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Control System Diagnosis Algorithm Optimization - the Combinatorial Entropy Approach

Henryk Borowczyk

Air Force Institute of Technology, 6 Ks. Boleslawa St., 01-494 Warsaw, Poland
(e-mail: borowczyk@post.pl)

Abstract: This paper presents combinatorial measures of the system condition uncertainty (diagnostic entropy) and the diagnostic symptoms information. The multi-valued diagnostic model has been assumed. Proposed measures can be used for the diagnostic model analysis and the diagnosis algorithm optimization. Optimization method exploits indispensable symptoms at every stage of the optimization process providing minimum number of symptoms in diagnosis algorithm.

1. INTRODUCTION

One of the most important problem in technical diagnostics is the assessment of optimal set of symptoms. Applied optimization method depends on the form of diagnostic model (Blanke *et. al.*, 2003, Jamsa-Jounela *et. al.*, 2003, Kiencke and Nielsen, 2005) and optimization criterion. The diagnostic model describes relations between a system condition (the set of conditions and healthy condition) and diagnostic symptoms (Frank et. al., 2000; Iserman, 2004; Korbicz *et. al.*, 2004; Lunze, 1998; Niziński and Michalski, 2002). Recently, more attention is paid to the qualitative (approximate, multi-valued) models (Iserman, 2004; Korbicz *et. al*. 2004, Lunze, 1998, Borowczyk, 1984). Qualitative models can be applied to determine a diagnosis algorithm (Borowczyk, 1984), approximate inference within expert systems (Lee, 2000, Iserman, 2004), etc.

One of the way of diagnosis algorithm assessment consists in applying the information-based analysis (Borowczyk, 1984; Młokosiewicz, 1985; de Kleer and Williams, 1987; Rosenhaus, 1996; Niziński and Michalski, 2002), i.e. description of the system condition uncertainty and amount of information delivered by means of individual symptoms and sets thereof. This aim can be reached with the Shannon-introduced quantities: the entropy, and the amount of information (Shannon, 1948).

There are some other kinds of entropies which can be considered – Renyi's entropy (Csiszár, 1974), structural α-entropy (Havrda and Charvát, 1967), functions $z_\alpha(t)$ (Behara and Nath, 1973). Information measures characterization (from the information theory point of view) have been extensively discussed in (Aczél and Daròczy, 1975, Ebanks *et al,* 1998).

This paper exploits measures developed in (Borowczyk, 1984) – a combinatorial diagnostic entropy $H_{Bc}(.)$ and combinatorial symptom information $J_{Bc}(.)$ – which have been introduced taking diagnostics point of view into account.

2. ASSUMPTIONS

1. A finite set of conditions is determined:

$$E = \{e_i\},\ i = 1,...,n \tag{1}$$

2. Probabilities $P(e_i)$ of conditions $e_i \in E$ are non-zero:

$$\forall_{i=1,\dots,n} P(e_i) > 0,\ P(E) = 1 \tag{2}$$

3. Determined is a finite set of symptoms

$$D = \{d_r\},\ r = 1,...,t \tag{3}$$

and a finite set of values taken by the symptoms

$$A = \{0,\dots,\lambda - 1\} \tag{4}$$

Function $R(.)$ mapping D and E into A is the λ-valued function

$$R(d_r / e_i) = g_{ir},\ g_{ir} \in A \tag{5}$$

4. For all the symptoms the following holds:

$$\forall_{d_r \in D} \forall_{e_i \in E} \exists_{g_{ir} \in A} P[R(d_r/e_i) = g_{ir}] = 1 \tag{6}$$

5. The multi-valued diagnostic model has been presented in the form of a diagnostic matrix G.

$$G = \left[g_{ir}\right]_{n\,x\,t} \tag{7}$$

where: $g_{ir} = R(d_r/e_i)$

The above assumptions establish the multi-valued diagnostic model of wide class of technical objects (e.g. Kościelny, 1995).

