KNOWLEDGE ENGINEERING AND DIAGNOSTICS - TODAY AND TOMORROW

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Summary

The paper addresses several issues concerning knowledge engineering in the context of technical diagnostics. The goal consists in preparing, verifying, validating and then implementing domain-specific knowledge, capable of aiding diagnosticians and other personnel in operating machinery and equipment. New trends in knowledge engineering focus our attention on discovering useful knowledge from huge databases that collect process data acquired from machinery, and making this knowledge even more easily available for humans. The paper concludes with discussion about prospective potential issues for next decades of this century.

Keywords: knowledge engineering, knowledge sources, domain experts, knowledge discovery, user interface

INŻYNIERIA WIEDZY I DIAGNOSTYKA – DZISIAJ I JUTRO

Streszczenie

W referacie omówiono kilka problemów inżynierii wiedzy widzianych w kontekście diagnostyki technicznej. Celem tego postępowania jest przygotowanie, zweryfikowanie, walidowanie a następnie zastosowanie wiedzy specyficznej dla danej dziedziny, która mogłaby wspomóc diagnostów i inny personel w prowadzeniu maszyn i urządzeń. Nowe trendy w inżynierii wiedzy skupiają naszą uwagę na odkrywaniu użytecznej wiedzy w ogromnych bazach danych zawierających dane procesowe zgromadzone dla maszyn, a także na zwiększeniu dostępności do tej wiedzy. W podsumowaniu przedstawiono przyszłe potencjalne zastosowania w kolejnych dekadach naszego wieku.

Słowa kluczowe: inżynieria wiedzy, źródła wiedzy, eksperci dziedzinowi, odkrywanie wiedzy, interfejs użytkownika

1. INTRODUCTION

Technical diagnostics deals with machinery and equipment (further on referred to as objects). Its goal is to detect, localize and diagnose possibly faults of the object under consideration. To this end, a comprehensive activity is undertaken that has been called "diagnostic testing" [1]. It includes: planning diagnostic experiments (active or passive ones), observing objects of diagnosing, collecting data and preprocessing it in order to gather evidence, and finally - diagnostic reasoning. All of these stages of diagnostic testing are in fact knowledge-intensive. Furthermore, they face the diagnostician with the need to possess comprehensive and multidisciplinary knowledge.

The paper addresses several issues concerning knowledge engineering in the context of technical diagnostics. The goal consists in preparing, verifying, validating and then implementing domain-specific knowledge, capable of aiding diagnosticians and other personnel in operating machinery and equipment. Of special importance are new trends in knowledge engineering that focus our attention on discovering useful knowledge from huge databases that collect process data acquired from machinery, and making this knowledge even more easily available for humans.

The paper is composed as follows. In the next Section we argue why knowledge is required if one deals with diagnostic problems. We also point out two different types of knowledge: procedural and declarative one. In 3rd section we discuss possible knowledge sources, emphasizing importance of databases as basic today's sources of knowledge. Section 4. deals with contemporary issues of knowledge engineering and is organized according to main knowledge sources and types of knowledge in question. Without diminishing importance of knowledge acquired from experts, particular attention id paid to learning and discovering knowledge from databases. Section 5. is concerned with future issues of knowledge engineering in technical diagnostics. The paper ends with some conclusions.

Table 1. Knowledge used during diagnostic testing

Activity/Stage	**Knowledge needed**	**Kind of knowledge**
Planning diagnostic experiments	Deep domain knowledge about the object, population of objects, faults, reliability, dynamics, causal relationships, ...	Procedural, declarative
Observing objects of diagnosing and acquiring signals, process parameters and other evidence	How to carry out measurements, which measuring points, which quantities, ...	Procedural, declarative
Preparing database	How to estimate features of signals, how to preprocess signals and features	Procedural, declarative
Diagnostic reasoning	Reasoning methods, meta-knowledge, reasoning-specific knowledge represented using some means	Procedural, declarative

2. WHY IS KNOWLEDGE NECESSARY IN TECHNICAL DIAGNOSTICS?

Needs of modern societies systematically grow up. To fulfill them, diverse processes are to be run involving availability of many technical means that allow running these processes.

