APPLYING Dia Med HYBRID ALGORITHM TO THE DIAGNOSIS OF DYNAMIC SYSTEMS

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Lucrarea de față adaptează şi compară un sistem hibrid original (–Dia Med-, construit inițial pentru diagnoza medicală), cu diagnoza sistemelor dinamice. Termenii de referință ai comparației sunt sistemele de inferență fuzzy (în forma sugerată de Frank), şi algoritmul lui Koscielny de ajustare dinamică a bazei de reguli fuzzy pentru diagnoză, în scopul de a evita explozia exponențială a spațiului problemei în cazul sistemelor complexe.

The present paper adapts and compares an original hybrid system –Dia Med, initially designed for medical diagnosis, for the diagnosis of dynamic systems. The terms of reference for the comparison are fuzzy inference systems (in the form suggested by Frank), and Koscielny's algorithm that dynamically adjusts the diagnosis fuzzy rule base, in order to overcome "the curse of dimensionality" when dealing with complex systems.

Keywords: fault diagnosis, fuzzy inference, fuzzy decision, non-monotonic reasoning.

Introduction

Diagnosis of dynamic systems contains two major distinct steps: fault detection and fault diagnosis (Fig. 1).

Fault detection consists of analytic or heuristic symptom generation (symptoms are usually based upon residuals in this case, a residual being "a signal that reflects inconsistencies between nominal and faulty system operation" [1]).

Fault diagnosis determines the type, size and location of the fault as well as its time of detection, based on the observed analytical and heuristic symptoms [2]. For this step, if no knowledge of deep fault-symptoms causalities is available, classification methods which map a symptom vector into a fault vector are appropriate (exp: statistical and geometrical classification, neural nets, fuzzy clustering). If, on the contrary, a priori-knowledge of fault-symptom causalities is available (e.g. in the form of causal nets), diagnostic reasoning strategies can be applied (forward/ backward chaining, approximate reasoning for probabilistic-

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bayesian nets & conditional probabilities or possibilistic reasoning with fuzzy logic [2]).

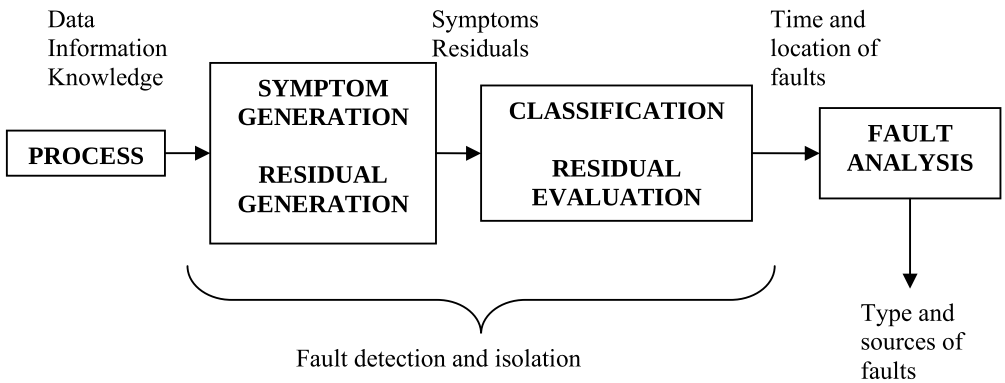

Fig. 1.Schematic representation of the procedure of fault diagnosis [3].

Section 1 of the current paper compares two approaches to fault diagnosis: a fuzzy inference system proposed by Frank in [3], and an original tackling for diagnostic hypotheses' selection by means of fuzzy decision [4]. For large, complex systems, we also compare two alternatives to avoid the "curse of dimensionality" that affects the method from [3]: Koscielny's approach [5] and DiaMed approach [6] (Section 2). The last section (Conclusions) concludes the paper, outlining, once more, the drawbacks and advantages of each of the presented methods.

1. Fuzzy decision versus fuzzy inference systems

1.1.Fuzzy inference systems for system modeling and fault diagnosis

This section illustrates how fuzzy logic can be used by the decision –making inference engine for fault diagnosis.