3. POSTULATED PROPERTIES OF THE COMBINATORIAL DIAGNOSTIC ENTROPY

A set of postulated properties of the combinatorial diagnostic entropy $H_{Bc}(E)$ can be found on the base of its 'conceptual' similarity with the Shannon entropy.

Therefore, reasonable seems the postulate that $H_{Bc}(E)$ be a function of $n = card(E)$:

$$H_{Bc}(E) = f(n) \tag{8}$$

What else should be expected is the monotonic increase of $H_{Bc}(E)$ with the growth of n :

$$f(n) \geq f(n') \Leftrightarrow n \geq n' \tag{9}$$

Two other properties result from setting the uncertainty to zero. If it is known *a priori* that the set of conditions is one-component only ($n = 1$), the system condition is then definitely determined and $H_{Bc}(E)$ should take value zero:

$$H_{Bc}(E)\big|_{n=1} = 0 \tag{10}$$

Another extreme case takes place when the selected symptoms generates the conditions-set partition in the form of one-component subsets $\{\{e_i\}\}$, $i = 1,\ldots n$. It means that all the pairs of conditions have been distinguished by the selected symptoms; hence, the uncertainty equals zero:

$$H_{Bc}(E / \{\{e_i\}\}) = 0 \tag{11}$$

The last postulated property is defined with the following relationship

$$H_{Bc}(E / \{E_j\}) = \sum_{j=1}^{\lambda-1} H_{Bc}(E_j) \tag{12}$$

where:

$$H_{Bc}(E_j) = f(n_j) \tag{13}$$

It means that if the conditions-set partition is given in the form

$$\{E_j(d_r)\} = \{E_0(d_r), \cdots, E_{\lambda-1}(d_r)\} \tag{14}$$

where

$$\underset{j=0,\ldots,\lambda-1}{\forall} E_j(d_r) = \{e_{i_j} : R(d_r / e_{i_j}) = j; i_j = 1,\ldots,n_j, j \in A\} \tag{15}$$

and

$$\begin{aligned} &\text{a)} \quad \underset{\substack{j,l=0,\ldots,\lambda-1 \\ j \neq l}}{\forall} E_j(d_r) \cap E_l(d_r) = \varnothing, \quad \bigcup_{j=0}^{\lambda-1} E_j(d_r) = E \\ &\text{b)} \quad \sum_{j=0}^{\lambda-1} n_j = n, \quad \sum_{j=0}^{\lambda-1} p_j = 1, \quad p_j = \sum_{i_j=1}^{n_j} P(e_{i_j}) \end{aligned} \tag{16}$$

the condition uncertainty is a function of n_j, $j = 0,\ldots,\lambda-1$.

4. THE COMBINATORIAL DIAGNOSTIC ENTROPY

It follows from the above-presented considerations that function $H_{Bc}(E)$ should have the following properties:

$$H_{Bc}(E) = f(n) \tag{17}$$

$$\begin{aligned} &H_{Bc}(E) \geq H_{Bc}(E') \Leftrightarrow n \geq n', \\ &n = Card(E), \quad n' = Card(E') \end{aligned} \tag{18}$$

$$H_{Bc}(E)\big|_{n=1} = 0 \tag{19}$$

$$H_{Bc}(E / \{E_j\}) = \sum_{j=1}^{m} H_{Bc}(E_j), \; Card(\{E_j\}) = m \tag{20}$$

$$H_{Bc}(E / \{\{e_i\}\}) = 0, \; i = 1,\ldots,n \tag{21}$$

The form of the function $f(n)$ can be defined with two methods: a) formal deduction based on the set of postulated properties b) arbitrary acceptance of a certain form of the function and proving that it shows the postulated properties. In this paper the latter of the methods will be applied. Further considerations will be based on the following theorem:

Theorem 1

If a finite set of conditions $E = \{e_i\}$, $i = 1,\ldots,n$, is given then function

$$H_{Bc}(E) = \binom{n}{2} = 0{,}5n(n-1) \tag{22}$$

which determines the number of all unordered pairs of conditions shows the postulated properties (17) – (21).