Although technical means and processes they are carrying out seem to be incomparable, they have mutual properties indeed. For both these objects such requirements are put forward as: minimization of risk to humans and environment, and better performance, efficiency, respective product quality, rational cost, higher reliability of operation, fault-tolerant behavior, etc. As a result of that the objects become more complex, engaged power of drives grows, working speed of parts increases, and dimensions and/or masses and inertia increase as well. Furthermore, machinery and equipment in the most cases has to be considered as dynamic objects, while static description, without taking into account object's history, changing environment etc. seems to be ever more and more inadequate. There is no doubt that diagnostics of processes inherently requires dynamic approach. All these factors cause systematic growth of requirements that have been faced with persons who are involved in building these technical means, and the operating them. Consider that each domain of technical activities requires definite knowledge and skill that is usually possessed by domain experts, who acquire them by learning, long-term professional activity, by observation or by studying specialist literature.

Let us consider what kind of knowledge (if any) is required to efficiently carry out the complete diagnostic testing. As it was mentioned in previous section, at least four stages may be distinguished (Table 1), completely differing from each other in kind of knowledge required to complete respective tasks. However, each stage is knowledge-intensive.

In the Table 1 two fundamentally different kinds of knowledge are enumerated: procedural and declarative one. Procedural knowledge concerns processes, while declarative one corresponds to facts:

objects, classes of objects, relationships between objects, their features and classes, attributes of objects etc. [2].

To conclude one can mention that **diagnostic testing involves multi-aspect operation on information carried by data and supported by knowledge attributable to the respective stage of the complete process**. It is obvious that knowledge is an inherent factor of this process; if no diagnostic knowledge is available, technical diagnostics cannot be carried out.

3. KNOWLEDGE SOURCES

An important problem concerns sources of knowledge required during diagnostic testing. Basically there are two fundamental knowledge sources: domain experts, and databases. Both of them may provide valuable declarative knowledge. Nowadays, procedural knowledge is acquired mainly from domain experts, while declarative knowledge is mainly acquired from data (cf. Fig. 1).

The aforesaid types of knowledge sources differ essentially. One of the most important discerning criterion consists in evaluating performance of process of knowledge acquisition from the given source, which might be expressed in quantity of elementary statements representing knowledge (e.g. rules). Taking this criterion into account it is easy to state that automatic methods of knowledge acquisition from databases are incomparably more efficient. However, experts as knowledge sources are indispensable since they provide background knowledge of the problem domain that includes objects, classes of objects, relations between objects and classes, essential attributes of objects, and more. Therefore, experts shall not be eliminated from the knowledge acquisition process.

4. KNOWLEDGE ENFINEERING IN TECHNICAL DIAGNOSTICS – TODAY

The need to acquire diagnostic knowledge was identified in the 80' of previous century [21]. Although intensive research has been started since middle 80' there are only several research centers where this work is systematically carried out, including the author's Department.

There are some actors in this process with well-defined roles. Apart from an expert (whose participation is not required), an important one is knowledge engineer who is a person that investigates the given domain, identifies essential concepts of this domain and creates for the domain a formal representation of objects and relations that occur among objects. Furthermore, he/she manages the process of knowledge acquisition, works out the knowledge base and holds long-term maintenance upon it.

4.1. Experts' Knowledge

Experts may take part directly in knowledge acquisition process (as participants). There are many techniques for eliciting knowledge from experts, with the one based on questionnaires being still very popular. Furthermore, they may indirectly take part in the process by authoring publications, textbooks, handbooks and manuals, or even design documentation. All these publications may then be processed even without disturbing the author.

There are several models of the process introduced in [4]. Two approaches are currently used. Firstly, knowledge may be acquired from domain experts by knowledge engineers. On the other hand, a domain expert may act unaided using some tool(s) that help her/him represent her/his knowledge.