A precise and accurate analytical model for a dynamic system implies that any resulting modeling error will affect the performance of the resulting fault detection and isolation (FDI) scheme, which is particularly true of non-linear and uncertain systems, i.e. the majority of real processes [1]. Fuzzy logic rules can circumvent this problem, replacing an exact model and enabling the system behavior to be described by *if-then* relations. Moreover, fuzzy logic has the ability to represent symbolic information, which can be of great help in many particular situations.

Approximate reasoning is based upon the generalized modus ponens rule. This was the rule that also gave birth to the compositional inference rule for approximate reasoning [7]:

Premise: If x is A then Y is B
Fact: x is A'

Conclusion: y is B'

Conclusion B' can be determined as the composition of the fact described by the premise and the fuzzy implication operator: B'=A'° (A→ B). Therefore:

$$B'(v) = \sup_{u \in U} \min\{A'(u), (A \to B)(u,v)\}, \forall v \in V. \quad (1)$$

Sup-min composition was used. Among the operators frequently used in fuzzy control to model fuzzy implication we mention the Mamdani[†] implication.

Here is an example of fuzzy reasoning for MISO (multiple input single output) systems [11]:

R_1: IF x_1 is A_{11} AND ... AND x_m is A_{m1} THEN y is B_1
R_2: IF x_1 is A_{12} AND ... AND x_m is A_{m2} THEN y is B_2
...
R_n: IF x_1 is A_{1n} AND... AND x_m is A_{mn} THEN y is B_n
Fact: x_1 is x_{10}, x_2 is x_{20},... x_m is x_{m0},

Conclusion: Y is B

The conclusion shall be computed as Agg(Fact°R_1,… Fact°R_n):

$$B=Agg(x_{10}\times\ldots\times x_{m0} \circ R_1, \ldots, x_{10}\times\ldots\times x_{m0} \circ R_n).$$

The fuzzy output of this knowledge base is computed as follows:

- The firing degree of rule R_i is $A_{1i}(x_{10}) \times\ldots\times A_{mi}(x_{m0})$;
- The output of each rule R_i is $B_i'(w)=A_{1i}(x_{10}) \times\ldots\times A_{mi}(x_{m0})\rightarrow B_i(w)$, $\forall w \in W$, (W is the discourse universe of set Y);
- The global system output B is: $B(w)=Agg\{B_1',\ldots, B_n'\}, \forall w \in W$.

Aggregation is based upon operators such as t-norms (conjunctive meaning of aggregation) or t-conorms (disjunctive meaning of aggregation). The Cartesian product and the implication also benefit of a large variety of choices (for instance, the t-norm product).

[†] $x\rightarrow y=\min\{x,y\}$.

We notice in the model above that the function that defines the fuzzy set from the consequent of each rule represents a linguistic value for one and the same variable (y).

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Frank [3] proposes the use of fuzzy logic for residual evaluation in order to isolate the faults. Let $R=\{r_1, r_2,..., r_m\}$ be the set of residuals. Each residual r_i, $i=1,...m$, is described by a number of fuzzy sets $\{r_{i1}, r_{i2},...,r_{is}\}$, whose membership functions are identified using methods like domain expert knowledge or learning with neural networks. The causal relationships between the residuals and faults are expressed by if-then rules of the form:

IF (effect= r_{ip}*) AND … AND (effect=* r_{jq}*) THEN (cause= the* k^{th} *fault)*

The output of the fuzzy classifier is the vector of faults *F*. The fuzzy inference process will assign to each component F_l, $(l=1,...,n)$ a value between 0 and 1 that indicates the degree with which the normal state (the corresponding component is F_0) or the *l*-th fault affects the monitored system, $l=1,...,n$. If there is the premise that the system can be affected only by a fault at a time, then the faulty vector contains only one component larger than a preset threshold value, and whose corresponding faulty state represents the actual state of the monitored system. If multiple faults can affect the monitored system, then the components of the classifier output, which are larger than a preset threshold, indicate the faults that occurred in the system. The advantage of using the previous fuzzy classifier is the fact that the fuzzy rules provide details on the mapping of residuals to a faulty state. The disadvantage is that this fuzzy system does not represent a practical choice when dealing with a complex system, as the number of rules that describe the relationships residuals-faults is very large. A solution to overcome this curse of dimensionality is presented in [5]. This drawback can be significantly improved by the approaches from Section 2. We also note that, in Frank's approach, a rule is needed for each abnormal value of one and the same variable, but this shall be improved following.

