DATA SOURCES DIVERSITY IN TECHNICAL OBJECTS STATE ASSESSMENT WITH INFORMATION FUSION TECHNIQUES

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Summary

The paper deals with a relationship between diversity of diagnostic signals sources and efficiency of technical objects states assessment with use of classifier fusion techniques. There is often stated that there should be some differences in sources of signals that are classified and fused. The intuition tells that none or minimal improvement of classification rate is gained when the diversity within the fused classifier set is low. To prove this thesis an active diagnostic experiment was carried out. Diagnostic signals were generated on basis of the thermogram sequences acquired during rotating machinery operation by two IR-cameras. Because in both sequences regions of interests representing the same assemblies of the machine are present, it can be assumed that there is hardware redundancy applied. With use of k-NN classifiers and fuzzy integral and proportional conflict redistribution aggregation rules, the state of the machine is possible to be assessed. The analysis of obtained results showed that there was no strong relationship between the diversity of classifiers and the efficiency of state classification.

Keywords: machine diagnostics, termovision, classifier fusion.

RÓŻNORODNOŚĆ ŹRÓDEŁ DANYCH W OKREŚLANIU STANU OBIEKTÓW TECHNICZNYCH Z ZASTOSOWANIEM TECHNIK FUZJI INFORMACJI

Streszczenie

W artykule omówiono związek pomiędzy różnorodnością źródeł sygnałów diagnostycznych a efektywnością oceny stanu technicznego maszyny z wykorzystaniem technik fuzji klasyfikatorów. Często zasadne jest twierdzenie, że sygnały diagnostyczne powinny być pozyskiwane z różnorodnych źródeł. Intuicyjnie można przyjąć, że w przypadku wykorzystania w procesie fuzji zbliżonych klasyfikatorów, zwiększenie sprawności klasyfikacji będzie bliskie zeru. W celu udowodnienia tej tezy przeprowadzono aktywny eksperyment diagnostyczny. Sygnały diagnostyczne zostały pozyskane z sekwencji termogramów przedstawiających pracującą maszynę wirnikową. Sygnały zarejestrowano z wykorzystaniem dwóch kamer termowizyjnych. Klasyfikacji stanu maszyny dokonano przy użyciu klasyfikatora k najbliższych sąsiadów, a w procesie fuzji klasyfikatorów wykorzystano całkę rozmytą oraz regułę proporcjonalnej redystrybucji konfliktów jako operatory agregacji. Analiza otrzymanych wyników pokazała, że nie występuje silna relacja pomiędzy różnorodnością klasyfikatorów, a efektywnością oceny stanu technicznego.

Słowa kluczowe: diagnostyka maszyn, termowizja, fuzji informacji.

1. INTRODUCTION

In a process of technical object diagnosing three main stages can be distinguished: fault detection, localization and identification [2]. Nowadays, in diagnostic systems, tasks mentioned above are realized with use of various methods. In the case of objects with an uncomplicated structure the application of input-output models or the diagnostic signals observation with use of limitation control (eg. control of signals credibility, alarm bounds, signals change rate and verification of binary values) would be sufficient. For a group of more complex objects, with strong interactions between diagnostic signals, simple methods listed above are ineffective. For this reason methods that assure proper decision rate in diagnostic systems are still examined.

Among many elaborated methods, there are two widely used that could lead to increase of diagnostic signal reliability. In the classifier fusion techniques signals obtained with use of hardware or software redundancy are often applied. Having multiple diagnostic signals we can build many classifiers and then combine them in order to increase classification accuracy. The use of redundancy influence the diversity of a single classifiers. The classifiers build on a partially (or full) redundant data should result in a low increase of the fused classifier accuracy in comparison to each member classifier accuracy. This theoretical assumption is very intuitive. A dependent set of classifiers may be either better than the independent set or worse than the single worst member of the classifier group. The diversity can be both: harmful or beneficial [8].

In this study the influence of partially redundant and depending diagnostic signals used in classification on the machine technical state assessment was investigated. First two aggregation operators used in classifier fusion were introduced and the diagnostic experiment is described. Than the experimental result were studied. In the final part of the paper conclusions were presented.