There are different techniques applied in the first case, with special interviews often accompanied with filling-in problem-oriented questionnaires being the most frequently used. However, it is worth stressing that the knowledge engineer is a specific middleman in the process. Though introduced at the early beginning of Knowledge Engineering development, this method has numerous disadvantages. Communication problems may occur for lack of domain-specific knowledge of expert and difficulties with understanding what indeed the expert explains. Further on, the knowledge engineer has to interpret the "say-how" knowledge of expert, and then represent this knowledge in the knowledge base. Nevertheless, a significant number of successful applications was implemented and is reported in accessible publications.

The second approach is more promising, since it allows overcoming several shortcomings such as communication problems and simply lack of time. Direct participation of the knowledge engineer may be avoided or at least constrained to minimum by using specialized tools that help the expert to represent her/his own knowledge and maybe skill, and write it down into the database under construction. Different kinds of tools may be used starting from a very simple one called "paper form" which is a special questionnaire that enables the expert to represent single empirical diagnostic relationships [2]. Then the relationship is rewritten and put down into the knowledge base by a knowledge engineer. A kind of more advanced tool is the so-called "electronic form" developed in the author's team according to an original concept described in [5]. This tool developed by M. Wyleżoł may help the domain expert in representing not only declarative knowledge, but procedural knowledge, too [6].

4.2. Knowledge acquired from data

Nowadays, databases become important sources of declarative diagnostic knowledge. Databases may contain results of active and/or passive diagnostic experiments acquired during observations of the given object(s). Furthermore, data may be obtained during respectively planned and conducted numerical experiments. Such collections of data may be used in a semi-automatic or even automatic processing using Machine Learning (ML) or Knowledge

Discovery in Databases (KDD) and Data Mining (DM) methodology.

4.2.1. Machine Learning

Machine Learning was implemented in Technical Diagnostics in the last two decades of previous century. Several prerequisites are required in order to apply ML methodology. First of all, cases have to be represented by means of values of attributes that describe them, while a vector of attribute values – either qualitative or quantitative ones – corresponds to one single case. All examples constitute a relation of the relational database. It is required that all data be previously classified by attaching value(s) of decision attributes. Such a table of data is called "information system" (by Z. Pawlak [9]).

There are several ML methods available for knowledge acquisition in technical diagnostics, most of them being applied by the research group of the author. The most well known ones were learning covers (algorithm A^q by R. S. Michalski [7]) and induction of decision trees (algorithm TDIDT - *Top-Down Induction of Decision Trees* - by J. R. Quinlan [8]). A very useful concept has been the method of induction of rules using rough sets [9], efficiently applied in technical diagnostics by R. Nowicki et al. [10]. Detailed descriptions of the algorithms and problems encountered while acquiring knowledge using ML methods are contained in numerous source publications. They may also be found in [2]. There are other methods used in technical diagnostics, as conceptual clustering [11], induction of association rule trees (ART) [12], and the very new kernel-based learning methods such as Support Vector Machines (SVM) [13].

Let us consider the content of the given knowledge base as a diagnostic model of the object/process. Although ML methods are commonly used for building knowledge bases, they may be applied only for acquisition of static declarative knowledge. This seems to be very important constraint, since real objects and processes are inherently dynamic and considering them as static ones restricts applicability of our models to some neighborhood of the working point of the object. Furthermore, pre-classified training data are available very rare. As a result of that, modern knowledge engineering in technical diagnostics has to utilize other knowledge sources than pre-classified data.

4.2.2. Data Mining

Contemporary critical machinery is equipped with SCADA (Supervisory Control And Data Acquisition) systems that collect plenty of data on inputs, state and outputs. Although usually unclassified, they carry useful information on causal and diagnostic relationships between inputs, state and output. In general, databases of SCADA systems allow building diagnostic models of the system in question. To this end, modern KDD and DM methodology is applied.

Prior to start discussion of application of KDD and DM methodology in technical diagnostics it is worth emphasizing that contemporary SCADA systems may collect really huge databases including gigabytes or even terabytes of data. Taking this into account, the knowledge engineer is faced with very difficult problem of "seeking knowledge in the flood of facts"[1]. Only a few regularities are interested for the end-user, while billions of them, mainly of random character may be found in such a huge database. Therefore, KDD systems have to operate in automatic way, with control of the knowledge engineer reduced to minimum.