1.2.Fuzzy decision for fault's selection

The fuzzy decision model for diagnostic hypotheses' selection of DiaMed is a valid and more efficient alternative to the fuzzy approach previously presented. It allows that every fuzzy rule base which corresponds to a certain output variable y be rewritten in the form of a fuzzy decision function, as described below.

The key of Dia Med's representation is to define the faults $F = \{f_1,..., f_N\}$ by means of fuzzy weighted decision functions ($F_1^{w_1},...,F_N^{w_N}$) [4]:

- $F_i^{w_i} = h_i(R_{i_1}(o),..., R_{in_i}(o))$, where:

- $Symptoms(f_i) = \{r_{i_1},...,r_{in_i}\}$, and $i_1,...i_{n_i} \in \{1,...,K\}$ represent the indices of the residuals relevant for fault f_i;
- $R_j : dom_j \to [0,1]$, is a fuzzy function that defines residual r_j (dom_j represents the domain of the R_j function),
- w_i is the weight vector of symptoms within definition of fault f_i;
- h_i is an aggregation function defined by means of fuzzy operators which model a human expert's way of reasoning; and
- $o = (R_1(o),...,R_K(o))$ is a K-dimensional point that represents observations for a given system.

If *m* output variables are to be modeled, selection of fault hypotheses will only need *m* fuzzy decision functions, each of these being constructed by means of more complex and natural fuzzy aggregation operators which are also easier to interpret than a rule base built with the AND operator exclusively (see, for instance, compensatory operators, fuzzy integrals and so on).

The idea that underlies diagnosis here is to compute the indices $F_i^{w_i}(o)$ that measure the degree of match between the observations vector and the complex criterion which defines the fault f_i and to use these indices for a hierarchization of fault hypotheses, based on the particular evidences of a given case. The selection step compares the indices with a given threshold (e.g. 0.2). An example of such indices is given by the definition to follow.

Definition [4]. Let $f_i \in F$, and *s* a system under observation. The score of the fault f_i at a given system *s* is defined as:

$$Score(s, f_i) = S_g(M_{i_1}(o), ..., M_{in_i}(o)) \quad (2)$$

(where *g* is defined using w_i, the fuzzy measure of a set of symptoms –residuals- being the normalized sum of their weights, *o* is the observation vector associated with *s* and S_g is the Sugeno integral [8]).

Therefore, the selection level of the DiaMed hybrid system quickly focuses the search towards relevant directions, by means of simple and efficient computation, but deliberately ignores possible interactions among hypotheses for efficiency reasons, and it also lacks explanation facilities. These drawbacks can be dealt with reasoning techniques as the ones described in Section 2.

Moreover, a great advantage of the fuzzy decision functions described above is given by the fact that they are easier to build than fuzzy inference rule bases. To this end, an appropriate model is needed: fuzzy values "small" or "big" of a certain element shall not be considered as defects in themselves, but it is necessary to represent the value of the element as a function of other elements of the system, which are directly or indirectly related (see Fig. 2.1).

In conclusion, instead of aggregating different realization degrees of fuzzy values (small, big etc.) for one and the same output variable, a number is computed directly for each output variable, and this number shall be considered "small" or "big" rather by its relation with a certain dynamic context (values from other output variables), than by its value on an absolute scale.

2. Comparing two approaches to large systems

2.1.A dynamic algorithm for large systems

The author of [5] proposes a method to overcome the "curse of dimensionality" that affects Frank's approach. We resume the ideas from [5] following.

Definition[5]. A fault isolation system (FIS) is a quadruple <F, R, V, φ>, where:

- F is the set of states $F=\{f_0, f_1, \ldots, f_K\}$, f_0 is the normal state and the rest are the faulty states;
- $R=\{r_1,\ldots,r_J\}$ is the set of residuals (symptoms);
- $V = \bigcup_{r_j \in R} V_j$, where $V_j=\{v_{ji}\}$, ($i \in I_j$), is the linguistic variable that describes residual r_j, with its fuzzy values;
- $\varphi(f_k, r_j)=V_{kj}$ represents the set of linguistic values for residual r_j within definition of fault f_k (more definition rules can exist for one and the same fault).