2. CLASSIFIER FUSION

To combine (fuse) several individual classifiers two main stages must take place:

- Classifier outputs should be adjusted,
- Adjusted outputs are aggregated with use of the aggregation operator.

The adjustment is often performed on the stage of calculation of degrees of a support, evidences or other quantities that are used later in the aggregation process. In the study two aggregation operators were used. The first was based on the fuzzy integral calculation. The second one incorporates the proportional conflict redistribution (PCR) rules in the frame of Dezert-Smarandache theory of plausible and paradoxical reasoning.

2.1. Fuzzy integral

The classifier outputs can be organised in a decision profile as the following matrix [9]:

$$DP(x)=\begin{bmatrix} d_{1,1}(x) & \dots & d_{1,j}(x) & \dots & d_{1,c}(x) \\ \dots & & & & \\ d_{i,1}(x) & \dots & d_{i,j}(x) & \dots & d_{i,c}(x) \\ \dots & & & & \\ d_{L,1}(x) & \dots & d_{L,j}(x) & \dots & d_{L,c}(x) \end{bmatrix} \tag{1}$$

The use of a fuzzy integral (FI) aggregation operator measure allows measurement of the "strength" not only for individual classifiers but also for all subsets of classifiers that express how good is the experts ensemble for given input x. The process of combination is shown in fig. 1, and can be described as follows:

- For a input x the sorting of k-th column of DP(x) is performed, in order to obtain the vector $\left[d_{i1,k}(x), d_{i1,k}(x), \dots, d_{iL,k}(x)\right]^T$, where $d_{i1,k}(x)$ is the highest degree of support and $d_{iL,k}(x)$ is the lowest.
- Fuzzy densities, $g^{i1},\dots,g^{iL}$, are arranged correspondingly to the degree of the support vector.
- The first element in the fuzzy measure vector, $g(1)$, is set to g^{i1}.
- $g(t)$ is calculated recursively, for $t=1,\dots,L$ using following equation:

$$g(t)=g^{it}+g(t-1)+\lambda g^{it}g(t-1) \tag{2}$$

where λ is the unique real root (>-1) of the polynomial:

$$\lambda+1=\prod_{i=1}^{L}\left(1+\lambda g^{i}\right), \qquad \lambda\neq 0 \tag{3}$$

- The final degree of support, for the class ω_k is calculated with the following formula:
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$$\mu_k(x)=\max_{i=1}^{L}\left\{\min\left\{d_{it,k}(x), g(t)\right\}\right\} \tag{4}$$

which is called *Sugeno fuzzy integral*.

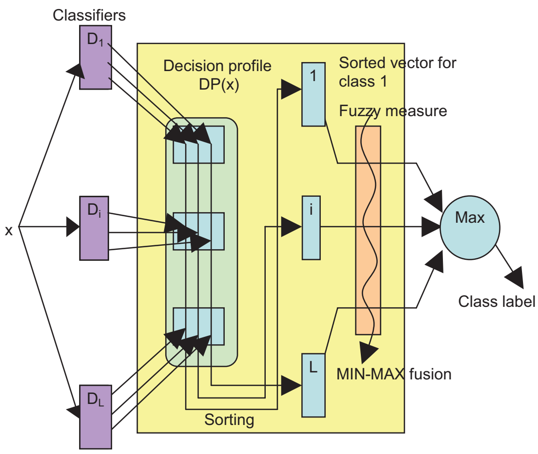

Fig. 1. Fusion scheme with use of the fuzzy integral [14]

2.2. Proportional Conflict Redistribution

Proportional conflict redistribution takes place in the framework of Dezert-Smarandache theory (DSmT) of plausible and paradoxical reasoning [4]. The DSmT has been developed to overcome several limitations of Dempster-Shafer (DST) evidence theory [12], and can be regarded as its generalization. In the DSmT possible propositions of the same event are stored in the frame of discernment Θ. The general basic belief assignment (gbba) is a primitive of DSmT theory. Each of evidence defines a mass function m, mapping the power set Θ to the interval between 0 and 1. Properties of mass assignment are as follows:

$$\begin{aligned} & m(\varnothing)=0 \\ & \sum_{A \in 2^{\Theta}} m(A)=1 \end{aligned} \tag{5}$$

