Multimodal Statement Networks for Diagnostic Knowledge Modeling and Integration

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Abstract: This paper addresses selected aspects of diagnostic knowledge management. Not only does it introduce the process of modeling with the use of multimodal statement networks, but it also presents methods of diagnostic model development, nature of its individual layers and elaborates on the construction process of diagnostic knowledge base along with its verification. The main purpose of the presented method is to aid in design of diagnostic systems for complex objects requiring inference process that takes places under condition of uncertainty with partially contradictory knowledge being observable. Chosen elements were implemented in free *REx* software developed in R language.

1 INTRODUCTION

Diagnostic knowledge modeling is a process of preparation and storage of knowledge for the needs of constructing information systems inter alia diagnostic expert systems. The process is expected to produce transparent, comprehensible and consistent records of diagnostic knowledge that consider the nature of selected domain it pertains to. Since diagnostic information may derive from multiple sources, the integration of knowledge is essential, its main purpose being construction of a relevant knowledge base of diagnostic systems. Both quality and availability of knowledge sources play a crucial role in ensuring the effectiveness of inference realized by the diagnostic system. The integration requirement particularly applies to diagnostic systems designed for complex objects. The knowledge of complex objects may be extensive and be obtained from independent experts; it may derive from various literary sources and be implicitly represented, for instance in the form of data acquired during diverse diagnostic experiments.

Integration of knowledge from multiple sources requires development of new methods of diagnostic knowledge modeling with application of easily interpretable manners of knowledge representation. Furthermore, the knowledge modeling process should enable independent experts' contribution to diagnostic system preparation as well as ensure that modifications and knowledge updates are easily performed.

An introduction of a unified knowledge representation for multiple types of knowledge sources constitutes the key step to obtain a convenient tool for knowledge modeling in general, and diagnostic knowledge in particular. Unfortunately, it is a difficult task because of heterogenous characteristic of diagnostic data and commonly used heterogenous diagnostic models. Considering the nature of diagnostic knowledge, the inference process should be based on reasoning under uncertainty conditions. This, in turn, requires that special forms of this knowledge representation as well as appropriate inference algorithms be implemented.

A wide range of techniques of diagnostic modeling using different knowledge representation and inference algorithms is known to be currently available. A scope of them can be find in (Korbicz et al., 2004). Apart from process models (object models) used in model based diagnosis, typical diagnostic models which mapping observed measurement signals into qualitative description of technical states of process can be generally classified in terms of their transparency into two groups. The first group comprises black box models which structure and parameters are generally identified during the machine learning process and can not be tuned or updated without restarting learning process. Neural networks classifier is an example. Parameters of these models are gen-

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erally hard to understand and their integration with explicit expressed knowledge (e.g. opinions) is often impossible. The second group is the part of transparent diagnostic models (e.g. graphical models) (Cowell et al., 2003), (Kohler and Friedman, 2009), which structure and parameters may have own physical interpretation or contractual meaning and which make it easier to integrate knowledge from multiple sources. In this paper we focus on transparent forms of knowledge representation for complex objects treating only black box models as a source of data reconstruction or a source of preprocessed input data.

Aspects of diagnostic knowledge management concerned with modeling, storaging, updating and verification of consistency of modeled knowledge are main objective of this paper. The general modeling process is conducted with the use of multimodal statement networks introduced in (Cholewa, 2010), including, inter alia, types of network layers, methods of layer interoperability, as well as construction and development of models. Furthermore, methods of verification of consistency of modeled knowledge were addressed as well. Multimodal models enrich the available range of methods (Cholewa, 2010). To name a few, examples may include multiaspect models (Skupnik, 2009) or models with context inference (Timofiejczuk, 2012).

Finally, the authors presented free software (*REx*) (Cholewa et al., 2011), which provides a possibility to perform actions described in this paper that are related to modeling and management of diagnostic knowledge.

2 MULTIMODAL STATEMENT NETWORKS

One of the convenient methods of information representation in expert systems includes a statement which is equivalent to assertion on recognition of an indicative expression resulting from observed facts, or representing an opinion. One may distinguish between simple and complex statements. Simple statements are presented in the form of a pair $< c, v >$, where c is the content of the statement, and v is the value (e.g. logical value) of the statement. Complex statements, however, are presented in the form of $< \mathbf{c}, \mathbf{v} >$, where $\mathbf{c}$ is a set of possible variants of the statement content, and $\mathbf{v}$ is a set of values of subsequent variants of its content. Provided the statement content is constant, and that the set of variants of statement content is an exhaustive set of mutually excluding variants of statement content, then the complex statements may be represented by means of adequate sets of simple statements.

