Risk Pattern Identification in the Treatment of Infants with Respiratory Failure Through Rough Set Modeling

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Abstract. We discuss some application of rough set tools for modeling networks of classifiers. They enable to recognize risk patterns of changes in the newborn clinical status, i.e., patterns of changes that with the high probability are leading to death. Such networks of classifiers are constructed using an ontology of concepts delivered by experts. The article includes results of experiments, that have been performed on medical data obtained from Neonatal Intensive Care Unit in Department of Pediatrics, Jagiellonian University Medical School. These experiments were concerned with the identification of the infants' death risk caused by respiratory failure.

Keywords: Risk pattern, rough sets, concept approximation, dynamical system, respiratory failure.

1 Introduction

Many real life problems can be modeled by systems of complex objects and their parts changing and interacting over the time.

The objects are usually linked by some dependencies, sometimes can cooperate between themselves and are able to perform flexible autonomous complex actions (operations, changes). Such systems are identified as *complex dynamical systems* [3, 27] or *autonomous multiagent systems* [21, 18, 20, 27]. For example, one can consider *road traffic* as a dynamical system represented by road simulator (see, e.g., [5]). Another example can be taken from the medical practice. It concerns with the treatment of infants with respiratory failure, where a given patient is treated as an investigated complex dynamical system, whilst diseases of this patient are treated as complex objects changing and interacting over the time (see Section 2).

An efficient monitoring of complex dynamic system can be made using so-called behavioral patterns. Any behavioral pattern can be understood as a way to represent some behavior of complex objects and their parts changing over time. 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 identification of them. If in the current situation some risk patterns are identified, then the control object (a driver of vehicle, a medical doctor, a pilot of aircraft, etc.) can use this information to tune 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, very important element in treatment of the infants with respiratory failure is appropriate assessment of the risk of death. The appropriate assessment of that risk leads to the decision of launching a particular mode and level of treatment. Therefore, in case of identification of some complex behavior that cause a danger of death, some other methods of treatment can be used (even much more radical) in order to avoid 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., [18, 9, 19, 20]), especially if one considers the introduction of some form of learning by cooperating agents (see, e.g., [25, 7, 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 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.

In this paper, we discuss some rough set (see [17]) tools for perception modeling that have been developed in our project as part of a system for modeling networks of classifiers. Such networks make it possible to recognize risk patterns of objects and their parts changing over time. They are constructed using an ontology of concepts delivered by experts aiming to approximate reasoning on concepts embedded in such an ontology.

Our practical experiments were concerned with the identification of the risk of death of the infant caused by respiratory failure. Therefore in the Section 2 we present a piece of medical knowledge about the treatment of the infants with respiratory failure.

In our approach we use the notion of *temporal pattern* (see Section 3) 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 4), that represent more complex features of complex objects. More complex behavior of complex objects or groups of complex objects can be represented in the form of *behavioral graphs* (see Section 5 and 6). 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 7).

To illustrate the method and to verify the effectiveness of classifiers based on behavioral patterns, we have performed an experiment with the medical data sets obtained from Neonatal Intensive Care Unit in Department of Pediatrics, Jagiellonian University Medical School, Cracow. We present results of our experiments in Section 8.

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., [6, 7, 4, 5]), and is related to companion research on interactive behavior and learning by swarms of cooperating agents (see, e.g., [18–20].

2 Neonatal respiratory failure

The new possibilities in medical intensive care have appeared during last decades due to the progress in medical and technical sciences. This progress allowed us to save the life of prematurely born infants including the smallest born between 20 and 24 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 multi-organ complications is possible with appropriate treatment. Prematurity can be characterized as an inappropriate maturity of organs leading to their dysfunction after birth.

The respiratory system dysfunction appearing in the first hours of life and leading to the 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 multi-organ 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 in 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 they 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, heart 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.

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 about launching a particular method and level of treatment. The life of 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.

Due to such difficulties computer techniques can be very useful 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 make it possible computer presentation of some information based on the observed patterns, which might be helpful in planning the treatment. The example is the tool detecting patterns of changes in the newborn clinical status, which with the high probability are leading to death. This kind of patterns will be called as the risk patterns (see Section 7).