If we consider as possible fuzzy values (N+, P, N- negative –, positive= normal, negative+), then a definition rule for fault f_k could have the following form:

IF $(v_1 = N+)$ *and… and* $(v_j = P)$ *and… and* $(v_J = N-)$ *THEN fault* f_k

where v_j are the fuzzy values with maximum realization degree for residual r_j.

The firing degree of each rule is computed as an index that measures the distance between a residual r_j and its values obtained for a certain fault f_k, the final diagnostic being composed of faults with a maximum firing degree. The approach is difficult to apply when diagnosing large complex systems, because of the cardinality of faults and residuals sets. The paper [5] proposes to dynamically restrict the set of residuals to a subset R* of residuals effectively used at a certain moment, by considering their dependence on a set F* of currently possible faults (and which is also dynamically tailored). We briefly resume this algorithm below.

1)Cyclic testing of symptoms values.

The fault isolation procedure is launched when a residual r_{j0} (possibly attached to an alarm) having the membership value corresponding to a negative attribute larger than a predefined threshold value T is detected:

$$\exists r_j^0, (v_{ji} \neq P) \wedge (\mu_{ji} > T),$$

where v_{ji} is the fuzzy value of residual r_j, and μ_{ij} is the realization degree of fuzzy value v_{ji} for the concrete practical value of r_{j0}.

Initializations:

- $R^*=R_N^*(m=0)=r_{j0}$ (R* is the testing set, that is- the set of residuals interesting for a given context of faults, and R_N^* is the set of residuals that have an abnormal fuzzy value greater than T when computed for the concrete value of the respective residual;
- F*=Ø.

2) Create FIS*, which includes the currently identified fault.

a) $F^* = \{f_k \in F \mid \exists r_j \in R_N^*(m) \cap \varphi(f_k, r_j) \neq P\}$

(f_k= faults for which there exists an already selected residual that occurs with an abnromal value within the definition of f_k, $\varphi(f_k,r_j)$= the fuzzy value of r_j within definition of f_k);

b) $R^* = \{r_j \in R \mid \exists f_k \in F^*(m) \cap \varphi(f_k, r_j) \neq P\}$

(extend the set of residuals with those occurring with abnormal values within the definition of already selected defects);

c) $R_N^* = \{r_j \in R^* \mid (v_{ji} \neq P) \wedge (\mu_{ji} > T)\}$.

Steps 1 and 2 are repeated while R_N^* still undergoes changes. Finally, FIS*=<F*,R*, V, φ*> (φ* is the restriction of φ to the newly computed sets F*, R*).

2.2.Refinement and explanation of the diagnostic decision in DiaMed

The second level of DiaMed [6] (which is used for discrimination and explanation) represents an alternative to the approach from [5] to avoid the curse of dimensionality. Though it needs a more detailed model of the system, it has the advantage of better explanation facilities.

DiaMed approach is more appropriate for those technical processes where the basic relationships between faults and symptoms are at least partially known, and this a-priori knowledge can be represented in the form of causal relations:

fault →events →symptoms

As long as we give the system an appropriate representation (following the scheme in Fig. 2.1), we can effectively use the reasoning procedure from [6]. The representation is based on a direct argumentation scheme [9][‡].

[‡] An *argumentation framework* AF ("Argumentation Framework") is a pair AF=<AR, *attacks*>, where AR is a set of arguments, and *attacks* is a binary relation over AR: *attacks* $\subseteq AR \times AR$.

An argument A is *acceptable* with respect to a set S of arguments iff any argument that defeats A is defeated by an argument in S.

A conflict-free set of arguments S is *admissible* iff any argument in S is acceptable with respect to S. (A set S of arguments is *conflict-free* if there are no arguments A, B in S such that A attacks B).

Definition 2.1[6]. A multiple diagnosis (i.e. a non-empty set of possible faults at a given system) is an admissible hypotheses set that covers all observations and is minimal with this property.

