INDUSTRIAL DIAGNOSTICS USING ALGEBRA OF UNCERTAIN TEMPORAL RELATIONS

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ABSTRACT

Industrial diagnostics is an important application area for many AI formalisms. Temporal diagnostics, based on analyzing temporal relations between values of crucial variables, is one possible approach to industrial diagnostics. Often, the information obtained from an industrial object can be uncertain, making the task of diagnostics more complex. In this paper, we propose an approach to temporal industrial diagnostics, which uses algebra of uncertain temporal relations. We estimate temporal relations between the set of symptoms (crucial values of important variables) obtained from an industrial object to build the temporal relational network for this particular situation. After that, we compare the obtained network with known temporal scenarios (patterns) of failures, using the numerical measure of the distance between a network and a scenario. Using this approach we derive the probabilities of possible diagnoses for the particular situation. We also show how the learning for the database of scenarios can be performed, which will make diagnostics for future cases more precise.

KEY WORDS
Industrial diagnostics, temporal scenario, temporal relation, uncertainty.

1. Introduction

In many industrial process control and monitoring tasks there is a need to identify and classify the situation occurred. This is crucial for enabling process improvements and the successful operation of industrial equipment. The examples of such situations are: automated inspection (flaw location) [11], automated diagnosis of failures occurred [8], and real-time diagnosis of the situation to prevent failures in future.

One of the means, which can help to perform these tasks, is temporal diagnostics, i.e diagnostics based on temporal data. The main advantage of this type of diagnostics is that it considers not only a static set of symptoms, but also the time of monitoring. This enables us to have a broader view on the situation: sometimes just considering temporal evolution of relations between different symptoms can give us a hint as to precise diagnostics. Especially important in this approach is to have ready temporal scenarios of possible critical situations that can occur. Any particular situation can be compared with existing scenarios and possibly classified as belonging to one of them.

A number of techniques to temporal diagnostics have been proposed so far, but problems still exist that require further attention. One such problem shows up when the temporal information obtained from an industrial object is uncertain. During the past several decades a number of uncertainty management techniques have been proposed, and many of them have been applied to the field of diagnostics, i.e. [4]. Although there have been successful applications in fields such as medical diagnosis, there are also problems in industry which currently cannot be solved. Some problems arise in trying to implement uncertainty techniques in industrial diagnostic field; such problems in automated inspection are discussed in [11]. Formalisms for dealing with uncertainty are often divided into numerical and symbolic ones. Among the numerical ones those most often used in diagnostics are the probability theory and the fuzzy sets theory.

A probabilistic extension for model-based diagnosis was proposed, for example, in [9]. In that paper model-based diagnosis was considered as an uncertain reasoning problem. The authors argue that the use of probabilities in diagnosis is beneficial to the performance of diagnostic engines. The architecture of the diagnostic system proposed in [9] is capable of detecting failures that are difficult to detect using a conventional diagnostic engine. A statistical interpretation was attributed to nonmonotonic reasoning, allowing the use of a hybrid (probabilistic-logical) inference engine in this system.

Fuzzy temporal reasoning was implemented within diagnostic reasoning, for example, in [3] and [10]. In the latter, disorders are described as an evolving set of necessary and possible manifestations. Ill-known moments in time, e.g. when a manifestation should start or end, are modeled by fuzzy intervals, which are also used to model the elapsed time between events, e.g. the beginning of a manifestation and its end. The information about the intensity and time when manifestations started and ended are also modeled using fuzzy sets.

In many practical situations in industrial field the diagnosis of machine failure can be made by analyzing the set of temporal relations between values of the variables crucial for the process controlled, and by comparing this set with existing temporal patterns of known failures. Moreover, it could even be possible to predict such failure, if this temporal diagnostics is performed in real time and the patterns of possible failures are present. This would be even more valuable for practitioners in the field, since it could help to prevent, for example, the breakage of expensive industrial equipment.

In this paper we propose an approach to industrial temporal diagnostics using the algebra of uncertain temporal relations [7], [6]. The core of our approach is the analysis of the temporal relations between the set of symptoms (crucial values of important variables) obtained from an industrial object. Based on this information we build a relations network, where nodes are the symptoms and arcs are the temporal relations between them. Comparing the derived network with known temporal scenarios we estimate the probabilities of possible diagnoses. The obtained relational network can be used to improve the knowledge base of temporal scenarios.