3 Temporal patterns

In many complex dynamic systems, there are some *elementary actions* (performed by complex objects), that is 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, temperature, weight, etc. In case of the medical example (the treatment of the infants with respiratory failure), we distinguish some elementary actions, such as increase in FiO_2 (the percent of oxygen concentration in inhaled gas), decrease in PaO_2 (the arterial oxygen tension), decrease in PaO_2/FiO_2, 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*. 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 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 using 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 parameter, initial and final values of selected parameter, deviation of selected parameter values).
– *local pattern*. A crisp (binary) characterization of occurrences of elementary actions (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 parameter. For example, in case of the medical example one can consider sensory patterns such as minimal PaO_2/FiO_2, first PaO_2/FiO_2 or last creatinine blood level in the given 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 the medical example we have exemplary local patterns such as "Did PaO_2/FiO_2 increase in the time window?" or "Was PaO_2/FiO_2 stable in the time window?" and sequential patterns such as "Did the PaO_2/FiO_2 increase before the closing of PDA?" or "Did the PaO_2/FiO_2 increase before a PaO_2/FiO_2 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.

4 Approximation of temporal concepts

The temporal patterns mentioned in Section 3 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 the treatment of the infants with respiratory failure one can define complex concepts such as "Is the infant suffering from the RDS on the level 1?", "Was an multi-organ failure detected?", or "Is the progressing of multi-organ failure in sepsis on the level 4?".

The approximation of temporal concepts is defined by classifiers, which are usually constructed on the basis of decision rules. However, if we want to apply classifiers for approximation of temporal concepts, we have to construct a suitable decision table called a *temporal pattern table* (see Figure 1).

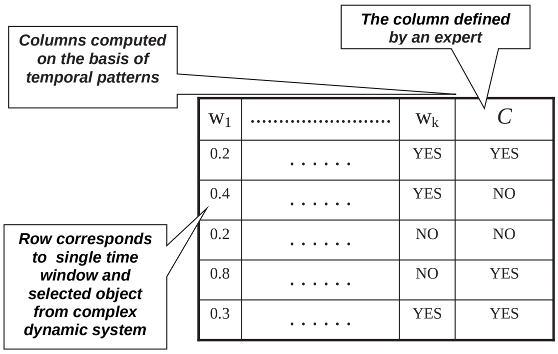

Fig. 1. The scheme of the temporal pattern table (PT)

A temporal pattern table (PT) is constructed from a table T that stores 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 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.

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 (AR) schemes that can be used to approximate temporal concepts (see, e.g., [4]).

5 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 a data set that has been accumulated for a given complex dynamical system. Figure 2 presents a behavioral graph for a single patient exhibiting a behavioral pattern of patient by analyzing of the multi-organ failure caused by sepsis. This graph has been created on the basis of observation of medical data sets (see Section 8) and the SOFA scale (Sepsis-related Organ Failure Assessment - see [24] for more details).

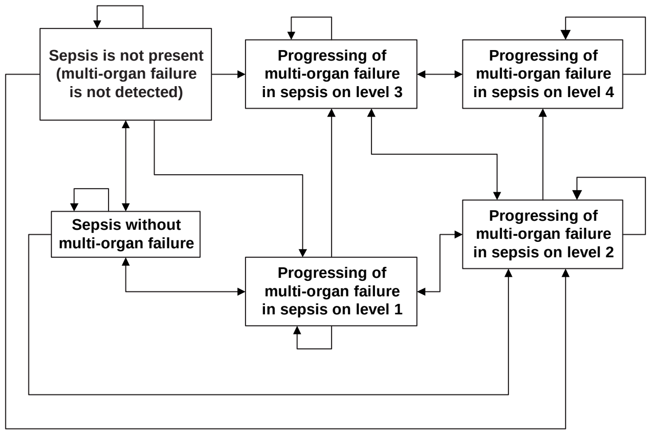

Fig. 2. A behavioral graph of sepsis by analyzing of the multi-organ failure

In this behavioral graph, for example, connections between node “Progressing of multi-organ failure in sepsis on level 1” and node “Progressing of multi-organ failure in sepsis on level 3” indicates that after some period of progressing of multi-organ failure in sepsis on level 1 (rather slow progressing), a patient can change his behavior to the period, when progressing of multi-organ failure is rapid. In addition, a behavioral graph can be constructed for different kinds of diseases (like RDS, PDA, Ureaplasma lung infection - see Section 2) or groups of diseases causing for example a respiratory failure (see Section 2 and 6). Therefore, we consider such behavioral graph as a model of a behavioral patterns.