Definition 2.2[6]. A solution to a diagnostic problem is a complete and consistent (admissible) assignment of truth values for each active variable (i.e. activated through the selection of certain hypotheses), which covers all confirmed symptoms. A solution is minimal if it has the minimum number of nodes, while still respecting the previous conditions.

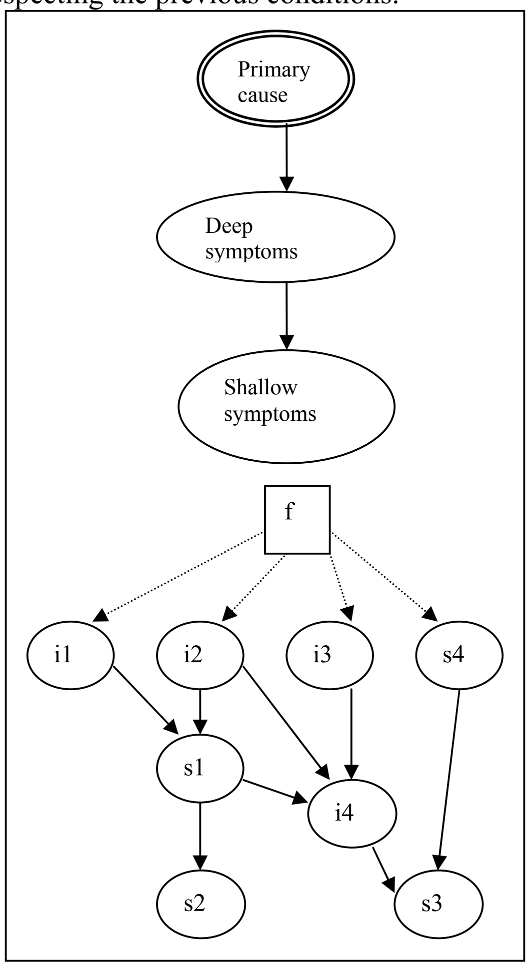

Fig. 2.1.General structure of a causal model and a sub-net (f-fault, i-intermediary nodes, s –symptoms / residuals)

The diagnostic hypotheses selected by the first level of DiaMed form a set of active variables (ActiveVar) over which the algorithm of [VerSchi] is applied in a modified form. Its steps are basically the ones following [6]:

1.Try to determine an admissible state assignment for variables selected in ActiveVar, mainly solving the CSP problem defined by the set of constraints in which variables of ActiveVar take part.

2.Print solutions (Definition 2.2.); record inadmissible assignments.

3.If we do not have solutions, or simply if the user wishes to clarify things further, extend previous inadmissible assignments with “defenses”, following the steps below:

- perform new tests, apply selection step again on the new set of evidences, and adjust ActiveVar accordingly; also correct the set of new applicable constraints;
- for each inadmissible assignment, keep its variables (V) fixed (with the value already assigned) and apply CSP over the newly added variables from ActiveVar.

4.Repeat from step 1 until no more tests are possible, or simply until the user stops the algorithm.

This algorithm represents an efficient and dynamic scheme of dealing with nonmonotonic reasoning, with explanations for decisions embedded in the structure of the arguments. Its main advantage over Koscielny’s approach was already emphasized - it resides in its higher level of transparency of the diagnostic decision, based on a more detailed model of the system under observation. Also, the details embedded within the model form a better structure, that allows for a more intelligent scheme for the dynamic selection of a possible sub-model. Moreover, admissibility represents a more natural choice to represent diagnosis in real situations.

Conclusions

The present paper aimed to confront the original hybrid model of DiaMed (initially used for medical diagnosis) with the problem of fault diagnosis for dynamic systems. Fuzzy inference systems were used as a term of reference, as they are closest to fuzzy decision, among diagnosis methods. The drawback of DiaMed arises from the need for a detailed model of the structure and interactions which occur in the system. Nevertheless, the cost is worth paying: we get better precision, better explanations, more natural and easier to interpret representation as a payback. Moreover, efficiency wins from the fact that fewer faults are effectively modeled inside the diagnosis system (as opposed to the fuzzy inference approach). Practical applications are yet to be considered and compared with the alternative approaches.

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