The paper is organized as follows. In Section 2 we present our approach to temporal diagnostics in general. In Section 3 we briefly overview the basics of the formalisms used. Section 4 discusses how a relational network describing the current situation can be obtained from the information collected on the industrial object. In Section 5 we present an approach to generation and recognition of temporal patterns and show how the database of temporal scenarios can be updated to improve the precision of the diagnostics in future. Finally, in Section 6 we present our conclusions and point out some directions for further research.

2. The Approach to Temporal Diagnostics

In this section we will overview the approach to temporal diagnostics using the algebra of uncertain temporal relations proposed in this paper.

Figure 1 presents the conceptual schema for industrial diagnostics using uncertain temporal scenarios.

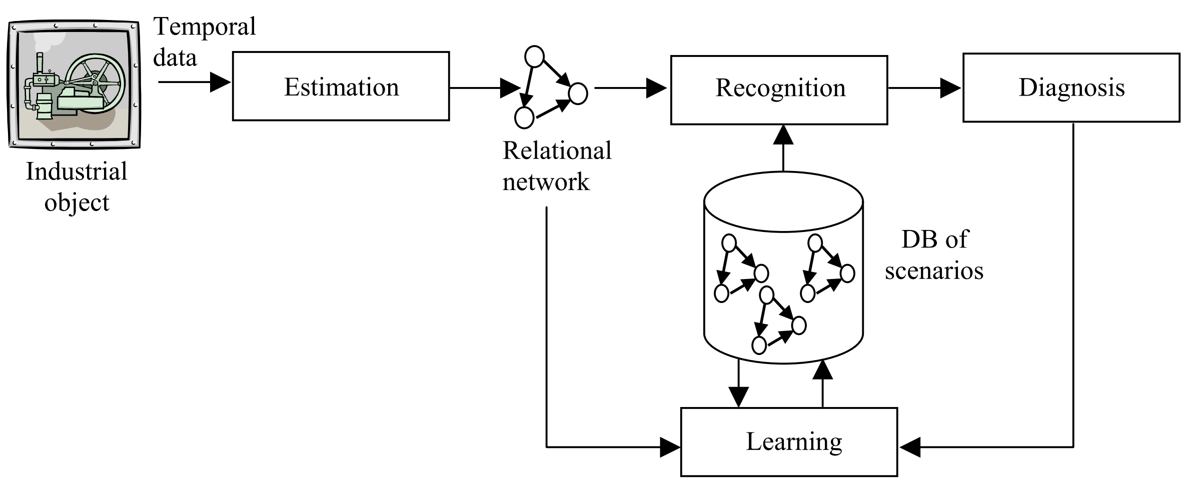

Figure 1. Conceptual schema for industrial diagnostics using uncertain temporal scenarios

In Figure 1 we can observe a particular industrial object, from which we collect information using sensors or other electronic measurement equipment. We assume that the operation of this particular industrial object is controlled and monitored using numerical information possibly collected from different sensors or other measurement devices attached to the object. This type of information may include the measurement of temperature in some particular block, measurement of pressure, rotation speed, etc. We further assume that we know some symptoms that are used in description of failure situations. For example, when the temperature in Block A exceeds 100°C the steam boiler will blow up, or if the rotation speed of the engine exceeds 5000 rotations/minute then most probably it will need full rebuild after that. The symptoms need not necessarily lead to the immediate failure of the mechanism, but preferably should point to the situation that is not dangerous at the moment but can come close to it if no preventive action is undertaken. For example, when the steam pressure in the boiler exceeds the maximum value it will heat the boiler to 150°C, making it to blow up after 20 minutes. The symptoms observed are marked with timestamps, and using the estimation mechanism, which will be discussed in Section 4, a network of uncertain temporal relations describing the situation at the object is composed.