6 Behavioral graph for a group of objects

Now, we introduce a method for approximation of temporal concepts for a group of objects based on so-called *group temporal pattern table* (see Figure 3). Although this table is constructed using the standard methodology presented in the Section 4 (for the construction of the temporal pattern table), for our purposes we need some important differences. To construct such table, assume that behavioral graphs for all objects belonging to a group of objects have been constructed. For each behavioral graph we can define new temporal patterns using only two kinds of temporal patterns, namely, local patterns and sequential patterns, since information about sensor parameters is not directly accessible.

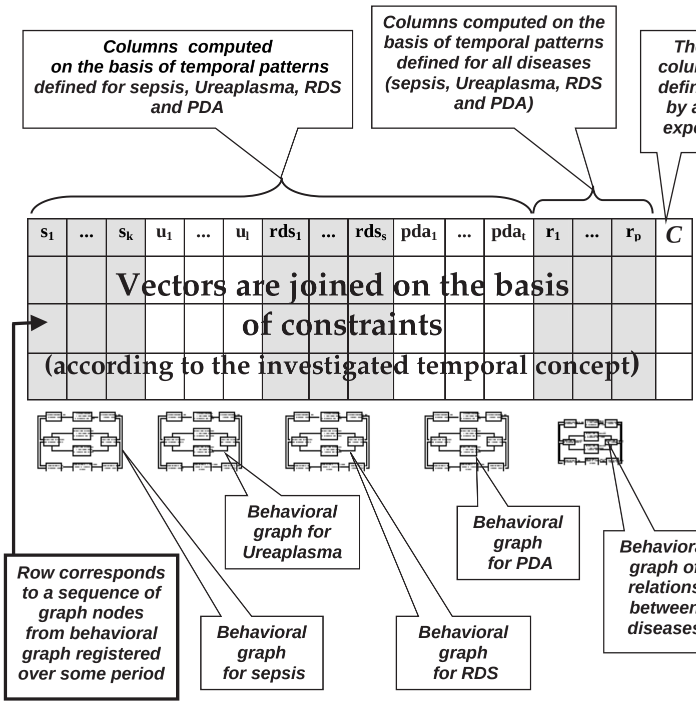

Fig. 3. The scheme of the group temporal pattern table (GT) for sepsis, Ureaplasma, RDS and PDA

A group temporal pattern table GT is constructed in the following way (see also Figure 3)). Any row-object in GT is created for any object in group G using a path of nodes observed in a given behavioral graph of the object-patient. The path in any behavioral graph should be understood as a sequence of graph nodes (temporal concepts) registered over some period, i.e., over a number of time windows. For any such path, a vector of values is computed (a vector of values of condition attributes of table GT) using temporal patterns provided by the expert for the approximation of a concept C. Additional attributes are defined using behavioral graphs of all objects simultaneously. These attributes describe temporal relations between objects in group G.

The temporal concepts defined for group of objects and approximated by AR-schemes, can be treated as nodes of a new graph, that we call as *a behavioral graph for a group of objects*. One can say, 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 4 we present 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 8) and with support of human 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".

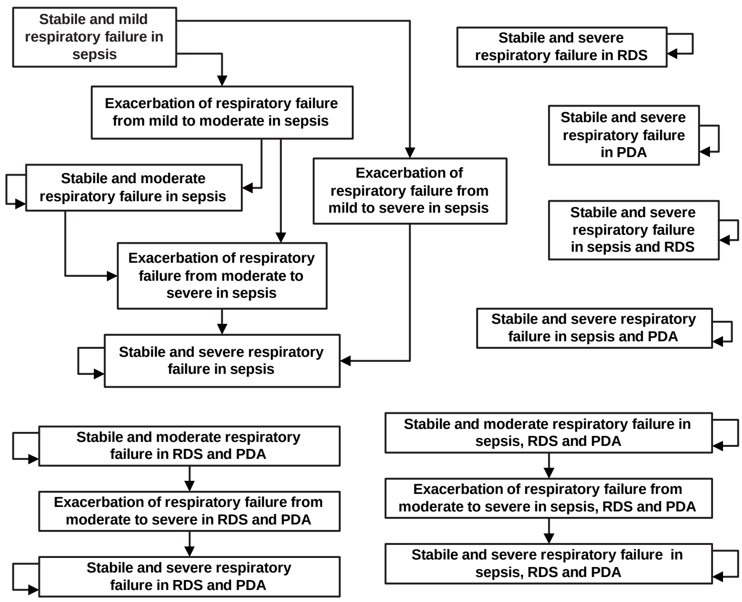

Fig. 4. A behavioral graph of the infant during high death risk period due to respiratory failure