J. M. Żytkow and the author initiated a research on application of KDD methodology to technical diagnostics in 1997 [14]. This research was focused on finding regularities in data. Regularity is defined by some pattern and range within which this pattern holds. There are several kinds of regularities that are useful in technical diagnostics, such as contingency tables, associations, logical equivalences, and equations (functional regularities). The range is understood as a subset of data that satisfies some complex logical condition, which may be a conjunction of simple conditions such as inequalities.

For diagnostic needs the most useful form of regularities are equations [14]:

$$X = g(Y,U) \,, \tag{1}$$

where X is the object's state, U corresponds to control, and Y to output. If such regularities exist within the database or its subset, they allow exact and unambiguous predictions of object's state.

It is worth considering that results of measurements and observations are burden with noise, incomplete, approximate and/or fuzzy. Therefore, data contained in databases are carriers of incomplete information of quantitative dependencies between attributes.

Discovery of static declarative knowledge consists of two independent stages: finding regularities, and then discovering equations. In the first stage regularities are identified by means of contingency tables. Since discovery of equations is very time consuming, contingency tables allow selecting such subsets of data (i.e. ranges) for which there is a significant chance for equations to be discovered. As it was mentioned earlier, usually millions of possible regularities occur in the database. Only the most significant ones should be selected and then processed in order to obtain functional dependencies (equations). To this end, a probability Q of event that the regularity under consideration is a kind of statistical fluctuation is evaluated. Only these regularities are taken into account, for which this prob-

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[1] Title of the paper by R.S. Michalski presented on the Conference on Intelligent Information Systems in 1994.

ability $Q<10^{-5}$ that corresponds to very small probability of event in question.

Functional dependencies may be discovered using diverse methodologies such as the exemplary one called BACON-3 [15]. This method consists in stepwise generalization of simple equations and is discussed in [2]. The process may be carried out in automatic way. However, several parameters for controlling this process have to be selected properly.

4.2.3. Applications

There are numerous applications of automated methods of knowledge acquisition from data. Some of them may be found in [2, 16, 17]. They concern acquisition of diagnostic knowledge from databases with the use of both the ML and KDD methods.

4.3. Combined approach

One of the most important issues concerns performance of knowledge acquisition process. Let us consider simple knowledge base collecting pieces of knowledge represented by means of rules. If knowledge is acquired from domain experts, it seems to be likely that no more than a few dozen of rules may be represented a day. Furthermore, adding new rules to the existing knowledge base causes even more and more difficulties, due to the necessity to assure error-free contents of the knowledge base. On the other hand, hundreds of non-contradictory rules may be learned from examples during one second.

Contemporary applications take advantage of multiple techniques. Experts provide description of the problem domain, including: important objects and processes, classes of objects, relations between classes of objects and individual objects, relevant properties, attributes and their values, etc. This stage includes creation of domain ontology and provides the most crucial knowledge about the problem domain. Although in theory it is possible to apply automatic methods for discovery of the domain description, a very important principle formulated by R. S. Michalski holds: learning may result in only slight increment of the complete amount of knowledge. Therefore, knowledge acquired "from scratch" by discovery methods does not allow solution of any complex real-world problem.

Furthermore, expert(s) may create an initial version of the knowledge base, basing upon their own knowledge and experience, possibly supported by accessible publications.

At this point all to be carried out by experts themselves would have to be done, and is the right time to start automatic methods of knowledge acquisition in databases. If there is an earlier version of knowledge base available, it may be improved by using incremental learning (Fig. 2). In remaining cases, either ML methodology (if examples are classified), or KDD methodology (otherwise) may be applied. At this phase, repeated activity of experts is of great value, since they should validate the knowledge base. To this end, several iterations of knowledge acquisition process might be necessary.