Proof (draft)

To prove Theorem 1, a series of subsidiary theorems – lemmas 1 ÷ 6 (without proofs) will be used.

Lemma 1

Function (22) fulfils (17)

Lemma 2

Equivalence (18) takes place for the function (22).

Lemma 3

For a one-fault system, function (22) takes value equal to zero.

Lemma 4

If given is set partition $\{E_j\}$, $j = 1,\ldots,m$ then the following relationship takes place:

$$H_{Bc}(E / \{E_j\}) = \sum_{j=1}^{m} H_{Bc}(E_j) \tag{23}$$

Lemma 5

If the conditions-set partition is given in the form of one-component subsets $\{\{e_i\}\}$, $i = 1,\ldots,n$, then the system condition uncertainty equals to zero.

$$H_{Bc}(E / \{\{e_i\}\}) = 0 \tag{24}$$

What has been proved by means of the lemmas 1 – 6 is that function (22) shows the postulated properties (17) - (21), which completes the proof of main Theorem 1.

5. THE COMBINATORIAL INFORMATION OF DIAGNOSTIC SYMPTOMS

The initial system condition uncertainty (prior to the selection of any symptom) is equal to:

$$H_{Bc}(E) = 0{,}5n(n-1) \tag{25}$$

If any symptom $d_r \in D$, has been selected as the first one in the sequence, it generates the conditions-set partition of the following form:

$$\{E_j(d_r)\} = \{E_0(d_r), \cdots, E_{\lambda-1}(d_r)\} \tag{26}$$

and relationships (27) are satisfied

$$\begin{gathered} \underset{\substack{j,l=0,\dots,\lambda-1 \\ j \neq l}}{\forall} E_j(d_r) \cap E_l(d_r) = \varnothing, \\ \bigcup_{j=0}^{\lambda-1} E_j(d_r) = E \quad \sum_{j=0}^{\lambda-1} n_j = n \end{gathered} \tag{27}$$

The condition uncertainty after selection of symptom d_r that generates set partition (26), equals :

$$H_{Bc}(E/\{E_j\}) = 0{,}5 \sum_{j=1}^{\lambda-1} n_j (n_j - 1)$$

Since the set partition (26) is explicitly defined by means of the symptom d_r generating it, the above formula can be written down in the form:

$$H_{Bc}(E/d_r) = 0{,}5 \sum_{j=0}^{\lambda-1} n_j (n_j - 1) \tag{28}$$

It's easy to notice that the condition uncertainty after the selection of the symptom d_r is not greater than the initial uncertainty, i.e.:

$$H_{Bc}(E) \geq H_{Bc}(E/d_r) \tag{29}$$

Equality in (29) occurs in the case described with the following condition

$$H_{Bc}(E) = H_{Bc}(E/d_r) \Leftrightarrow \underset{j \in A}{\exists} (n_j = n) \tag{30}$$

It means that the value of the symptom d_r does not depend on the system condition, and such a symptom should be removed. On the grounds of relationships (29) and (30), the notion of the symptom combinatorial information can be defined.

Definition 1

The symptom d_r combinatorial information is equal to the difference in the condition uncertainty before this symptom has been selected and the uncertainty remaining after the selection.

If the symptom d_r is selected as the first one in the sequence, then, according to the Definition 1, the following can be written down:

$$J_{Bc}(d_r) = H_{Bc}(E) - H_{Bc}(E/d_r) \tag{31}$$

where: $J_{Bc}(d_r)$ - the combinatorial information of the symptom $d_r \in D$.

After substituting (25) and (28) into (31) and account taken of relationships (27), the information can be presented in the following form:

$$J_{Bc}(d_r) = 0{,}5 \sum_{j=0}^{\lambda-1} n_j (n - n_j) \tag{32}$$

From (29) and (31) it becomes evident that the information $J_{Bc}(d_r)$ can take non-negative values $J_{Bc}(d_r) \geq 0$. The formula (31) and earlier considerations give grounds to formulate the conclusion - the information $J_{Bc}(d_r)$ equals the number of all unordered pairs of conditions distinguishable due to the symptom d_r:

$$J_{Bc}(d_r) = \sum_{j=0}^{\lambda-2} \sum_{k=j+1}^{\lambda-1} n_j n_k \tag{33}$$

This confirms the coherence of the introduced measures of the system condition uncertainty and the symptoms information.