In a set of statements, one can observe a set of statements with known values, and a set of statements with unknown values. The statements of known values include primary statements whose values were directly determined by external processes, such as measurement data or a user input, as well as constant statements whose values were arbitrarily assumed by e.g. a knowledge engineer. In turn, a set of statements of unknown values includes secondary statements whose values are strictly contingent on other statement values, and are not directly defined by external processes as well as isolated statements independent of other statements. The main purpose of inference is to determine values of secondary statements for desired values of primary statements. A division into the sets of primary and secondary statements is subject to change depending on data available from external sources at a given moment of time. For instance in the case of diagnosis process secondary statements are related mainly to fault or malfunction and primary statements to observed process variables or user input. In the case of root cause recognition, the secondary statements are related to the unknown causes of observed faults (primary statements). Because the process of inference is bidirectional the first case of inference and the second one can be conducted in the same model.

Statements may be studied as approximate statements provided their content and/or values are approximate. Approximate values of statements can be defined as degrees of truth or degrees of belief in the truth of statements. The value of approximate statements s is to be considered as a point value $b(s)$, or as an interval value, e.g. $b(s) = [0.6, 0.9]$. Such an approach also allows for considering the point value as a special form of an interval value, e.g. for $b(s) = 0.3$ the interval value shall be represented as $b(s) = [0.3, 0.3]$.

In (Cholewa, 2010) the author introduced concepts of multimodal statement networks (multimodal model) where selected nodes represent statements. The network structure is a multilayer one and is defined as a directed hypergraph described by ordered triple:

$$< V, E, \Gamma >, \tag{1}$$

where V is the set of all hypergraph vertices, E is the set of hypergraph edges, and Γ is the set of hypergraph modes representing selected layers of the network (Heath and Sioson, 2009). The network layers are defined as

$$\Gamma_n = \{V_n, E_n\}, \Gamma_m = \{V_m, E_m\}, \tag{2}$$

where $V_n \subset V$, $V_m \subset V$, $E_m \subset E$, $E_n \subset E$. It is assumed that $card(V_m \cap V_n \geqslant \emptyset)$ and it is estimated that the covering degree of vertices of component models is not significant $card(V_m \cap V_n) << card(V)$. Multimodal networks consider different types of interactions which occur between elements of this network.

While implementing the belief networks, the correct determination of values of conditional probability tables poses the greatest difficulty. This procedure may be simplified by introduction of knowledge representation in the form of necessary and sufficient conditions. If the belief in the truth of statement s_p is always accompanied by the belief in the truth of statement s_n, however, not necessarily inversely, then statement s_p constitutes the sufficient condition for statement s_n, whereas statement s_n is a necessary condition for statement s_p.

Assuming that the degree of belief in the truth of s_p and s_n statements have the following value:

$$b(s_p) \in [0,1], \quad b(s_n) \in [0,1]. \tag{3}$$

The information on s_p being a sufficient condition for s_n may take the following form:

$$b(s_p) \leqslant b(s_n). \tag{4}$$

If the complete belief in the truth of s_p statement is $b(s_p) = 1$, then the result would be $b(s_n) = 1$, in other words, the complete belief in the truth of statement s_n. What is more, considering the absence of belief in the truth of statement s_p, i.e. $b(s_p) = 0$, only a trivial conclusion may be formulated, i.e. $b(s_n) = [0,1]$. The necessary and sufficient conditions may be presented in the form of graphs Fig.1, where the directed edge defines the increased value of the degree of belief in the truth of the statements.

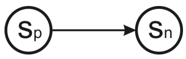

Figure 1: A graph presenting statement s_p as a sufficient condition for statement s_n , and statement s_n as a necessary condition for statement s_p.

The studied expert systems should enable inference even in imprecise, incomplete and, at times, even contradictory information environment. In such a case approximate knowledge may be represented as approximate necessary and sufficient conditions with the application of permissible deviation δ:

$$b(s_p) - \delta \leqslant b(s_n), \text{ where } \delta \geqslant 0 \tag{5}$$

The deviation value δ may be considered equal for all conditions, or be individually considered for each statement, or be individual $\delta_{p,n}$ for each condition defined for a pair of statements $\{s_p, s_n\}$.

$$b(s_p) - \delta_{p,n} \leqslant b(s_n), \text{ where } \delta_{p,n} \geqslant 0 \tag{6}$$

The advantage of multimodal statement networks is that selected nodes of the network may simultaneously occur in many layers. Furthermore, one may also implement different types of component networks based on necessary and sufficient conditions (called approximate statement networks), or bayesian networks. In order to obtain the final results of inference, it is essential that appropriate methods of results aggregation for the nodes shared by a number of layers be used.

