Context based diagnostics of rotating machinery

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Abstract

The paper deals with a methodology of context based reasoning, which was presented on the basis of diagnostics of rotating machinery. Usually, in diagnostics systems of such machinery the reasoning process does not include such factors as a context. However, in case of complex technical objects as well as different conditions of their operation the information on the context can simplify the inference process and even make it more efficient. Taking into account the rotating machinery, examples of contexts are specified conditions of their operation and also operation of some parts of the machinery. The paper describes the elaborated methodology on the example of identification of typical malfunctions and technical states of rotating machines. The most important part of the methodology is identification of contexts and associations observed during the machinery operation. The verification of the methodology was carried out on the basis of signals recorded during operation of a test stand which enables a simulation of typical malfunctions of the rotating machinery.

1 Introduction

Identification of technical states of technical objects and particularly rotating machinery is one of crucial points of its maintenance. One of problems related to technical diagnostics is the necessity to repeat numerous data sets and results of signal analysis, which in turn often requires the application of special diagnostic reasoning.

The research presented in the paper deals with the application and development of the methodology of context based reasoning in technical diagnostics [1] [2]. In diagnostic systems the reasoning process usually does not include such factors as a context. However, the comprehension of the context allows the choice of the scope of knowledge which is essential from the point of view of the context and thus it facilitates the determination of a technical object state. What is more, the context is often unknown and taking it into consideration is connected with the necessity of discovering it. Examples of contexts in case of rotating machinery maintenance are specified conditions of their operation.

Considering elaborated methodology of context based diagnostics one assumed that the context is unknown. A suggested way of context identification was based on the knowledge recorded in form of diagnostic rules. The subject of the paper has been presented against the currently used methods of diagnostic reasoning as well as the methods used in applications related to the scope of the work. Elaborated approach has been compared with other ways of rotating machinery diagnostics. There were approaches based partly of contexts as well as those that did not take them into account.

The paper describes the elaborated methodology on the example of identification of typical malfunction and technical states of rotating machines. Some elements of the methodology such as ways of data coding, the way of automatic design of case base, and the way of diagnostic reasoning in context were discussed. The most important part of the methodology is contexts and associations identification, which can occur for the values of signal features observed during the object operation. The contexts are identified on the basis of cases and diagnostic rules whereas the way of context identification based on the results of signal analysis has been derived from the evolutionary algorithm application.

The research on the verification of the methodology has been carried in several groups of data recorded during observation of rotating machinery. One analysed also data generated on the basis of mathematical models of deterministic signals, which include the influence of change of selected signals such as instantaneous magnitude and frequency of selected signals, on the change of the same parameters of other generated signals. It allowed identification of changes of a given value in the context of changes of other values. The second group of signals has been recorded during the operation of laboratory stand which enables simulation of typical malfunctions of rotating machinery. Throughout this part of experiment, a dozen of simple states has been simulated and their combinations.

It should be stressed that both the elaborated ways of interpretation of signal analysis and the manner of diagnostic reasoning are characterized by a great universality. The presented approach can be also used in solving problems far from the ones which have been discussed. Further development of the methodology was also discussed [3]. At present some additional signals, especially derived from images and thermograms analysis are being considered as input data to the context based diagnostics of technical objects.

2 Characteristics of context-based reasoning

In case of the majority of diagnostic systems the knowledge is gathered in a given ordered manner. They are often systems based on a rule knowledge representation. The knowledge management in such systems is mainly directed to ways of searching through databases during the inference process and selection of appropriate rules [50]. In case of such approaches the fundamental assumption is the possibility to apply algorithms that let us optimally select or update only this part of the knowledge which is related to a considered problem. As examples of such approaches one may enumerate [50]:

- so-called knowledge packages (rule packages) which gather the knowledge dealing with a determined problems,
- additional clauses (e.g. in a premises part of the rule) which are checked during the database is searched through (so-called context rules).