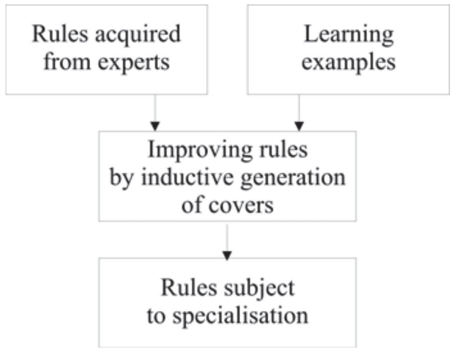

Fig. 2. Incremental learning in technical diagnostics

Summing up, the combined approach enables knowledge engineers to take advantage of strengths of all accessible knowledge sources. It transforms the knowledge acquisition process to a really efficient one that results in the more appropriate knowledge base, which better suits the needs of diagnostic personnel and/or automated diagnostic equipment.

5. FUTURE ISSUES

Knowledge engineering plays ever more and more important role in technical diagnostics, becoming ever more popular in the community of maintenance engineers, process engineers, diagnosticians, and other. Methods of knowledge acquisition and discovery, and their practical implementations, become subject of scientific and applied research. This trend, easy to be observed within the last decade in the USA and some European countries, is going ever more and more frequently to be the subject of research in domestic centers that develop diagnostics of machinery, equipment, and processes.

There are several factors that are driving forces behind further development of knowledge engineering applications to technical diagnostics. It is no doubt that one of that is constantly increasing capability of collecting data of diverse kinds. These datasets are excellent sources of diagnostic knowledge. Other key factors are: dramatically increasing computing power, rising rate of information and data exchange between scientific, R&D, and industrial partners. But perhaps the most crucial is rapid development of Artificial Intelligence methodology and understanding their role in computer-based assistance and support to diagnostic activities. This includes, but is not limited to, application of ever more and more sophisticated methods that are the basis of operation of efficient algorithms, and, as a consequence of that, computer applications and systems operating in a distributed environment.

All the factors mentioned above and many others allow to state that knowledge engineering plays very important role in technical diagnostics. Furthermore, this role will rapidly increase.

Although several important issues were addressed thorough the paper, including works carried out in the author's research group in the Department of Fundamentals of Machinery Design, obviously there are several other attempts that were not taken into account. The author identified some new research topics associated with knowledge engineering and technical diagnostics [2]. These topics of different complexity are worth dealing with in the very next time. They will be addressed briefly in the following.

Acquisition of declarative knowledge from experts. Although very satisfactory and interesting results were obtained, and numerous means of aiding process of acquisition of declarative knowledge from domain experts developed in the last two decades, many problems still remain unsolved. More attention should be paid to methods that allow acquiring knowledge represented by other means, such as taxonomies, ontologies, classifications, etc.

Individual research problems concern further development of methods of aggregating knowledge acquired from various experts, and aggregating their opinions. To make knowledge acquisition process more efficient, a great effort has to be made to develop means that aid accomplishment of this process. In particular, other information carriers could be applied, such as audio and video recordings. To this end, methods of other sub-domains of artificial intelligence may help, such as pattern recognition, speech understanding, scene analysis, context-based approach, etc. Crucial group of problems includes further verification and validation of elaborated methods and supporting means. Especially important is possibly close collaboration with domain experts from outside scientific community.

Acquisition and discovery of procedural knowledge. The role of procedural knowledge in technical diagnostics was discussed thorough the paper. According to the author's opinion [2], the technical diagnostics community does not make aware of the need to acquire such knowledge that, if it were written down in the knowledge base, could aid carrying out complex diagnostic operations.

The need to acquire procedural knowledge of how to carry out diagnostic tests of various types of machinery is of great importance. First of all, sources of such knowledge are domain experts – skilled diagnosticians. However, other possibility may be to discover procedural knowledge from data. An example of such an attempt is given in [17], where a kind of procedural knowledge about process control is discovered in the process database collected by SCADA systems.

This new approach to acquisition of procedural knowledge requires substantial development of respective methodology and tools aiding knowledge engineering in such a field.

Acquisition of knowledge about processes. Most research whose results are known is focused on acquisition of knowledge about static objects, which are considered in the neighborhood of some working point. This approach becomes often too simplified, and resulting knowledge is too rough to find successful implementations. However, industrial databases collecting plenty of data allow applying new methodology of discovery of knowledge about control of industrial processes. It is worth stressing, though, that amount of data contained in contemporary industrial databases does not make it possible to apply traditional methods of system identification. The complete discovery process has to run autonomously, with only very limited control of knowledge engineer.