If the symptom $d_s \in D$ has been selected as the second one in the sequence, then in each of the subsets $E_j(d_r)$ of the set partition (26) it generates the following set partition:

$$\underset{j=0,\dots,\lambda-1}{\forall} \{E_{j0}(d_r, d_s), \dots, E_{j\lambda-1}(d_r, d_s)\} \tag{34}$$

where:

$$E_{jl}(d_r, d_s) = \{e_{i_{jl}} : R(d_r / e_{i_{jl}}) = j \wedge R(d_s / e_{i_{jl}}) = l, \\ i_{jl} = 1, \dots, n_{jl}, \}$$

The following relationships are satisfied:

$$\begin{aligned} &a) \quad \underset{j=0,\dots,\lambda-1}{\forall} \; \underset{\substack{l,k=0,\dots,\lambda-1 \\ l \neq k}}{\forall} E_{jl}(d_r, d_s) \cap E_{jk}(d_r, d_s) = \varnothing \\ &b) \quad \underset{j=0,\dots,\lambda-1}{\forall} \bigcup_{l=0}^{\lambda-1} E_{jl}(d_r, d_s) = E_j(d_r) \\ &c) \quad \underset{j=0,\dots,\lambda-1}{\forall} \sum_{l=0}^{\lambda-1} n_{jl} = n_j \end{aligned} \tag{35}$$

The uncertainty after having selected both the symptoms, i.e. $d_r, d_s \in D$, can be written down in the following way:

$$H_{Bc}(E/d_r, d_s) = 0{,}5 \sum_{j=0}^{\lambda-1} \sum_{l=0}^{\lambda-1} n_{jl} (n_{jl} - 1) \tag{36}$$

The symptom d_s conditional information results from the general Definition 1

$$J_{Bc}(d_s / d_r) = H_{Bc}(E/d_r) - H_{Bc}(E/d_r, d_s) \tag{37}$$

After substituting (28) and (36) into (37), the following is arrived at:

$$J_{Bc}(d_s / d_r) = 0{,}5 \sum_{j=0}^{\lambda-1} \sum_{l=0}^{\lambda-1} n_{jl} (n_j - n_{jl}) \tag{38}$$

The above considerations can be generalized to the question of the symptom $d_s \in D$ information defining when the set of k symptoms $D_k \subset D$ have been selected earlier

$$D_k = \{d_{(1)}, d_{(2)}, \dots, d_{(k)}\} \tag{39}$$

and the set E partition is in the form

$$\{E_j(D_k)\} = \{E_0(D_k), E_1(D_k), ..., E_{m_k-1}(D_k)\} \quad (40)$$

where: m_k – the power of the family of subsets

Using general Definition 1, the conditional information of the symptom d_s, can be written down in the following form:

$$J_{Bc}(d_s / D_k) = H_{Bc}(E / D_k) - H_{Bc}(E / D_k, d_s) \quad (41)$$

and finaly:

$$J_{Bc}(d_s / D_k) = 0{,}5 \sum_{j=0}^{m_k-1} \sum_{l=0}^{\lambda-1} n_{jl}(n_j - n_{jl}) \quad (42)$$

It can be easily noticed that formulas (42) are the generalization of (38) - they become identical when $k = 1$ and $m_k = \lambda$.

Another issue of significance is to define the set of k symptoms $D_k \subset D$ information. In order to do this, the earlier introduced Definition 1 should be generalised to the following form:

<u>Definition 2</u>

The information $J_{Bc}(D_k)$ of the symptoms set D_k is equal to the difference between the initial uncertainty $H_{Bc}(E)$ and the uncertainty remaining after having selected all the symptoms from the set D_k - $H_{Bc}(E / D_k)$:

$$J_{Bc}(D_k) = H_{Bc}(E) - H_{Bc}(E / D_k) \quad (43)$$

After simple transformations the following is arrived at:

$$J_{Bc}(D_k) = 0{,}5 \sum_{j=0}^{m_k-1} n_j(n - n_j) \quad (44)$$

What comes out from the comparison between (32) and (44) is that both the formulas take identical form if D_k is a one-member set.