The both approaches make it possible to cluster the rules depending on object operating conditions, subassemblies or parameters. The application of such approach together with an appropriate manner of the inference process, let us direct the process to a given diagnose. It may be characterised as taking into account a given context. Ordering the rule into the packages requires that some principles related to this procedure have to be defined *a priori*. In such case the membership of a rule to the package is constant. The problem of selection of an order of the rules that should be considered is one of the biggest problems of the inference process. The solution to this problem may be the application of rule ordering in form of decisive trees.

Inference paths in the tree are separated depending on a kind of phenomena and specifically depending on the result of a test included to a given knot. It may be also understood as paths division regarding the inference context. It should be stressed that in the systems basing on the decisive trees the user does not have an influence on the kind of the knot and the inference path. The decisive knot is related to a decision which is dependent on the user. The fundamental problems of knowledge and inference process in form of the decisive trees are [50]:

- significant number of rule combinations that may be or should be taken into account in some situations,
- huge tree size,
- necessity of three updating what is related to completing the tree in numerous knots and brunches.

Above requirements often result in noticeable increase of the tree size. An alternative solution to the trees is the application of graphs. It is often used in case of system based on knowledge and rule representation if form of contexts [14]. In the bibliography there is also described an approach based on cases (Case based reasoning, CBR). It let us to take into account the inference context in wider range comparing to the previous approaches. However, the most important shortcoming of this way of inference is impossibility to obtain an explanation to the final solution [3, 46].

Summarizing, the characteristic properties of these tree manners of knowledge and inference process representations, one can state that in none of them the context is openly taken into account. When it is considered it is a static context or set of contexts. One may stress that one of the most important properties and advantages of context consideration during the inference process is its variability in time domain. The review of bibliography related to the applications of systems based on the knowledge representation in forms of decisive trees or cases let us state that the main reason of the majority of faults of such systems result from imperfections of the knowledge representation and management. These shortcomings are mainly results of the fact that the context is not considered at the stage of the knowledge acquisition [14]. The most significant disadvantages of the systems based on the knowledge representation where neither the context nor its dynamics are not taken into account are [2,14]:

- practically complete excluding the user from the inference process; the user in case of composed problems can indicate the inference context; it should be stressed that a faulty conclusion mainly result from such problems,
- a context describing an occurrence dealing with the acquired knowledge included in the system base are not saved,
- the knowledge base is often incomplete what carries with it that it does not include the whole knowledge necessary to finding a solution to all possible problems within given range,
- in the majority of such systems do not provide the explanation to the resulting solution or this explanation does not include the information on the related context.

3 Elaborated methodology

The main fields of the application of the elaborated methodology are cases where input data is difficult to be directly compared. The main goal of the application of the methodology is to identify context of an object operation as well as identify associations occurring within this context. The association is a relationship between object properties and object state. The knowledge of such associations and contexts of object operation let us focus the inference process according to the present object operation and state. The general scheme of the algorithms consisting of the methodology was presented in Fig. 1. There are some fundamental elements of the methodology that are enumerated and explained below.