3 DIAGNOSTIC KNOWLEDGE MODELING

Declarative diagnostic knowledge may manifest nature of uncertain knowledge. Thus, the sources of this uncertainty is to be given particular attention as the information included in diagnostic signals may be irrelevant and insufficiently correlating to the object state (Cempel and Natke, 2011). It may also result from measurement errors or incomplete information caused by a faulty measurement path. Knowledge defined by independent experts may be ambiguous, e.g. a semantic range of notions used by different experts may be various, or partially contradictory when experts' opinions on the same topic differ; it may also be quite frequently articulated in an approximate manner.

Modeling of diagnostic knowledge using multimodal statement networks may involve:

- considering the need and the purpose of division of a complex diagnostic model into a set of simple models represented by layers of a multimodal model. This stage should emphasize the improvement of modeled knowledge transparency, or ensure a possibility for selected fragments of domain knowledge to be analyzed in an independent manner by a group of independent experts.
- agreeing on strategy of multimodal model development (describing modeled knowledge by means of a model),
- developing layers of a multimodal model using available representations of statement network layers (developing structure and determining parameters of selected layers of the model),
- validating model layers (studying layers with the use of sensitivity analysis, measuring conditional independence, analyzing syntactical correctness of connected knowledge),
- synthesizing layers of the multimodal model,

- tuning parameters of the multimodal model, including parameters related to synthesis of selected model layers.

The stages described above assumed that knowledge modeling is realized with a so-called closed world assumption, i.e. a finite set of available statements as well as content variants of these statements.

Application of a method of a domain knowledge modeling, considering general multimodal model structure, is strictly dependent on a number of factors. It may be partially dependent on the structure of a diagnosed object as well as subject to availability of knowledge sources pertaining to that object. A need of appropriate knowledge de-fragmentation facilitating interpretation and further editions may also affect the division.

One strategy of diagnostic modeling is the use of a multiscale model which constitutes a special form of a multimodal model with its layers representing diagnostic knowledge at various detail levels, and thus, resembling a hierarchical structure. An example is multiscale model in which one of the layers represents a particular fragment of a subsystem, whereas another layer represents a component of this subsystem, e.g. hydraulic system and a centrifugal pump. Yet another example is a model whose layers represent uneven degree of granulation of the domain knowledge in question. For instance, while the first layer describing general knowledge derived from ISO directives concerns operation of a given object and permissible level of relative vibration in bearing support structures for given machine types, the second layer includes detailed, specific knowledge of the selected rotor bearing support structure.

Diagnostic knowledge modeling with a use of multimodal models is a simplified modeling process, and goes beyond the mentioned strategies of diagnostic knowledge modeling with multiaspect and multiscale models. Figure 2 presents an example of multimodal network with fragments of multiscale and multiaspect networks. A diagnostic model of a rotor supported by 2 hydrostatic bearings may include the following exemplary layers:

- L0 layer represents a portion of knowledge concerning a general technical condition of an object as well as a technical condition of the object subsystems, e.g. statements with the following content: technical condition of object ={normal, faulty}; technical condition of hydraulic subsystem ={normal, faulty}, etc.
- L1 layer describes general diagnostic knowledge of the object, for instance, value of component frequency corresponding to rotor rotational speed ={high, medium and low}, level of dynamic unbalance ={permissible, exceeded, impermissible},
- L2 describes general knowledge of a chosen subsystem e.g. hydraulic system. A layer may contain statements concerning values of stream mass levels of a working fluid {low, medium, high}, pump rotational speed {low, high},
- L2.1 and L2.3 layers present diagnostic knowledge of chosen components of hydraulic system described in L2 layer (pumps, an electro hydraulic actuator); exemplary statements include operation temperature of pumps measured on the housing {low, regular, high}, leakage in pump on the suction site {no, yes},
- L3 describes knowledge of the object functional state that is recognized on the basis of selected primary statements such as shaft rotational speed {constant, quasi variable, variable}, functional state {operation mode number 1, operation mode number 2}.

