during another (completely different) session with the road simulator.

In our experiments, we compared the quality of three classifiers: *Rough Set classifier with decomposition* (RS-D), *Behavioral Pattern classifier* (BP) and *Behavioral Pattern classifier with the fast elimination of behavioral patterns* (BP-E). For induction of RS-D, we employed RSES system generating the set of minimal decision rules that are next used for classification of situations from the testing data. However, we had to use the method of generating decision rules joined with a standard decomposition algorithm from the RSES system. This was necessary because the size of the training table was too large for the directly generating decision rules (see [32]). The classifiers BP and BP-E are based on behavioral patterns (see Section 6) but with application of fast elimination of behavioral patterns related to the investigated group of objects (see Section 8). We compared RS-D, BP and BP-E using accuracy of classification. Table 1 shows the results of applying these classification algorithms for the concept related to the $overtaking$ behavioral pattern.

One can see that in case of perception of the overtaking maneuver (decision class Yes) the accuracy and the real accuracy ($real\ accuracy = accuracy \times coverage$) of algorithm BP are higher than the accuracy and the real accuracy of algorithm RS-D for the analyzed data set. Besides, we see that the accuracy of algorithm BP-E is only 4 percent lower than the accuracy of algorithm BP. Whereas, the algorithm BP-E allows us to reduce the time of perception, because during perception we can usually identify the lack of overtaking earlier than in the algorithm BP. This means that it is not necessary to collect and investigate the whole sequence of time windows (that is required in the BP method) but only some first part of this sequence (see Figure 11). In our experiments with the classifier BP-E it was enough to use on average 5.3% percent of the whole time sequence window for objects from the decision class No (the lack of overtaking in the time window sequence).

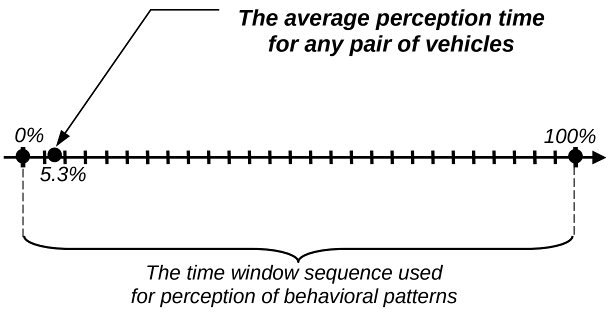

Figure 11. The illustration of the average perception time by ENP method of the *no overtaking* behavioral pattern

9.2. Results for the medical data

The medical data, that we used in our experiments were 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). The detailed information about treatment of 340 newborns are available in the data set, such as 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 end of the 2 day of life. Additionally, the children suffering from the 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.

As a measure of classification success (or failure) we use the most common measure called *accuracy*. The accuracy we define as the ratio of the number of properly classified cases in the testing set to the total number of tested cases. Additionally, we calculated values of accuracy for tested objects from decision classes Yes (the high risk of death) and No (the low risk of death) separately. We have applied the “train and test” method for estimating accuracy of our classifier. A training set consisted of 5810 objects, whereas, a testing set consisted of 5289 objects. Table 2 shows the results of applying this algorithm for the concept related to the risk pattern of death due to respiratory failure.

Notice, that the accuracy of decision class Yes in medical statistics (see [1]) is called as sensitivity (the proportion those cases having a true positive test result of all positive cases tested), whereas the accuracy of decision class No is called as specificity (the proportion of true negatives of all the negative

Table 2. Results of experiments for the risk pattern of death due to respiratory failure

Decision class	Accuracy
Yes (the high risk of death)	0.992
No (the low risk of death)	0.936
All classes (Yes + No)	0.956

samples tested). So, we can see, that in case of our classifier, the sensitivity is meaningfully higher than the specificity. The reason is because the sensitivity of our algorithm has been increased by tuning our classifier in order to avoid classification mistakes for a patient belonging to the decision class Yes. It seems to be this purpose has been achieved. Moreover, we see both main parameters of our classifier (i.e., sensitivity and sensitivity) are sufficiently high.

10. Conclusion

In this paper, we discussed some rough set tools for perception modeling. They make it possible to identify behavioral patterns of objects and their parts changing over time. We have presented the complete approach to the perception of behavioral patterns, that is based on behavioral graphs and the ENP method. We have also reported results of experiments performed on two data sets, i.e., data recorded in the road simulator and medical data.

The performed experiments show that the quality of unseen object classification based on presented networks of classifiers are sufficiently high. Therefore we conclude, that our methods can be treated as a useful tool in the practice, especially in the medical practice, because this approach may be helpful in planning treatments.

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