A database of temporal scenarios of possible failures and critical situations at the object is the core of our approach to temporal diagnostics. After obtaining the relational network from the information gathered at the object we try to classify the situation, comparing this network with scenarios from the database. Since the relational network includes uncertain relations as well as the scenarios within the databases, it is often impossible to classify the situation precisely. Using our mechanism of scenario recognition we estimate probabilities that the situation at the object is developing according to different possible scenarios. When the diagnosis is clear, we can upgrade our knowledge about this case within the database by updating the most probable scenario with the relational network analyzed. This learning should also take into account information obtained from other similar industrial objects, where similar situations have taken place.

3. Basic Concepts

In this section we will briefly overview the basic formal concepts of the algebra of uncertain temporal relations used in our temporal diagnostics approach. The interested reader can find further information in [7], [6], and [5].

There are three basic relations that can hold between two points: "before" (<), "at the same time" (=), and "after" (>). Let us define a set of these relations as $\mathbf{A}=\{<,=,>\}$. There are thirteen Allen's interval relations [1] $\mathbf{X}$={eq,b,bi,d,di,o,oi,m,mi,s,si,f,fi).

An uncertain relation between two temporal primitives is represented as a set of probabilities of all basic relations that can hold between these primitives [7]. For example, $\mathbf{r}_{a,b}\{e^{\alpha}| \alpha\in A\}$ is the uncertain relation between temporal points *a* and *b*, including the probabilities $e^{<}_{a,b}$, $e^{=}_{a,b}$, and $e^{>}_{a,b}$. An uncertain relation $\mathbf{R}_{A,B}\{e^{\chi}| \chi\in \mathbf{X}\}$ between intervals *A* and *B* includes thirteen probabilities of Allen's relations. The sum of all probability values of the basic relations within **r** or **R** is equal to 1. We suppose that two uncertain relations are *equal* if and only if the corresponding probabilities of the basic relations within them are equal. When $\exists \mathbf{e}^{\chi}_{A,B}=1$ within $\mathbf{R}_{A,B}\{e^{\chi}| \chi\in \mathbf{X}\}$ we call such $\mathbf{R}_{A,B}$ a *totally certain relation* (TCR). When all the probability values within **r** or **R** are equal we call such relation a *totally uncertain relation* (TUR).

The distance (denoted as **d**) between two uncertain temporal relations is a variable belonging to the interval [0,1]. When **d**=0 the uncertain relations compared are equal, and when **d**=1 the relations are totally different. The examples of totally different relations are the point relations "<" and ">". One approach to estimate the value of **d** for uncertain relations between temporal points was proposed in [2]. In its physical interpretation the approach is based on the assumption that the two relations to be compared are distributed on a virtual lath, where the basic relations within the uncertain ones are assumed to be physical objects. For every relation we find out the balance point, which in physical interpretation is the moment of mass for the physical objects distributed on the lath. We assume that the distance between two neighbor objects on the lath is equal for all neighbor pairs. The module of the mathematical difference between the values of the balance points for these two relations is the value of the distance between these relations. So, for example, the distance between the uncertain relations $\mathbf{R}_{A,B}$ and $\mathbf{R}_{C,D}$ is calculated by formula:

$$\mathbf{d}_{\mathbf{R}_{A,B},\mathbf{R}_{C,D}} = \left|\mathrm{Bal}(\mathbf{R}_{A,B}) - \mathrm{Bal}(\mathbf{R}_{C,D})\right|, \text{ where,}$$

$$\mathrm{Bal}(\mathbf{R}_{A,B}) = \frac{1}{12}\sum_{\mathbf{i}=0}^{12} \mathbf{i}\times \mathbf{e}^{\chi_{\mathbf{i}+1}}_{A,B}.$$

A mechanism for reasoning with uncertain temporal relations, proposed in [7] and [6], includes three operations: inversion, composition, and addition. The unary operation of inversion (~) derives the relation $\mathbf{R}_{B,A}$ when the relation $\mathbf{R}_{A,B}$ is known. The binary operation of composition (⊗) derives the relation $\mathbf{R}_{A,C}$, when there exist relations $\mathbf{R}_{A,B}$ and $\mathbf{R}_{B,C}$. The binary operation of addition (⊕) combines two uncertain interval relations $\mathbf{R}_{(A,B)_1}$ and $\mathbf{R}_{(A,B)_2}$ into a single relation $\mathbf{R}_{A,B}$. The multiple operation of addition is an extension of the binary addition. This operation combines a number of uncertain relations into one relation, i.e.,

$$\mathbf{R}_{A,B}=\oplus(\mathbf{R}_{(A,B)_1}, \mathbf{R}_{(A,B)_2}, \ldots, \mathbf{R}_{(A,B)_\mathbf{k}}).$$

In the interest of space we omit in this paper the formal definitions of these operations, since they can be found in the above mentioned references.