Development of methodology of knowledge discovery in databases. This field of research has enormous potential perspectives of development, because of increasing number of database systems collecting data about objects and processes. Prospective research problems may concern development of methods of discovering knowledge of qualitative character represented by means of varying means. An especially interesting application is linguistic summary of databases with considerable usage of natural language [18].

Other interesting problems concern discovering dependencies of quantitative character, with special attention paid to dependencies represented by means of multivariable functions. This field of knowledge engineering especially triggers development of new means for aiding knowledge discovery process, which could relieve the user of carrying out arduous and repeatable operations. Furthermore, ways to present discovered knowledge to the end-user should be improved.

Development of means for aiding operations within technical diagnostics. The goal is to build new applications and other means that are easy-to-use, user-friendly, require small resources, and may interchange information with the end-user using natural language and very intuitive interface. These means of aiding diagnosticians are in fact the key to break barriers that the potential users put up against common usage of intelligent systems in the technical diagnostics.

Augmented reality. This is a very new information technology, which the author is going to apply in technical diagnostics. Unlike the virtual reality that is targeted to virtual (unreal) world, the augmented reality (AR) in some sense "improves" real world by providing additional information that aids the user in completing diagnostic tasks. Pieces of information such as working instructions, evidence, rules etc. may be viewed by the user as graphically embedded within the real three-dimensional world. The real challenge to knowledge engineering is to acquire knowledge that might help the diagnostician in perceiving causes of problems that the object or process is experienced with, and then finding optimal solution thereof.

Embedded networked sensing. One of the very new technologies introduced right now. It is based on a self-organizing network of small units called "mots" that are miniaturized microcomputers equipped with varying sensors (with respect to local requirements) and communication capabilities. Energy supplying single unit comes from miniature battery, solar cell, or e.g. from vibrations. There is no cabling necessary. Due to very low cost and in contrast high reliability, mots may autonomously create the perceiving network.

This approach has nowadays some true diagnostic implementations [19]: in an Intel factory a monitoring system is just being built whose goal is to supervise pumps and other equipment. It is expected that the cost of the complete system including 4 thousands of mots will not exceed 1 million dollars.

A very promising opportunity might be to arrange mots in a self-organizing neural network with inputs from sensors the individual nodes are equipped with. Such an intelligent system could be able to conclude about the state of the object in real time, while costs of the system could be very low, and the system itself could be fault-tolerant and reconfigurable. However, this concept needs intensive research in the very next time.

6. CONCLUSION

In the paper some important issues of knowledge engineering from the viewpoint of technical diagnostics were dealt with. Although knowledge engineering seems to be a new domain, it has found many fruitful implementations since introducing it into technical diagnostics in 80' of the previous century.

At the very beginning knowledge engineering started with developing expert systems to aid diagnosticians in their work. Today these tools remain one of the most frequently used. However, new developments of computer and information technology enable making several mile steps towards ever more friendly, reliable, fault-tolerant solutions, capable of automatic operating in harsh environment and providing right diagnostic information just to the person who requests it. To this end, a crucial role is played by respective user interface and communication ability of the systems.

The expected and anticipated forthcoming solutions of knowledge engineering problems addressed to technical diagnostics should help in achieving a very general goal what was pointed out by W. Cholewa: there is the need to create the environment called "Ambient intelligence".

Ambient Intelligence [20] is understood as an environment that is sensitive and responsive to the operation of people. From diagnostic viewpoint it should aim at improving operation of a diagnostician in her/his environment by providing the desired functionality by means of intelligent, personalized, and interconnected systems and services. The key requirement is that the diagnostician be surrounded by many interconnected, invisibly embedded systems, which are intelligent: capable of recognizing users, adapting to their preferences, and offering natural ways of interaction. As a conclusion it is worth emphasizing that achieving such a long-term goal seems to be the most important task, to which knowledge engineering may add inherent methods, tools and knowledge.