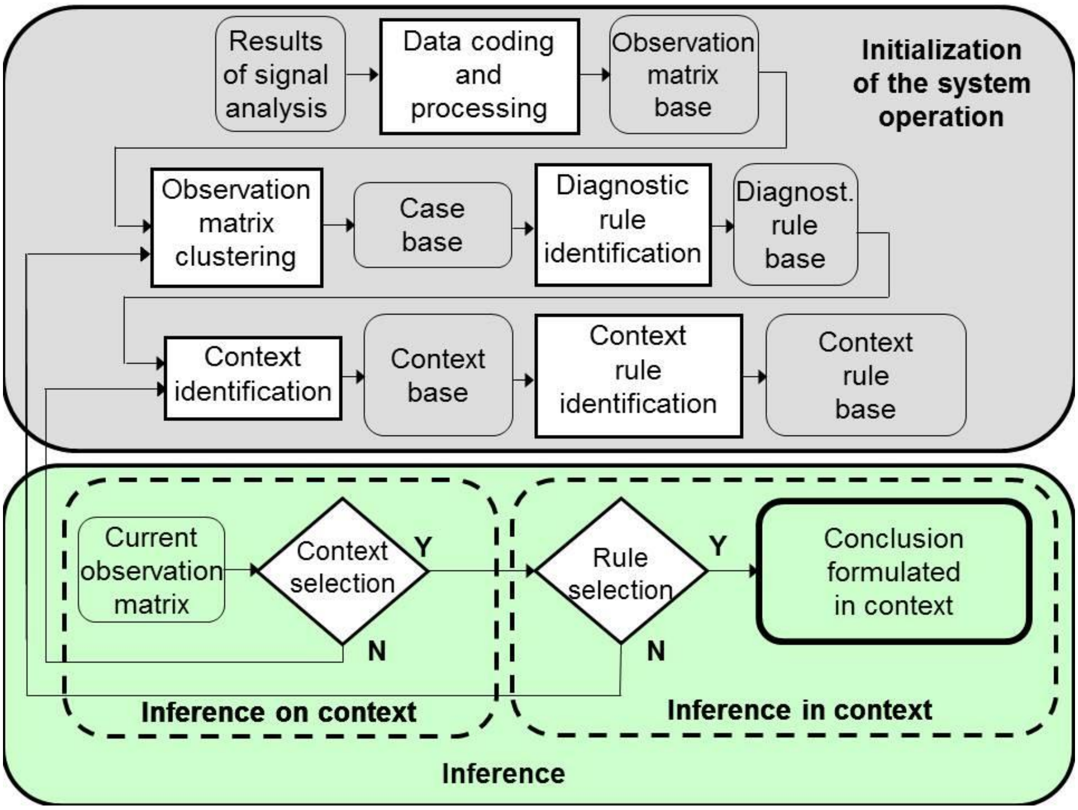

Fig. 1. General scheme of the methodology

Observation (observation matrix) $O(t)$ is a result of the analysis of n diagnostic signals (signal features) which may be represented in different domains.

Current observation (current observation matrix) is a result of signal analysis or parameters of the object operation recorded in the time moment currently considered by the system.

Case X is registered in the form of a genotype and exemplifies a group of observations $\{O(t)\}$; the case is the result of observations clustering performed accordingly to characteristic similarities between some occurrences (malfunctions, object operation conditions). Values representing the case are not dependent on time. The cases can be registered differently, depending on a method of observation clustering $\{O(t)\}$.

Context C is a range of knowledge which is represented by a genotype of the following form:

K =< k1, k2, . . . , kn >, n 2 N

where:

ki =< ki1, ki2, . . . , kim >,m 2 N, gdzie : ki,j 2 {w}

where: values w are resulting from an algorithm of determination and identification of a context. The values correspond to xi,j and can be represented by deterministic values ki,j , fuzzy periods ki,j or functions $fk(oij) = \mu kij$, what is dependent on the applied manner of data clustering.

Context set $\{C\}$, taken into account during the inference process can be determined by experts. One of the most important aspects of the research described in the paper is an assumption that this set is unknown and is being detected on the basis of data recorded during object observation. Context detection was based on the evolutionary calculations. In the course of the calculations the contexts are estimated on the basis of the case set $\{X\}$. The context is a generalized representation of the case set. The cases $\{X\}$, belonging to the context C, meet the assumption (when the case and context are represented by the fuzzy functions):

All elements of the elaborated methodology, the observation, case and context can be characterized as associations. However, there are no premises and inference parts distinguished similarly to the diagnostic rule. One of the most important aspects of the methodology is the fact that unknown conclusions can be determined on the basis of known cases (rules) within a given context.

Elaborated way of cases and contexts encoding of let us register in one genotype the whole diagnostic rule. The case with the conclusion determined is called the **diagnostic rule** and is recorded as follows: $XR =< x1, x2, . . . , xn|XCon >, n\ 2\ N$

where: xn aresignal features, and $XCon$ is the conclusion of the diagnostic rule. The context with the conclusion determined is called a **contextual rule** and it is registered as follows:

CR =< k1, k2, . . . , kn|CCon >, n 2 N where: genes are kn and $CCon$ is the conclusion of the contextual rule.