7 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 4 for a infant during respiratory failure related to the pattern of high death risk period due to respiratory failure. This behavioral graph can be treated as an example of risk pattern. We can see that the path of temporal patterns: (“Stabile and mild respiratory failure in sepsis”, “Exacerbation of respiratory failure from mild to severe in sepsis”, “Stabile and severe respiratory failure in sepsis”) is matching a path from this behavioral graph, while the path: (“Stabile and severe respiratory failure in sepsis”, “Exacerbation of respiratory failure from moderate to severe in sepsis”, “Stabile and moderate respiratory failure in sepsis”) 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. When the path of temporal patterns is too short, it could be impossible to discern one behavioral pattern from the other. For example, we can make a mistake between a death-risk pattern and a more optimistic one (leading to life).

8 Experimental Results

To verify the effectiveness of classifiers based on behavioral patterns, we have implemented the algorithms in a *Behavioral Patterns* library (BP-lib), which is an extension of the RSES-lib 2.1 library forming the computational kernel of the RSES system (see [22]).

The experiments have been performed on the medical data sets obtained from Neonatal Intensive Care Unit in Department of Pediatrics, Jagiellonian University Medical School, Cracow. The data was 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 and imagine techniques results, Detailed diagnoses during hospitalization, procedures and medication were also recorded for all treated patients. 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, children suffering from the

Table 1. 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

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, which consists of 11099 objects. Each object of this table describes parameters of one patient in single time point.

We have applied the "train and test" method for estimating accuracy of our classifier. A training set consists of 5810 objects, whereas, a testing set consists of 5289 objects.

Table 1 shows the results of applying this algorithm for the concept related to the risk pattern of death due to respiratory failure.

It should be emphasized, that the accuracy of decision class Yes (the high risk of death) in medical statistics is called as *sensitivity*, whereas the accuracy of decision class No (the low risk of death) is called as *specificity* (see [1]). 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 in order to avoid misclassifications for a patient belonging to the decision class Yes. It seems that this purpose has been achieved. Moreover, we suppose that both main parameters of our classifier (i.e., sensitivity and sensitivity) are sufficiently high.

9 Conclusion

In this paper, we discussed some rough set tools for perception modeling that are developed for a system for modeling networks of classifiers. Such networks make it possible to recognize the risk pattern of changes in the newborn clinical status, i.e., the pattern of changes that with the high probability are leading to death. 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 medical practice, because this approach may be helpful in planning of the treatment. Furthermore we would like to develop a software environment for the automatic treatment planning of the newborns with the respiratory failure.