The presented model only illustrates the structure of a multimodal model. Depending on the requirements, this model may be extended or re-constructed. It is also possible to develop layers that would include, inter alia, diagnostic knowledge for remaining components subsets, physical states of chosen working fluids. Furthermore, additional layers may supplement the already available knowledge, however, may be also introducing different opinions by independent experts. What is so essential about layers of the developed multimodal model is that not only does one observe relatively low covering degree of vertices in subsequent layers of the model, but also that it, to a large extent, refers to the specific knowledge of the examined object. In the case of modeling of a class of significantly similar objects for which general domain knowledge may be distinguished, the knowledge may be also a subject of ontological modeling.

4 KNOWLEDGE MANAGEMENT

Implementation of effective diagnostic systems involves processing of large sets of diagnostic knowledge. One of the key objectives is to devise efficient management methods. Among elements directly relating to knowledge management for the needs of diagnostic modeling one can distinguish the following phases taking place in machine and process diagnostics:

- diagnostic knowledge acquisition,
- verification of acquired knowledge,

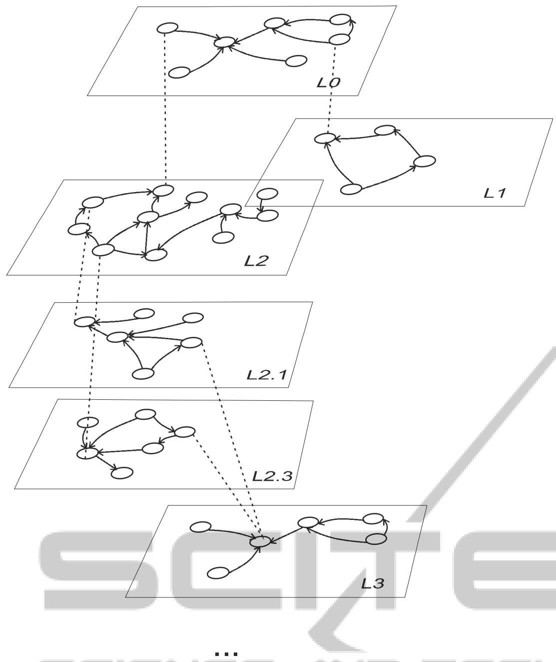

Figure 2: An exemplary structure of a multimodal model. L0 - general layer, L1- layer with general knowledge, L2- layer with a chosen subsystem, e.g. hydraulic system, L2.1-centrifugal pump, L2.3-electro hydraulic valve, L3-layer with description of functional state.

- connection of knowledge to a knowledge base,
- application of collected knowledge in the diagnostic process,
- evaluation of sets of collected data, modifications and updates entry.

The manner in which knowledge is represented has to correspond to the method of inference being in line with algorithms, and, simultaneously, it has to allow knowledge engineers to add, modify and delete base components. Modifying the knowledge base may be required in the case of contradictory information/errors, or when new elements have to be connected to the available set.