Using Definition 2, the total information of the symptoms set D_k and the symptom $d_s \notin D_k$ can be presented in the following form:

$$J_{Bc}(D_k, d_s) = H_{Bc}(E) - H_{Bc}(E / D_k, d_s) \quad (45)$$

After transformations, the following is arrived at:

$$J_{Bc}(D_k, d_s) = 0{,}5 \sum_{j=0}^{m_k-1} \sum_{l=0}^{\lambda-1} n_{jl}(n - n_{jl}) \quad (46)$$

What results from the above-considered issues can be used to prove the Lemma 6 and the Theorem 2.

<u>Lemma 6</u>

The total information of the symptoms set $D_k \subset D$ and the symptom $d_s \notin D_k$ is equal to the sum of the set D_k information and conditional information of the symptom d_s

$$J_{Bc}(D_k, d_s) = J_{Bc}(D_k) + J_{Bc}(d_s / D_k) \quad (47)$$

<u>Theorem 2</u>

The information of the symptoms set $D_K = \{d_k\}$, $k = 1, ..., K$, $D_K \subset D$ equals to the sum of conditional information of individual symptoms.

$$J_{Bc}(D_K) = \sum_{k=1}^{K} J_{Bc}(d_{(k)} / D_{k-1}) \quad (48)$$

where $D_0 = \varnothing$

The symptom combinatorial information shows the property of additivity, as does information in the sense meant by Shannon.

6. A PRELIMINARY ANALYSIS OF THE DIAGNOSTIC MODEL

There are three significant issues which have to be analysed before starting optimization of diagnosis algorithm:

- a sufficiency of symptoms set - has D provided distinguishing of all pairs of object conditions?
- a symptom pairs redundancy;
- an existence of indispensable symptoms.

If some pairs of conditions are not distinguishable one have to include some addition symptoms into set D. If such symptoms do not exist indistinguishable conditions form compound condition with probability equal the sum of individual probabilities.

The problem of symptom pairs redundancy can take one of two forms:

- symptoms d_r and d_s are equivalent - distinguish identical pairs of conditions (generate identical partitions of the set E)
- symptom d_s is dominated by d_r - set of condition pairs distinguished by d_s is a subset of the set of condition pairs distinguished by d_r.

The conditions of symptom pairs equivalence take the form:

- the necessary condition

$$J_{Bc}(d_r) = J_{Bc}(d_r) \quad (49)$$

- the sufficient condition

$$J_{Bc}(d_r) = J_{Bc}(d_s) \wedge J_{Bc}(d_s / d_r) = 0 \quad (50)$$

The following relationship defines symptom d_s dominated by d_r:

$$J_{Bc}(d_s / d_r) = 0 \wedge J_{Bc}(d_r / d_s) > 0 \quad (51)$$

All symptoms equivalent d_r or dominated by d_r have to be removed from the diagnostic model.

After above mentioned operations diagnostic model does not contain indistinguishable conditions and equivalent or dominated symptoms.

Symptom d_r^i is indispensable if the following holds:

$$\exists_{e_k, e_j \in E} R(d_r^i / e_k) \neq R(d_r^i / e_l) \wedge \forall_{d_s \in D \setminus \{d_r^i\}} R(d_s / e_k) = R(d_s / e_l) \tag{52}$$

It means that at least one pair of conditions exist which is distinguished only by symptom d_r^i. All indispensable symptoms set up the core $Y(D)$ of any diagnostic algorithm which can be designed using symptoms from set D (Parchomienko and Sogomonian, 1980, Borowczyk, 1984).