where 2^{Θ} is the power set on which the gbba is defined. The 2^{Θ} is the set of all subsets generated from Θ with union operator only. A subset with none-zero mass is called a focal element, and the value of *m(A)* represents the degree of evidential support of exact set *A*. The final aggregation of two or more belief assignments can be realized with one of proportional conflict redistribution rules. The probably most sophisticated rule is PCR6, defined by eq. (6) [5]:

$$m_{PCR6}(X)=m_c(X)+$$
$$\sum_{i=1}^{M} m_i(X)^2 \sum_{\substack{\bigcap_{k=1}^{M-1} Y_{\sigma_i(k)} \cap X \equiv \varnothing \\ (Y_{\sigma_i(1)},\ldots,Y_{\sigma_i(M-1)}) \in (2^{\Theta})^{M-1}}} \left(\frac{\prod_{j=1}^{M-1} m_{\sigma_i(j)}(Y_{\sigma_i(j)})}{m_i(X)+\sum_{j=1}^{M-1} m_{\sigma_i(j)}(Y_{\sigma_i(j)})} \right) \tag{6}$$

where m_c is the conjunction rule defined as follows:

$$m_c(X)=\sum_{Y_1 \cap \ldots \cap Y_M = X} \prod_{j=1}^{M} m_j(Y_j) \tag{7}$$

The factor σ_i is a counter ($\sigma_i = 1,\ldots,M$) used to avoid situation when $j=i$:

$$\begin{cases} \sigma_i(j)=j & \text{if } j<i \\ \sigma_i(j)=j+1 & \text{if } j \geq i \end{cases} \tag{8}$$

The process of combination with use of PCR6 rule is shown in fig. 2.

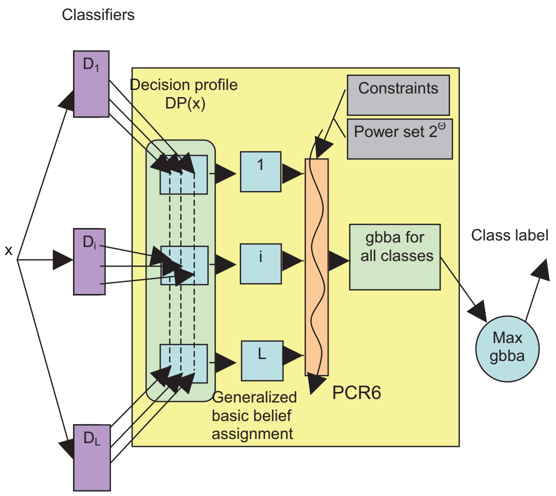

Fig. 2. Fusion scheme with use of the PCR6

2.3. Support and mass function calculation

A simple method for support/evidence calculation on the basis of k-Nearest Neighbours classifier has been introduced in [10]. Each classifier gives output in the form of a class label (on the abstract level). To obtain a class distribution a distance measure is used. The distance is calculated from given sample x, to number of known samples. Identification of *k* nearest neighbours of the sample *x* is made irrespective to the class label. From chosen *k* samples a vector k_i with samples belonging to the class $C_i, i=1\ldots M$ (*M* is the number of classes) can be obtained. According to that the degree of support and/or the mass function is calculated [10]:

$$m(\{C_i\})=\frac{k_i}{\sum_{j=1}^{M} k_j} \tag{9}$$

For each class the classification result and the class distribution is obtained.

3. DIAGNOSTIC EXPERIMENT

Fusion of classifiers required needed to investigate the influence of the signal sources diversity on the final decision about the machine technical state, demands several preliminary operations consisted of:

- Gathering thermovision images.
- Processing images and estimation of diagnostic signals.
- Classifying the machine technical state.
- Building a decision profile.
- Fusing obtained classifier outputs with use of chosen methods.

3.1. Diagnostic signals evaluation

In order to classify a machine technical state an active diagnostic experiment was performed. The laboratory stand consists of a model of rotating machinery and (fig. 3) thermovision acquisition system. Acquisition of thermograms was performed with two IR cameras that differed in matrix resolution (640x480 and 320x240). Cameras optical axes were placed perpendicularly and parallel (with small deviation) to the shaft. Thermograms were recorded every 15 seconds by both cameras and exemplary ones were presented in fig. 4 and fig. 5. In each thermogram 3 Regions of Interest (ROIs) were defined, representing bearing housings and belt pulleys.