In order to effectively use knowledge in the form of multimodal networks, appropriate sets of considered statements, also referred to as thesauri, are being developed under a closed world assumption. Each element of this set, i.e. an individual statement, is usually defined by a chosen set of attributes facilitating statement management. With an exception of statement content and value assigned to it, each statement may be described by, among others, an identifier, an abbreviation, key words, statement versions, author, etc. The following statement may serve as an example:

```
id: glst-053,
content: excessive vib. in bearing node N5,
version: 001,
id-source: mast-023,
value: 1,
abbreviation: vibration-n5,
key-words: vibration, bearing,
author: mamarowicz.
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Complex statements are additionally defined by content variants of the statement. Some of the attributes are optional and do not significantly affect the quality of communication with thesaurus. Nonetheless, some of them, for instance statement identifier and version, are crucial for proper collection and application of particular statements.

Explanation systems also aid in handling of the statement sets (Cholewa, 2004). Their main purpose is to determine chosen terminology that is used in construction of particular statements. A developed system of explanations, also referred to as a dictionary, comprises explanations of chosen definitions relating to given elements as well as subsets of monitored objects, possible faults, fault symptoms, diagnostic methods and techniques, etc. Additionally, it is possible to create explanations to the content of each statement in order to obtain a more detailed statement, or to draw particular attention to chosen specific contexts of use of a statement in the process of construction and application of diagnostic models.

Statements may be used in developing multimodal statement networks which e.g. could present knowledge describing known cause-and-effect dependencies related to addressed problems. Definition of particular networks involves, above all, tasks of determining topological structure, i.e. defining particular nodes and relations occurring between them. Therefore, visualization of the developed statement networks is so crucial. For individual networks, it boils down to visualization of graphs, and it is important that an optimal algorithm of node distribution be chosen so that a clear form of network, i.e. one without broken edges, can be obtained (Tamassia, 2007). In the case of multimodal models a three dimensional visualization may pose an interesting solution, shown in Fig. 3. It allows for simultaneous browsing of all model layers and easy identification of shared nodes. A number of solutions devised for multimodal models include additional virtual layer onto which all nodes used for construction of component networks were distributed. This layer facilitates information exchange as well as data input and network data reading.

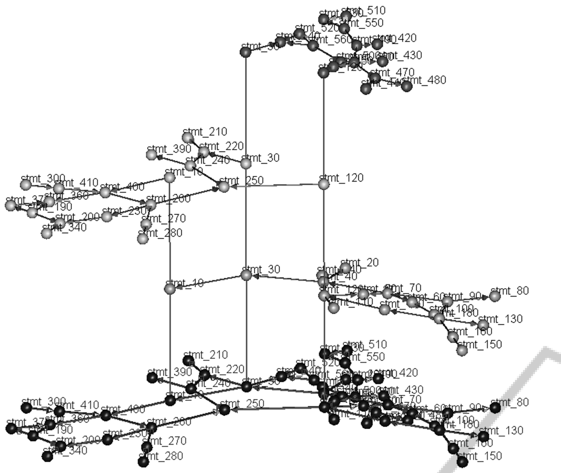

Figure 3: An example of multimodal network visualization, in system *REx*.

5 FORMAL VERIFICATION OF KNOWLEDGE

A formal verification of diagnostic knowledge is an important stage of construction of a knowledge base. A syntactic verification, which consists in formal searching of typical errors in adequately formalized and stored knowledge in data base, is a commonly applied method of verifying diagnostic knowledge. Among the methods of formal syntactic verification of knowledge base, one may enumerate methods basing on error detection through knowledge base searching, as well as methods using parasyntactic logic (Nguyen, 2005). These processes most frequently consist in elimination of redundancies, loops, excess, e.g. subsumed rules or rules not affecting the distinguishing between secondary statements, etc. For the majority of knowledge management systems it is a stage which, depending on knowledge representation method, can be realized in an algorithmic manner. Systems with rule-based knowledge serve as an example.

Further methods of knowledge verification include examination of structure of stored knowledge. This applies to knowledge representation that refers to tree or network structures to which graphical networks discussed in this paper, may also be assigned. Syntactic verification of such structures is simpler. For instance, considering the layers represented by means of belief networks due to non-cyclical and directed graph structure, it is not possible to add knowledge which could lead to looping of inference algorithm, which could take places in regular rule-based systems. Another element that facilitates knowledge verification is a convenient visualization tool of the network structure as well as appropriate navigating tools. This is particularly crucial when dealing with spatial networks such as multimodal statement networks.

In the case of flat network or tree models, identification of looping rules is not necessary provided. Inference in the system takes place within the closed world assumption, and a defined set of statement contents is semantically coherent. The accuracy of the variant semantics of chosen statements is subject to knowledge management using thesaurus discussed in Section 4. This, however, does not exclude a necessity of knowledge verification in terms of its semantics. For diagnostic systems based on knowledge one may distinguish the following causes of semantic inaccuracy and knowledge inconsistency:

- knowledge was defined on the basis of learning data that included errors, for instance contradictory information. This may lead to an inaccurate structure of mutual relations between statements that can result in emergence of associations being statistically independent, or to definition of inaccurate values of graphical model parameters. An example includes inaccurate values of conditional probabilities tables for layers represented by means of belief networks. And for these values the graphical model does not manifest expected sensitivity to changes in values in selected primary statements (use of relevant associations),
- data on the object as well as primary statements on the object are not consistent in the temporal sense, as a result, a part of data obtained during the system operation is not consistent with other data or other statements. Correct definition of knowledge in inference for inconsistent information in the temporal sense may lead to contradictory conclusions. Additionally, such inconsistency may also result from errors of spatial inconsistency of data that are caused by, among others, wrong identifiers on diagnostic signal tags,