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References

1. Altman, D., G.: *Practical Statistics for Medical Research.* Chapman and Hall/CRC, London, 1997.
2. Anderson, J., R.: *Rules of the mind.* Lawrence Erlbaum, Hillsdale, NJ, 1993.
3. Bar-Yam, Y.: *Dynamics of Complex Systems.* Addison Wesley, Reading, MA, 1997.
4. Bazan J., Skowron A.: Classifiers based on approximate reasoning schemes. In Dunin-Keplicz, B., Jankowski, A., Skowron, A., and Szczuka, M. (Eds.): Monitoring, Security, and Rescue Tasks in Multiagent Systems MSRAS, *Advances in Soft Computing*, Springer, Heidelberg, 2005, 191–202.
5. Bazan J., Peters, J., F., Skowron, A.: Behavioral pattern identification through rough set modeling. In *Proceedings of RSFDGrC'2005*, LNAI **3641**, Springer, Heidelberg, 2005, 688–697.
6. Bazan, J., Nguyen, Hoa, S., Nguyen, Son, H., Skowron, A.: Rough set methods in approximation of hierarchical concepts. In *Proceedings of RSCTC'2004*, LNAI **3066**, Springer, Heidelberg, 2004, 346–355.
7. Nguyen, Hoa, S., Bazan, J., Skowron, A., Nguyen, Son, H.: Layered learning for concept synthesis. In LNCS **3100**, *T*ransactions on Rough Sets, **I**, Springer, Heidelberg, 2004, 187–208.
8. Birattari, M., Di Caro, G., Dorigo, M.: Toward the formal foundation of ant programming. In LNCS **2463**. Springer-Verlag, Berlin, 2002, 188-201.
9. Bonabeau, E., Dorigo, M., Theraulaz, G.: *Swarm Intelligence. From Natural to Artificial Systems*, Oxford University Press, UK, 1999.
10. Fahle, M, Poggio, T. (Eds.): *Perceptual Learning*, The MIT Press, Cambridge, MA, 2002.
11. Harnad, S. (Ed.): *Categorical Perception. The Groundwork of cognition*, Cambridge University Press, UK, 1987.
12. Kieras, D., Meyer, D., E.: An overview of the EPIC architecture for cognition and performance with application to human-computer interaction. *Human-Computer Interaction* **12**, 1997, 391-438.
13. Langley, P., Laird, J., E.: Cognitive architectures: Research issues and challenges. *Technical Report*, Institute for the Study of Learning and Expertise, Palo Alto, CA, 2002.
14. Laird, J., E., Newell, A., Rosenbloom, P., S.: Soar: An architecture for general intelligence. In *Artificial Intelligence* **33**, 1987, 1–64.
15. Newell, A.: *Unified Theories of Cognition*, Cambridge, Harvard University Press, MA, 1990.
16. Pal, S., K., Polkowski, L., Skowron, A. (Eds.): *Rough-Neural Computing: Techniques for Computing with Words. Cognitive Technologies.* Springer, Heidelberg, 2004.
17. Pawlak, Z.: *Rough Sets: Theoretical Aspects of Reasoning about Data. Volume 9 of System Theory, Knowledge Engineering and Problem Solving.* Kluwer Academic Publishers, Dordrecht, The Netherlands, 1991.
18. Peters, J. F.: Rough Ethology: Towards a Biologically-Inspired Study of Collective Behavior in Intelligent Systems with Approximation Spaces. In *Transactions on Rough Sets*, **III**, LNCS 3400, 2005, 153-174.
19. Peters, J., F.: Approximation spaces for hierarchical intelligent behavioral system models. In Dunin-Keplicz, B., Jankowski, A., Skowron, A., and Szczuka, M., editors, Monitoring, Security, and Rescue Tasks in Multiagent Systems MSRAS, *Advances in Soft Computing*, Springer, Heidelberg, 2004, 13–30.

20. Peters, J., F., Henry, C., Ramanna, S.: Rough Ethograms : Study of Intelligent System Behavior. In *Proceedings of IIS05*, Gdańsk, Poland, June, 2005, 13-16.
21. Luck, M., McBurney, P., Preist Ch.: *Agent technology: Enabling Next generation. A roadmap for Agent Based Computing.* Agent Link, 2003.
22. The RSES Homepage at `logic.mimuw.edu.pl/~rses`
23. Veloso, M., M., Carbonell, J., G.: Derivational analogy in PRODIGY: Automating case acquisition, storage, and utilization. In *Machine Learning* **10**, 1993, 249–278.
24. Vincent, JL., de Mendonca, A., Cantraine, F., et al.: Use of the SOFA score to assess the incidence of organ dysfunction/failure in intensive care units: results of a multicenter, prospective study. Working group on "sepsis-related problems" of the European Society of Intensive Care Medicine. In *Crit Care Medicine* **26**, 1998, 1793-1800.
25. Dorigo, M., Birattari, M., Blum, C., Gambardella, L., M., Monada, F., Stutzle, T, (Eds.): Ant Colony Optimization and Swarm Intelligence. In LNCS **3172**. Springer-Verlag, Berlin, 2004.
26. Sutton, R., S., Barto, A., G.: *Reinforcement Learning: An Introduction.* Cambridge, MA: The MIT Press, 1998.
27. Urmson, C. et al.: High speed navigation of unrehearsed terrain: Red team technology for Grand Challenge. Report CMU-RI-TR-04-37, The Robotics Institute, Carnegie Mellon University, 2004.
28. Zadeh, L., A.: A new direction in AI: Toward a computational theory of perceptions. *A*I Magazine, **22**,(1), 2004, 73–84.