4. Deriving Uncertain Relations

In this section we show how we compose a network of uncertain temporal relations using the information collected at the industrial object observed (Figure 2). We suppose that an industrial object is monitored using a number of sensors or other measurement devices, and we know the set of symptoms critical for successful operation of the machine. When a particular symptom is observed it is marked with a timestamp indicating the time when the symptom occurred. Many of the sensors do not continuously collect information: for example, we can measure the pressure inside the boiler every 10 seconds.

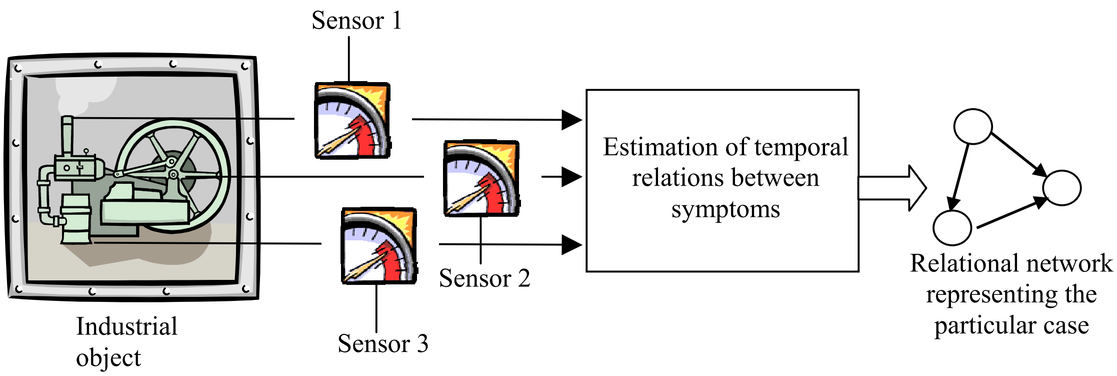

Figure 2. Schema for composing a network of uncertain temporal relations using the information from the industrial object

In this case, the timestamp is indeterminate, meaning that we do not know exactly at which particular moment of time the symptom occurred; instead we are given the time interval for the event. When temporal information is represented using indeterminate temporal primitives it is in most cases impossible to estimate temporal relations between them precisely. Instead of that, we derive uncertain relations, where the basic relations that can hold between two temporal primitives are attached with their probabilities. The formal mechanism for performing this task is presented in [5]. The mechanism takes as an input the information about indeterminate temporal primitives like, for example, critical increase of pressure inside the boiler during the interval [10 sec., 20 sec.], and produces uncertain temporal relations between these primitives. After that, we can compose a relational network consisting of these primitives and relations.

Formally, let us represent a network of binary uncertain temporal relations as a directed graph, the nodes of which represent symptoms and the arcs represent temporal relations between these symptoms. Formally, we represent such a graph as a set V of n variables $\{v_1,v_2,\ldots,v_n\}$ and binary uncertain relations between these variables represented as $\mathbf{r}_{v_i,v_j}\ \{\mathbf{e}^{\alpha} |\ \alpha\in \mathbf{A}\}$, where $v_i,v_j\in V$, if the variables are temporal points and as $\mathbf{R}_{v_i,v_j}\ \{\mathbf{e}^{\chi} |\ \chi\in \mathbf{X}\}$, where $v_i,v_j\in V$, if the variables are temporal intervals.

5. Temporal Scenarios: Generation and Recognition

In this section we show how to generate and to recognize temporal scenarios. Figure 3 presents the situation where the information about "Failure 1" is obtained from three industrial objects.