The fundamental elements of the inference system are:

- Case base $\{X\}$, determined on the basis of data initiating operation of the system
- $\{O(t)\}$ (observation matrices),
- Context identification module, which is aimed at discovery of associations understood as contexts of the object operation
- Context base including the context set $\{C\}$ and its characteristics,
- Inference module which performs the process of diagnose making.
- Assumptions related to the methodology of context based diagnosing deal with:
- Data and knowledge representation,
- Context identification,
- Inference process,
- Recording of the inference results.

The background of the methodology is the context based inference process. A diagnostic occurrence is understood to be the single observation of a given state of the object or a change of this state. The assumptions dealing with the application of such way of the inference are based on the results of the works devoted to this approach. The order of the algorithms was shown in Fig. 1. The complete system operates within two steps. **The system initialisation** performed as processing of data recorded during the object observation and signal analysis. This data is encoded, clustered and sent to the procedure of context identification. The results of the first step are input data into the inference step. **The inference**, which is carried out within two stages.

The first part of the inference step, labelled in Fig. 1 as „**inference on context**"(IOC), consists in selection of a single context (or contexts), in which the results of signal analysis are considered. The contexts of object operation which are used during the inference are identified on the basis of the case set which are results of initial data clustering. Moreover, one assumes that in the course of the inference process basing on the current data it is possible that in the database there is no a context related to the input data. In this situation the database should be updated. According to the elaborated algorithms this updating is performed systematically during the inference process. Summing up, it was assumed that the identification of the context of object operation is possible o the data recorded during the observation of technical object. The identified contexts are taken into account within the second stage of the inference process.

The second stage of the inference process, called „**inference in context**" (IIC) (Fig. 1) consists in determination of a given scope of the knowledge (diagnostic rule), consistent with characteristics of the selected contexts. The knowledge (cases and rules) distinguished with the accordance to the considered context is compared with observations

One assumes that the context identified make it possible to select a scope of the knowledge being the base for the inference process. The inference in the context consists in analysis the fitness between the observation and the knowledge within the context. An important factor is determination of estimators aiding the fitness determination. Apart from that it is also very important to take into account incompleteness of the database (context base) as well as approximation resulting from the analysis of the observed signals. To consider this factor one assumed that the context based inference is based on the application of fuzzy estimators.

4 Performed experiments

The verification of the methodology was carried with use of several groups of data recorded during observation of rotating machinery. The preliminary verification was based on data generated on the basis of mathematical models of deterministic signals. It allowed identification of changes of a given value in the context of changes of other values. The main group of signals was recorded during the operation of test stand which enables simulation of typical malfunctions of rotating machinery. Throughout this part of experiment, a dozen of simple states has been simulated and their combinations.

4.1. Observation of a test stand

The data includes vibration signals and marker signal for a selected angular placement of the shaft. All these signals were recorded during observation of the test stand RotorKit. The stand let us model typical malfunctions of rotating machinery. In the course of the data recording several configurations of the stand were observed. The shaft with two discs was mounted in bearings. The measurement set was shown in Fig. 2.

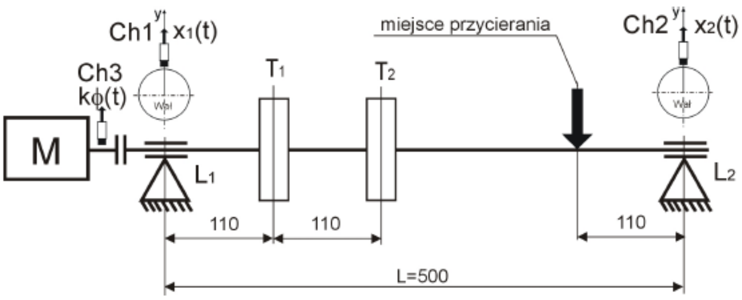

Fig. 2. Measurement set

Measurement points were marked by *Ch*3, *Ch*1 and *Ch*2. The discs placement *T*1 and *T*2 was not changed during the experiments. In the course of the observations slow and rapid changes of the object state were observed. They were caused by short-term friction, overloading and unbalances. A part of signals was recorded when in the neighbourhood of the observed object other objects were operating. The length of the observed signals was equal to t =120 [s]. The sampling frequency was f =1280 [Hz]. All observed signals were divided according to the object operation:

- Constant rotating speed (3000 and 6000 [$min{-1}$]),
- Run-up with different values of acceleration of rotating (7 and 9 [$min{-2}$]),
- (the value of the acceleration was constant in the course of the single observation)
- Operation with different values of delay (7 and 9 [$min{-2}$], decreasing rotating speed),
- Run-up with different values of acceleration, which was random,
- Operation with constant rotating speed (3000 and 6000 [$min{-1}$]), when one observed:
  - pseudo-random hits,
  - operation of other objects,
  - non-periodic friction,
  - non-periodic overload.
- The operation with the varying rotating speed oscillating irregularly around a given value (3000 [$min{-1}$] in the range ± 500 [$min{-1}$]),
- Run-up with constant angular acceleration/delay, when one observed:
  - irregular frictions,
  - irregular overloads,
  - constant operation of other objects,
  - rapid hits.

4.2. Results of the experiments

Signals recorded during the observation of operation of the test stand were processed and analysed with use of well-known statistical methods and short-time Fourier transform. The signal set contained two signals recorded in vertical directions on two bearings. All signals were analysed and interpreted within some periods. There were applied several approaches to division the signals into periods. After analysis the signals were encoded into genetic codes. The number of gens and the length of the genetic codes were also tested. One stated that it was sufficient to take into account features of only one of the analysed signals. The genetic codes consist of 10 gens and two chromosomes in which the results of encoding of mean values and elements of time-frequency characteristics were registered.

Experiment 1 (cases R – known, context C – one general)
The goals of the experiment:
1. The inference with use of only one general context.
2. Analysis of correctness of the selection of the case during the inference process.
Obtained results (Tab.1):
(the inference process was performed 96 times):
Since only one context was considered all cases in the database were checked. The mean value of all correct identification was equal to 59,8%; the worst value of the correctness value was 0% what correspond to the cases “I phase of run-up and friction”, the best value 100% was obtained for cases “operation with constant speed”.

Experiment 2 (cases R – known, contexts C – known)
The goals of the experiment:
1. The comparison of the results of the experiment 1 with inference with use of several contexts.
2. Estimation of correctness of the identification of contexts of object operation.
3. Estimation of selection of cases within given contexts.
4. Estimation of the algorithm of identification of diagnostic rules.
5. Estimation of algorithm of identification of contextual rules.

	I (96)	II (160)	III a (80)	III b (80)	IV (60)
				elitism	elitism
Contexts	One	Known (6)	Unknown	Unknown	Unknown
Cases	Known (15)	Known (15)	Known (15)	Known (15)	Unknown
Cases					
Correct	58,8 %	29,2 %	51,1 %	84, 9 %	61,1 %
Incorrect	28,5 %	65,4 %	39,1 %	13,3 %	31,8 %
Faults	11,7 %	5,4 %	9,2 %	1,8 %	7,1 %
Contexts					
Correct	---	80 %	---	---	---
Cx. Num.	---	---	5	20	16
Clustering					
Correct	---	---	---	---	72,1 %

Tab.1. Results of the experiments.

Obtained results (Tab. 1):
(the inference process was performed 160 times):
The analysis of the obtained results let us state that taking into account several contexts leads to the situation when different contexts are chosen for one single observation. As the result this observation can be considered with taking into account different criteria. The mean value of correctly identified contexts was equal to 80%. The worst value was 58% what correspond to the context determined as friction, and the best value equal to 100% is related to the context called pseudo hits. In the course of the inference process the mean value of all correct identifications was equal to 29,2%, what is a very poor result; the worst value (0%) correspond to the Ist and IInd phases of run-up, operation of other objects in the neighbourhood, friction, and rapid and sudden hits. The best value was 100% what was related to the object operation with constant speed and other object operating in the neighbourhood.

Identified rule	**Results of the application of elaborated algorithms**	**Similarity coefficient**
The Ist run-up stage	The Ist run-up stage	0,9899
	The Ist run-up stage and friction was observed	0,5693
The IInd run-up stage and there is the second object operating in the neighbourthood	The IInd run-up stage and there is the second object operating in the neighbourthood	0,4913
	The IInd run-up stage and heavy impacts were observed	0,0102
The Ist run-up stage and friction was observed	The Ist run-up stage and friction was observed	0,4798
	The IInd run-up stage and heavy impacts were observed	0,536

Tab.2. Results of identification of diagnostic rules (experiment 2).