BIBLIOGRAPHY

[1] MOCZULSKI W.: *Metoda wibroakustycznych badań maszyn wirnikowych w warunkach rozruchu lub zatrzymywania* (in Polish). PhD dissertation, Institute of Mechanics and Fundamentals of Machinery Design, Silesian University of Technology, Gliwice 1984.
[2] MOCZULSKI W.: *Diagnostyka techniczna. Metody pozyskiwania wiedzy* (in Polish). Silesian University of Technology, Gliwice 2002.
[3] MOCZULSKI W.: Methodology of Diagnostic Knowledge Acquisition. *Bulletin of the Polish Academy of Sciences – Technical Sciences*, 49(2):337–357, 2001.
[4] BUCHANAN B. G. et al.: *Constructing an Expert System*. [In:] F. Hayes-Roth, D. A. Waterman (Eds.), *Building Expert Systems*. Addison-Wesley, Reading, 1983.
[5] MOCZULSKI W.: Metody akwizycji wiedzy diagnostycznej (in Polish). *XXIII Sympozjum "Diagnostyka Maszyn". Proceedings*, pp. 44–49, Silesian University of Technology, Institute of Transport, Katowice, 1996.
[6] WYLEŻOŁ M.: *Metody pozyskiwania procedur i relacji diagnostycznych od specjalistów w dziedzinie eksploatacji maszyn* (in Polish). PhD dissertation, Silesian University of Technology, Department of Fundamentals of Machinery Design, Gliwice, 2000.
[7] MICHALSKI R. S.: A Theory and Methodology of Inductive Learning. *Artificial Intelligence*, 20:111–161, 1983.
[8] QUINLAN J. R., Induction of Decision Trees, *Machine Learning*, 1(1986), No. 1, pp. 81-106.
[9] PAWLAK Z.: *Rough Sets. Theoretical Aspects of Reasoning About Data*. Kluwer, 1991.
[10] NOWICKI R., SŁOWIŃSKI R., STEFANOWSKI J.: Rough Sets Analysis of Diagnostic Capacity of Vibroacoustic Symptoms, *Computers Math. Applic*., 24 (1992), No. 7, pp. 109-123.
[11] FISHER D. H.: Knowledge Acquisition Via Incremental Conceptual Clustering, *Machine Learning*, 2(1987), No. 2, pp. 139-172.
[12] BERZAL F. et al.: ART: A Hybrid Classification Model, *Machine Learning*, 54(2004), No. 1, pp. 67-92.

[13] CRISTIANINI N., SHAWE-TAYLOR J.: *An Introduction to Support Vector Machines*, Cambridge University Press, 2000.
[14] MOCZULSKI W., ŻYTKOW J. M.: Automated Search for Knowledge on Machinery Diagnostics. *Intelligent Information Systems. Proceedings of the Conference IIS'97*, pp. 194–203, Warszawa, 1997.
[15] LANGLEY P., SIMON H. A., BRADSHAW G. L., ŻYTKOW J. M: *Scientific Discovery: Computational Explorations of the Creative Processes*. MIT Press, Cambridge, MA, 1987.
[16] P. Kostka. *Metody klasyfikacji postaci kinetostatycznych linii wałów maszyn wirnikowych* (in Polish). PhD dissertation, Silesian University of Technology, Department of Fundamentals of Machinery Design, Gliwice, 2001.
[17] SZULIM R.: *Metoda pozyskiwania wiedzy do wspomagania prowadzenia złożonego procesu technologicznego* (in Polish). PhD dissertation, University of Zielona Góra, Institute of Electrical Metrology, Zielona Góra, 2004.
[18] ZADEH L. A., KACPRZYK J. (Eds.) *Computing with Words in Information/Intelligent Systems*, Series: Studies in Fuzziness and Soft Computing, Vol. 33, Springer, 1999.
[19] CULLER D. E., MULDER H.: *Smart Sensors to Network the World*, Scientific American, June 2004.
[20] VAN LOENEN E. J.: *Ambient Intelligence*. http://www.grenoble-soc.com/speaker_Loenen.htm
[21] CHOLEWA W., PEDRYCZ W.: *Systemy doradcze* (in Polish). Textbook No. 1447. Silesian University of Technology, Gliwice, 1987.

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