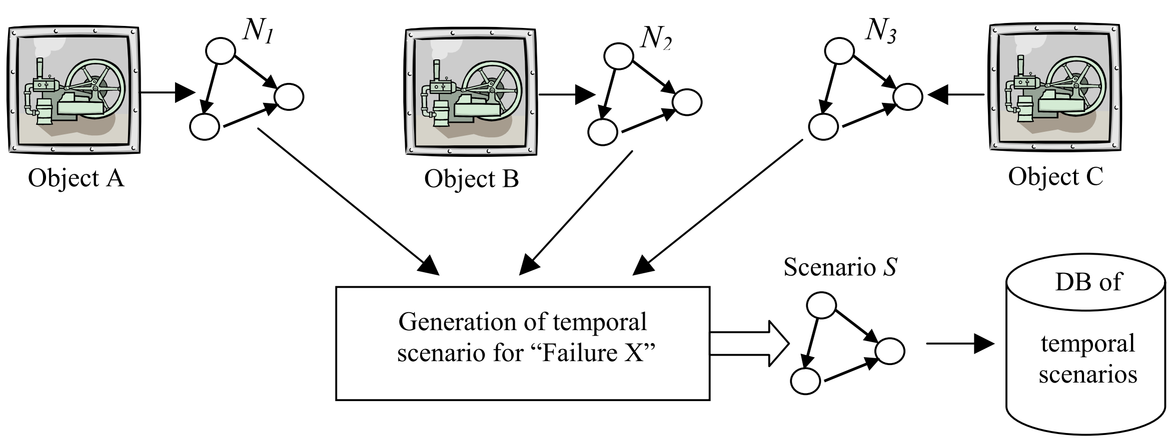

Figure 3. Conceptual schema for generation of temporal scenarios

The three objects in Figure 3 might be located in different places, and the information need not be obtained simultaneously. This means that, for example, the information for Object 1 could be obtained at the factory in Helsinki in September, from Object 2 from the factory in Jyväskylä in October, and from Object 3 also from Jyväskylä in November. We compose relational networks N_1, N_2, and N_3 describing "Failure 1" situation. After that, these networks can be composed into a temporal scenario.

Formally, we consider k networks N_1, N_2,…, N_k of uncertain temporal relations defined by the set of nodes $V=\{v_1,v_2,\ldots,v_n\}$, which is the same for each network, and the sets of uncertain temporal relations R_1, R_2,…, R_k given for each network. These sets of relations are such that an element of one set is not necessarily included in other sets, for example, a relation $\mathbf{r_{b,c}} \in R_1$, but $\mathbf{r_{b,c}} \notin R_2$.

We suppose that an uncertain temporal scenario is a network of uncertain temporal relations defined by the set of nodes $V=\{v_1,v_2,\ldots,v_n\}$, the set of relations $R=R_1\cup R_2\cup\ldots\cup R_k$, where the relations within R are obtained by multiple operation of additon of the corresponding relations between the same variables from all the sets R_1, R_2,…, and R_k according to the algorithm presented in Figure 4.

```
1.  for i=1 to n do
2.   for j=i+1 to n do
3.  | if (∃ r_{vi,vj} ∈ R1) or…or (∃ r_{vi,vj} ∈ Rk) then
4.  | |begin
5.  | |  for g=1 to n do
6.  | |    if not (∃ r_{vi,vj} ∈ Rg) then Reasoning( r_{vi,vj} , Rg)
7.  | |    // if "Reasoning" = False then (r_{vi,vj} ∈ Rg)=TUR
8.  | |    (r_{vi,vj} ∈ R) = ⊕ (r_{vi,vj} ∈ Rt), where  t=1,..k
9.  | |end
10. | else go to line 2
```

Figure 4. Algorithm for generating temporal scenarios

Within the procedure "Reasoning" in line 6 of the algorithm from Figure 4, we obtain the set $V'=\{v'_1,v'_2,..,v'_k\}$, where $V'\subseteq V$, which is a set of nodes derived using Dijkstra algorithm and representing the shortest path in the graph from v_i to v_j as $\mathbf{v_i}\rightarrow v'_1\rightarrow v'_2\rightarrow\ldots\rightarrow v'_k\rightarrow\mathbf{v_j}$. There is at least one element in the set V', otherwise the relation between v_i and v_j is present in the set R_g. After that, using the operation of composition we derive the relation $\mathbf{r}_{v_i,v_j}$.