To identify the diagnostic rules one of the elaborated algorithms was applied. The pattern rule set was determined. In Tab. 2 exemplary results were presented. There are shown two best equality factor obtained for considered rules. According to this the rule “the object in run-up” was identified with high value of the similarity factor (0,9899) as this rule and with the value (0,5699) as the rule „the object in run-up and friction was observed”. Two remaining rues in the table were also correctly identified. Despite of the fact that their similarity factors are low they are the highest values obtained for these rules. On the basis of the obtained results one may conclude that the values of this factor are dependent on the rule complexity. High values were obtained for simple rules.

To identify contextual rules one of the elaborated algorithms was applied. It required a pattern contexts set. As previously, two best results were shown. Both rules were identified correctly. However, the rule „operation with the constant speed and pseudo hits” was classified with the value equal to 1 as the rule “operation with constant speed” and with the value equal to 0,2808 as „pseudo hits”. Similar results were obtained for other rules presented in the table. The values of the similarity factor let us state that the context reflexing operation of the object in constant conditions are the best identified among all other contexts. The reason of such results is not a simple manner of encoding but rather the application of fuzzy numbers in genotypes.

Experiment 3 (cases R – known, contexts C – unknown)

The goals of the experiment:

1. The comparison of the inference process with one general context (experiment 1) with the inference on the basis of contexts identified.
2. The estimation of correctness of the evolutionary algorithm. Some additional options such elitism were also tested.
3. The estimation of correctness of the algorithm of diagnostic rule identification.

Obtained results (Tab. 1):

It was the first experiment in which the context base was not provided. The contexts identified were the results of application the evolutionary algorithm. The analysis of the obtained results makes it possible to state that a great similarity of the contexts identified to the contexts defined was observed. However, there is also significant difference between them. There were some observations that were without their contexts. The application of the elitism resulted in the fact that the context base included almost three times more examples in comparison to the application without elitism. The crucial role in this experiment played the fitness function. It was defined in such the way that made it possible to remove the contexts characterized by low cover in cases.

One also tested the number of the identified contexts depending on the values of crossover and mutation probability as well as the number of iterations of the algorithm. The analysis of the result revealed that the number of iterations did not influence the number of identified contexts. This number increased according to the increase of mutation probability. Obtained results are consistent with commonly known relationships between these parameters and their influence on the results of evolutionary approaches.

Experiment 4 (cases R – unknown, contexts C – unknown)

The goals of the experiment:

1. The estimation of correctness of the clustering.
2. The comparison of the inference basing on known contexts to the inference on the contexts identified on the basis of cases resulting from clustering.
3. The estimation of correctness of the evolutionary algorithm; the comparison of the number and forms of discovered contexts to pattern contexts.
4. The correctness of the algorithm of diagnostic rule identification.

Obtained results (Tab. 1):

The mean correctness of clustering was 72,1%. The number of the identified cluster was equal to the provided number. The difference was the number of elements in consecutive groups. Significantly low values of the assignation correctness were observed for the observation “the Ist phase of run-up and another object operating in the neighbourhood” and “the IInd phase of run-up and another object operating in the neighbourhood”. The high values were calculated for the operation with constant speed.

The mean value of the correct identification was 61,1%. These values are lower than in the experiment 2 but all considered cases were not the same in both experiments. As previously, high values of the equality degree were calculated for the rules representing one state.

5 Summary

The obtained results make it possible to state that the approach let us discover contexts of machinery operation on the basis of signals recorded during its operation. It was examined that the contexts were correct and can be the basis of inference process. Despite promising and correct results there are numerous elements of the methodology that should be improved. Some other applications are also possible to be checked.

One should stress that the elaborated ways of interpretation of signal analysis and the manner of diagnostic reasoning are characterized by a great universality. The approach can be also used in solving problems far from the technical diagnostics.

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