7. AN OPTIMIZATION OF THE DIAGNOSIS ALGORITHM

Every $k-th$ stage of proposed optimization method consists of following steps:

- calculate symptoms information $J_{Bc}(d_r / D_{k-1})$ (where $D_0 = \varnothing$);
- if $J_{Bc}(d_r / D_{k-1}) = 0$ for all $d_r \in D \setminus D_{k-1}$ - stop;
- remove redundant symptoms using relations (49) - (51);
- set up the core $Y_k(D \setminus D_{k-1})$ according to (52);
- if $Y_k(D \setminus D_{k-1}) \neq \varnothing$ include symptoms from $Y_k(D)$ into the set

$$D_k = D_{k-1} \cup Y_k(D \setminus D_{k-1}) \tag{53}$$

- if $Y_k(D \setminus D_{k-1}) = \varnothing$ include symptom $d_{(k)}$

$$d_{(k)} : J(d_{(k)} / D_{k-1}) = \max_{d_r \in D \setminus D_{k-1}} J(d_r / D_{k-1}) \tag{54}$$

into the set $D_k = D_{k-1} \cup d_{(k)}$.

An example of simple three-valued diagnostic model is shown in Fig. 1.

e_i	d_1	d_2	d_3	d_4	d_5
e_0	1	1	1	1	1
e_1	0	1	0	1	1
e_2	2	1	2	1	1
e_3	0	0	1	1	1
e_4	2	2	2	1	1
e_5	1	1	1	2	1
e_6	2	2	1	1	0
$J_{Bc}(d_r / D_0)$	16	14	14	6	6

Fig. 1 An example of three-valued diagnostic model – the first stage

Initial condition uncertainty - $H_{Bc}(E) = 21$.

At the first stage the diagnostic model contains neither equivalent nor dominated symptoms. The core $Y(D) = \{d_2, d_4\}$ hence $D_1 = \{d_2, d_4\}$

Fig. 2 shows diagnostic model after rearrangement according to symptoms d_2 and d_4 values.

e_i	d_2	d_4	d_3	d_1	d_5
e_3	0	1	1	0	1
e_1	1	1	0	0	1
e_0	1	1	1	1	1
e_2	1	1	2	2	1
e_5	1	2	1	1	1
e_4	2	1	2	2	1
e_6	2	1	1	2	0
$J_{Bc}(d_r / D_0)$	14	6	14	16	6
$J_{Bc}(d_r / D_1)$			4	3	1

Fig. 2 A diagnostic model – the second stage

At the second stage symptoms d_1 and d_5 are dominated by symptom d_3 and have to be removed.

The second stage core $Y(D \setminus D_1) = \{d_3\}$. According to (53)

$$D_2 = \{d_2, d_4, d_3\}$$

which provides conditions-set partition of the one-component form.

After rearrangement according to symptoms d_2, d_3, d_4 combinatorial information and logical values at each stage, the diagnostic model takes the form shown in Fig. 3.

e_i	d_2	d_3	d_4
e_3	0	1	1
e_1	1	0	1
e_0	1	1	1
e_5	1	1	2
e_2	1	2	1
e_6	2	1	1
e_4	2	2	1
$J_{Bc}(d_r / D_0)$	14	14	6

Fig. 3 A diagnostic model – the final stage

The final diagnostic model (Fig. 3) defines the diagnosis algorithm:

$$T = \{d_2, d_3, d_4\} \tag{55}$$

Algorithm (55) consists of indispensable symptoms only hence its cardinality is minimal.

8. CONCLUSIONS

A new combinatorial diagnostic entropy has been introduced. It describes the number of condition pairs which have to be distinguished during diagnosing process.

Treating the assumed combinatorial diagnostic entropy as a primary notion, the information delivered by symptoms has been defined. The relationships have been derived that facilitate explicit, quantitative assessment of the information of a single symptom as well as that of a symptoms set.

It has been proved that the information $J_{Bc}(.)$ shows the property of additivity.

Proposed method exploits indispensable symptoms at every stage of the optimization process providing minimum number of symptoms in diagnosis algorithm.

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