- knowledge of relations between statements was defined on the basis of independent knowledge sources, e.g. experts whose opinions may be partially contradictory.

Further discussions concern formal methods of identifying knowledge inconsistency relating to the last two mentioned causes.

Detection of inconsistency, that may occur as a result of measurement errors, spatial or temporal discrepancies of collected data, may be identified using statement networks as well. Examples include statement networks whose layers are represented by means of layers described through belief networks. Provided a graphical model is defined correctly, it is possible to detect contradictory information that leads to inconsistency in networks of this type. Since it may result from errors, error not necessarily being always the root cause, for instance, they may trigger considerably rare events analyzed by developed domain models, it is then the task of inference module to raise a notification of such an occurrence. For more information regarding the mentioned methods, authors refer to, among others, (Jensen and Nielsen, 2007), (Kohler and Friedman, 2009). Similar solutions are identifiable in networks represented by approximate statement networks. Contradictory information is simultaneously identified with a particular value of parameter δ in (5) and (6) occurring between the statements in which the inconsistency is detected in the process of inference. The δ parameter values are useful for identifying potentially contradictory information. Subsequently, in order to determine whether given inconsistency is triggered by inaccurate data or not, such an analysis is to be carried out independently for each individual network layer.

Detection of contradictory information established on the basis of various opinions of independent experts, is quite frequently considered a secondary requirement (Nguyen, 2005). The primary requirement is to develop a set of aggregated expert opinions. It is essential to note, however, that a proper method of opinion aggregation of a large group of experts should also facilitate identification of the sources of conflict. Any information pertaining to potential conflict may be useful in developing adequate aggregating functions, for instance weights assigned to given experts. Approximate statement networks also enable easy identification of inconsistency between opinions expressed by various experts. If the information newly added to the system (a change in values of selected primary statements) does not affect the value of parameter δ, where each layer is studied independently, but it triggers a change in this value once the selected layers have been studied, it may indicate potential inconsistency in the layers in question. In addition, inconsistency may also be detected on the basis of association analysis between statements described in different layers of multimodal networks.

6 REX SYSTEM

The research version of *REx* system, which operates in R language, was designed and developed not only for the purpose of modeling of diagnostic knowledge in the form of multimodal network statements, but also to support verification, testing and management of diagnostic knowledge. The essential system components include:

- Bulletin Board - a component that collects and shares information on values of selected statements,
- Data Uploader - a module responsible for information/data exchange with other systems,
- Explanation System - a component that collects and shares explanations for selected statements,
- Model and Benchmark Repository - a module that facilitates collection of thesauri and multimodal models,
- User GUI - Graphic User Interface that enables communication between the system and users not familiar with R language syntax,
- Data Acquisitor - a module responsible for acquisition of data from a technical object,
- Data Simulator - a module that simulates operation of a technical object,
- Knowledge Acquisitor - a module responsible for acquisition of diagnostics knowledge.

A prototype version of *REx* system includes Bulletin Board, Data Uploader, Model, Benchmark Repository and User GUI. The further components are in a testing phase with an emphasis on their practical application. Examples include a module that simulates operation of a technical object, and a module that acquires data from the technical object. *REx* can be used for own solutions within the R environment. *REx* package offers a possibility of:

- defining thesauri,
- defining subsequent layers, their structures and required parameters,
- entering data to input nodes,
- performing inference.

One implemented an algorithm for determination of results of network calculations that considers different types of networks stretched onto selected layers (of belief networks and approximate statement networks).

The installation pack can be downloaded at *http://www.ipkm.polsl.pl/index.php?n=Projekty.Rex*.

7 SUMMARY

Design and development of diagnostic systems with the use of multimodal statement networks requires implementation of a method of diagnostic knowledge modeling that allows for integrating knowledge from various sources. It also emphasizes the nature of modeled knowledge which may be approximate, incomplete, inconsistent, or partially contradictory. Introduced networks offer a possibility of modeling knowledge with a participation of independent experts who can develop selected layers of diagnostic models. Graphical models and multimodal statement networks require application of a number of additional tools intended for diagnostic knowledge management. These include the tools discussed in this paper, tools used for semantic and syntactic verification of implemented knowledge, as well as tools enhancing composition of a dictionary of statements and statement management. The presented aspects are being currently developed within the available software *REx* devised in R programming language. *REx* environment facilitates further research into advanced applications and development of multimodal statement networks for the purpose of modeling of diagnostic knowledge, and research into methodology of interoperability between multimodal model layers that would consider inconsistency occurring in both data and knowledge.

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