The complexity of the main body of the algorithm in Figure 4 is $O(n^2)$, where n is the number of nodes in the graph. Within the procedure "Reasoning" we apply Dijkstra algorithm, the complexity of which basically depends on its programming realization. In this way, the overall worst-case complexity of the algorithm is $O(n^4)$.

Let the network N_1 in Figure 3 be defined by the set of symptoms $V=\{a,b,c,d\}$ and the set of temporal relations between them $R_1=\{r_{a,b}, r_{b,c}, r_{a,c}, r_{d,c}\}$. Network N_2 is defined by the set V and $R_2=\{r_{a,b}, r_{a,c}, r_{b,d}\}$. Finally, the network N_3 is defined by the set V and $R_2=\{r_{a,b}, r_{b,d}\}$. In this case, the temporal scenario S in Figure 3 will be defined by the set $V=\{a,b,c,d\}$ and the set of relations $R= R_1\cup R_2\cup R_3=\{r_{a,b}, r_{b,c}, r_{b,d}, r_{a,c}, r_{d,c}\}$.

Recognition of temporal scenarios is performed as follows. Let us suppose that a relational network N is defined by the set of nodes $V=\{n_1, n_2,.., n_k\}$ and a set of relations between them R_n. Let us also suppose that an uncertain temporal scenario S is defined by the same set of nodes $V=\{n_1, n_2,.., n_k\}$ and a set of relations between them R_s. We suppose that the sets R_n and R_s are equal at the symbolic level of representation of relations, for example, both sets can include the relations $r_{a,b}$, $r_{b,c}$, $r_{b,d}$, $r_{a,c}$, and $r_{d,c}$. At the same time, each of these relations is defined by the set of probability measures for the basic relations that can hold between two particular temporal primitives.

The distance between the relational network N and the scenario S is calculated by formula:

$$\mathbf{D}_{N,S}=\frac{\sum_{\mathbf{i=1}}^{\mathbf{m}}\mathbf{w_i d_i}}{\sum_{\mathbf{i=1}}^{\mathbf{m}}\mathbf{w_i}},$$

where w_i - the weight of i-th relation in the scenario S, d_i – the distance between two i-th relations from R_n and from R_s. In practice, the relations within R_n and R_s are initially different. Therefore, before we calculate the distance value **D** we should include the additional relations within R_n (if needed) in the following way. If a relation, which is present within set R_s is absent within set R_n we try to derive it within the network N as it is in "Reasoning" procedure in Figure 4. If this procedure fails then we assign the value TUR for this relation.

In many situations it is necessary to know to which temporal scenario the network N belongs, or if it is impossible to know then how close to every scenario the network is. Using the measure of distance between a temporal scenario and a relational network we can calculate the distances between N and every temporal scenario, as it is shown in Figure 5.

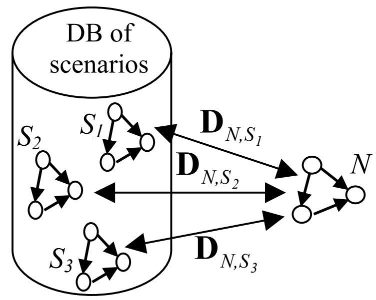

Figure 5. Conceptual schema for scenario recognition

The derived values can be represented as percentage values of similarity of the network N with every scenario.

6. Conclusions

In this paper we proposed an approach to industrial temporal diagnostics using algebra of uncertain temporal relations. Uncertain relations are represented using the probabilities of the basic relations. Using the information obtained from the industrial object observed we compose a relational network with uncertain temporal relations between symptoms. The derived network is compared with temporal scenarios of critical situations at the object, and the probabilities of possible scenarios are estimated.

The main advantage of temporal diagnostics is that it considers not only a static set of symptoms, but also the time during which they were monitored. This often allows having a broader view on the situation, and sometimes only considering temporal relations between different symptoms can give us a hint to precise diagnostics.

Experiments using the implementation of the formalism with artificial settings were carried out. As one of the direction for further research we consider experiments with real industrial datasets.

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