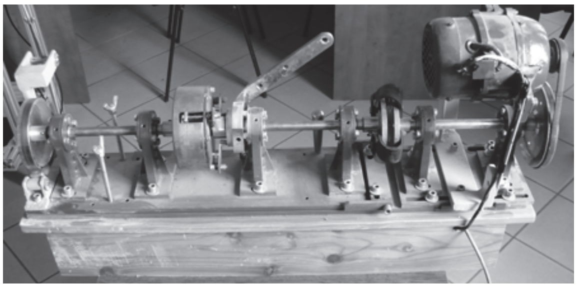

Fig. 3. View of the laboratory stand

The following technical states were simulated:
S1 – machine without faults (no load);
S2 – 30% load on the brake;
S3 – 50% load on the brake;
S4 – 70% load on the brake.

It is necessary to point that technical states that differs only in the load value are very similar and it is difficult to identify the weak change on the basis of diagnostic signals obtained by estimation of thermogram sequences [11].

Diversity of signal sources was limited, because data for diagnostic signals were acquired with devices using the same physical laws to measure spatial temperature distribution. Regions R3 and R6 represented the same bearing housing, thus some partial redundancy was introduced into the acquired data set.

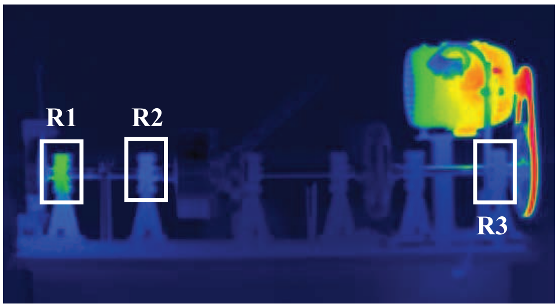

Fig. 4. Thermogram acquired by IR camera 1, with marked ROIs

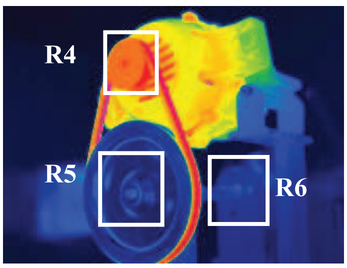

Fig. 5. Thermogram acquired by IR camera 2, with marked ROIs

Diagnostic signals must be determined through estimation of acquired thermovision images [3]. Sequences represented by six selected ROIs were transformed into frequency domain with use of 2D Fourier transform. For each considered thermogram two Fourier images (F-images) of magnitude and phase were calculated. In further studies only magnitude F-images were taken into consideration. Obtained F-images (fig. 6) were estimated with use of Circular Fourier Power (*CFP*) estimator, defined as follows [13]:

$$CFP = \sum_{r=\frac{X+D}{2}}^{r=\frac{X+D}{2}} \sum_{1\le x^2+y^2\le r} F(x,y) \qquad (10)$$

where: X, Y are F-image width and height in pixels, D – diameter of the considered centralized circle of the F-image in pixels, x=1,2,…,X, y=1,2,…,Y – pixel indexes of image width and height respectively. In the research the CFP feature was calculated only for the F-images of amplitude. Parameter D was determined experimentally during the previous research and was fitted to obtain maximum classification efficiency [1].

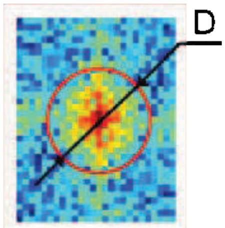

Fig. 6. F-image and CFP diameter

3.2. Classification

For the research purpose k-NN classifiers were used. The neighbours number was set on 10 on the basis of preliminary studies [1]. The classification performances were computed using the leave-one-out classifier error estimation method. In this method the whole training set containing N elements was divided into two subsets. First containing only one element is the testing subset. The training subset incorporated N-1 elements. The training and testing process was performed N-times. The classifier performance measure was the relative number of misclassifications, which was calculating using the following formula:

$$err = \frac{N_e}{N} \qquad (11)$$

where: N is the number of considered samples and N_e is the number of misclassified samples. On the basis of an error measure the classifier efficiency was determined as:

$$eff = (1 - err)\cdot 100\% \qquad (12)$$

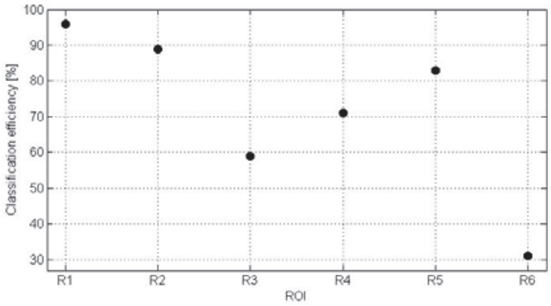

Fig. 7. Classification efficiency obtained for signals estimated for single ROI

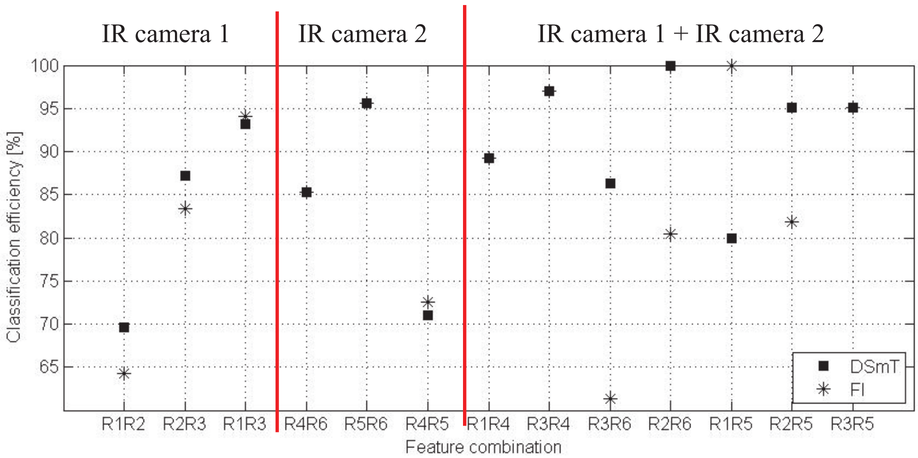

Fig. 8. Classification efficiency for various combinations of signals obtained for different ROIs

4. RESULTS

Basing on the classification scheme described in the previous section the technical state classification was performed. The first classification was made for features obtained from individual ROIs. In fig. 7 obtained results were presented graphically. It can be seen that for ROI marked as R1 maximal classification rate, equal to 96% were procured. For remaining ROIs the efficiency varieed from 34% for R6 to 89% for R2. Generally results given by classifiers trained with the data acquired by IR camera 1 observing parallel the shaft (R1, R2 and R3) were better than when dealing with data acquired by the IR camera 2.

Results of state recognition obtained after the classifier fusion with means of FI and DSmT were gathered and presented in fig. 8. In all cases the fusion of two classifiers was considered. Used features were strong bounded with the selected ROI, it can be revealed that when fused classifiers were trained on features calculated for ROIs only slight increase of recognition rate could be observed for just one case (R5R6, *eff* = 96,5%) in comparison to the best efficiency for an individual classifier. When the fused classifiers were trained, on signals estimated from ROIs selected from thermograms acquired by different cameras, considerable increase of classification efficiency can be observed. Combinations of R2R6 and R1R5 led to the accuracy rate of 100%. It also must be noticed that overall classification efficiency was better as in the case of fusing signals generated from ROIs placed within one thermogram.

When analyzing results the special attention must be drown to the case when features were calculated for thermogarms acquired by various cameras but representing the same bearing housing. For the single classifier efficiencies obtained for features calculated for ROIs R3 and R6 were equal 59% and 31% respectively. The aggregated efficiency of features from both ROIs was higher as those for single ones and is as high as 62% when the final decision about the machine technical state was made with use of the fuzzy integral aggregation operator, and 87% in the case of PCR6 aggregation rule. These values indicate that the fact that partial hardware redundancy can lead to very good results, even when single classifiers have fairly strong support for misclassifications. Thus the diversity of signal sources was not indispensible for proper machine technical state assessment with use of the classifier fusion techniques.

Another interesting matter is the influence of weakest individual classifier on the result of classifier fusion. The lowest classification accuracy for single classifiers was 34% for R6. When signal obtained for R6 was classified and then combined with output from other classifier trained by signal calculated for ROI placed in thermogram acquired by the second IR camera lowest accuracy was almost twice as high as for the single R6 classifier.

Summarizing it can be stated that among tested fusion methods the best results can be obtained with use of the proportional conflict redistribution rules. However, differences between methods can often be omitted.

5. CONCLUSIONS

In the paper the fusion of classifier trained on features calculated for thermograms acquired by two IR cameras in order to assess observed machine technical state was presented. After performing a number of experiments it can be stated that dependency between data sources diversity and the classification efficiency is not clear. The diversity is not indispensible to observe increase of classification accuracy rates, when individuals classifiers are fused in order to made the decision about the machine technical state.

Further investigations will survey the fusion of classifiers trained on diverse data, e.g. thermograms and vibration signals. Also analytical redundance will be taken into consideration, e.g. calculating multiple features from one thermogram, as the training data for classifiers used in the fusion process.

REFERENCES

[1] Fidali M., Jamrozik W.: *Search for optimal estimators of thermogram Fourier images*. Burczyński T. Cholewa W., Moczulski W., eds. Recent developments in artificial intelligence methods, AI-Meth Series, Gliwice, 2009.

[2] J. Korbicz, J. Kościelny, Z. Kowalczuk, and W. Cholewa, eds.: *Fault Diagnosis. Models, Artificial Intelligence*. Applications. Berlin, Heidelberg, New York, Hong Kong, London, Milan, Paris, Tokyo, Springer, 2004.

[3] Fidali M.: *An idea of continuous thermographic monitoring of machinery*. in QIRT 2008 Proceedings, 9th International Conference on Qualitative InfraRed Thermography, July 2-5, Kraków, Poland, 2008.

[4] J. Dezert and F. Smarandache, DSmT: *A new paradigm shift for information fusion.* CoRR, vol. abs/cs/0610175, 2006.

[5] A. Martin and C. Osswald: *A new generalization of the proportional conflict redistribution rule stable in terms of decision.* CoRR, vol. abs/0806.1797, 2008.

[6] L. I. Kuncheva: *"Fuzzy" vs "non-fuzzy" in combining classifiers designed by boosting.* IEEE Transactions on Fuzzy Systems 11: 729–741, 2003.

[7] A. Verikas, A. Lipnickas, K.Malmqvist, M. Bacauskiene, A. Gelzinis: *Soft combination of neural classifiers: A comparative study.* Pattern Recognition Letters, 20: 429–444, 1999.

[8] S. Hashem: *Treating harmful collinearity in neural network ensembles. In A. J. C. Sharkey, editor.* Combining Artificial Neural Nets. Springer-Verlag, London, 1999, pp. 101–125.

[9] C. A. Shipp , L. I. Kuncheva: *Relationships between combination methods and measures of diversity in combining classifiers.* Information Fusion, 3(2): 135–148, 2002.

[10] D. Han, C. Han, and Y. Yang, *Multiple k-nn classifiers fusion based on evidence theory, in Automation and Logistics,* 2007 IEEE International Conference on, pp. 2155–2159, Aug. 2007.

[11] Jamrozik W., Fidali M.: *Classifier fusion using the PCR6 rule for assessment of machine technical state.* Burczyński T. Cholewa W., Moczulski W., eds. Recent developments in artificial intelligence methods, AI-Meth Series, Gliwice, 2009.

[12] G. Shafer: *A mathematical theory of evidence.* Princeton university press, 1976.

[13] Fukushima M., Ogawa K., Kubota T., and Hisa N.: *Quantitative tissue characterization of diffuse liver diseases from ultrasound images by neural network. IEEE Proc. Nucl. Symp.* 2:1233-1236, 1997.

[14] Kuncheva L. I.: *Combining pattern classifier*. Wiley, USA, 2004.

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