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Application of evolutionary algorithm to limitation of a set of statistical features of thermovision images

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Thermovision is more and more often used in machinery and apparatus diagnostics. With the aid of a thermographic camera non-contact simultaneous temperature measurements can be carried out at many points of an object and they can be recorded in a form of a thermographic image. The thermographic image can be a source of diagnostic information. Extraction of this information requires the necessity of application of different methods of the analysis of thermographic images. From thermographic image a huge amount of features can be extracted which causes problems with efficient assessment of technical state due to informational noise. There are methods which allow to search and find relevant features that are useful for diagnostic processes.

In the paper application of evolutionary algorithm for selection of optimal diagnostic features has been shown. In case of assessment of selected features neural classifier has been used. A set of 259 features for each image has been considered. After searching process two features have been selected and the obtained classification results have been of very good quality. Efficiency of classifier has been in some cases 100% and not less than 97%. The results have shown that the evolutionary algorithm can be applied to selection of relevant diagnostic features.

Keywords: infrared thermography, evolutionary algorithms, neural networks, diagnostics

1. Introduction

Thermography measurements are more and more often maintenance, condition monitoring and diagnostics of machines and devices [10, 18].

Thermovision assessment of machine technical state is based on a thermal image called a thermogram which is generated in the thermovision camera during object observation. The thermogram represents temperature distribution on the object surface and can be interpreted by an experienced operator by means of additional computer software with implemented simple tools of image analysis.

Thermographic image is a source of diagnostic information. Some of this information can be extracted with the humane eye but much more useful diagnostic information can be extracted through application of suitable methods of image processing and analysis.

There are a lot of image analysis methods which can be used to analyze different class of images [7, 8]. Most of the existing methods can find application to thermogram analysis [20] and give useful diagnostic information which allow to improve and automatize the diagnostic process.

As a result of image analysis features (parameters) are obtained and their values can be treated as diagnostic symptoms and they can be applied to assessment of technical state of an object. In case of continuous thermo-diagnostics of objects a number of recorded images is huge. The size of a set of features extracted from thermographic images depends on a number of applied methods of image analysis. In connection with large numbers of methods which can be used to analyze recorded images, sets of determined features can be also enormous.

On the basis of results of the research reported in literature [5, 9] it can be stated that large set of diagnostic features can be a source of ambiguities in estimation of technical state due to informational noise. Redundancy as well as differences between diagnostic features cause that determination of reasonably small size of the feature set for diagnostic purposes is very difficult. In case of limitation of features set a variety of different methods can be used [5, 16]. As an example of such a method is an evolutionary algorithm can be named. These algorithms are very efficient at searching and optimizing multidimensional sets of features which has been confirmed by different applications [2, 6, 14, 19].

In the paper the application of an evolutionary algorithm for the limitation and selection of set of features extracted from thermovision images recorded during continuous observation of rotating machinery is presented.

2. ANALYSIS OF THERMOGRAPHIC IMAGES

2.1. Thermographic signal and an idea of its analysis

A thermographic image can be treated as a digital image described by a discrete function of temperature values of two variables $T(x, y)$, where x and y are coordinates of coordinate system determining spatial resolution of the image [10, 15, 20].

During continuous object observation with the use of a thermovision device, a sequence of thermographic images in time t can be recorded. On the basis of acquired series of thermograms, a multidimensional thermographical signal $ST(T(x, y), t)$ can be defined. If we consider a concept [4] of conventional real time partition into "micro" (dynamic) and "macro" (operation) time, often applied in machine diagnostics [3, 9], then the thermographic signal can be defined in these both domains.

Taking into account "micro" and "macro" time concepts, the process of analysis of thermographic signals can be divided into two stages. The first stage is connected with thermogram analysis and feature extraction. It enables us to determine diagnostic signals in "micro" and/or "macro" time (Fig. 1).

The second stage of analysis refers to the analysis of diagnostic signals which were determined at the first stage. For these purposes classical signal analysis methods can be applied.

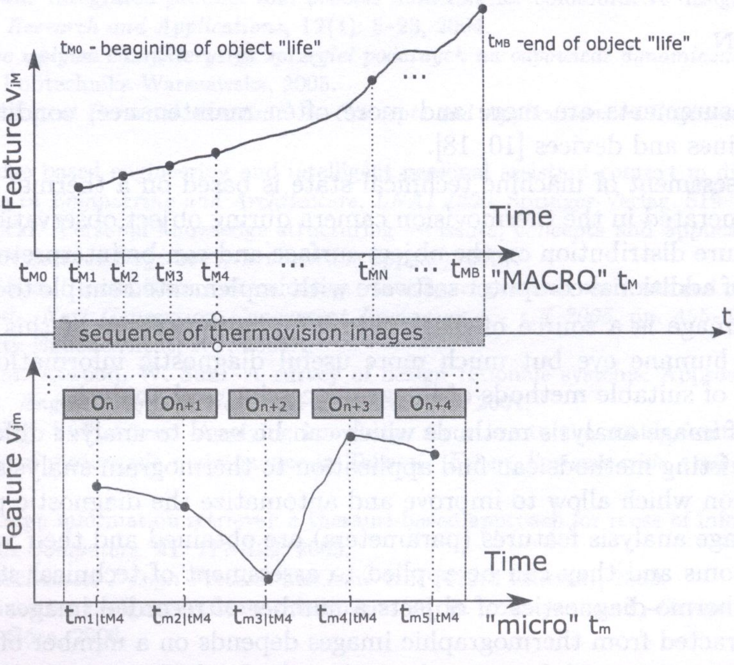


Fig. 1. Idea of analysis of thermographic signal in both "micro" and "macro" time domains

2.2. Statistical features of images

Image analysis is a wide domain of science which includes a lot of different kinds of methods. These methods are described in a variety of papers [7, 8, 12, 20]. One of the well known groups of image analysis methods is a method dedicated to digital-image texture analysis [8, 11, 12].

The major issue in texture analysis is feature extraction. This operation allows us to compute a characteristics of a digital image that let us describe numerically its texture properties. Feature extraction is the first stage of image texture analysis. This stage can be used also for thermovision images and the obtained results can be applied to such approaches as image discrimination, classification or object shape determination.

Among different methods of texture analysis statistical methods can be enumerated which make it possible to represent the texture indirectly by non-deterministic properties that determine the distributions and relationships between grey levels of an image [12].

Statistical methods allow us to determine features of an image on the basis of different statistical characteristics calculated from [8, 11]:

- histogram of an image.
- gradient matrix.
- run-length matrix.
- co-occurrence matrix.
- autoregression model.

In case of the proposed diagnostic method based on thermographic images it is important to find such relevant features of images which can be applied in effective manner for the evaluation of machine technical state. This is not a simple task due to the large set of features which can be extracted from the image with the use of statistical methods of image analysis. Therefore, it is important to identify a limited set of relevant and optimal diagnostic features.

2.3. Acquisition of thermographic images

In order to verify usability of statistical analysis methods for the analysis of thermovision images as well as for machinery diagnostics, an active diagnostic experiment has been carried out. The experiment has been performed with the use of a laboratory stand. The stand is located in the Laboratory of Technical Diagnostics of Department of Fundamentals of Machinery Design and consists of a laboratory model of rotating machinery and thermovision system (Fig. 2). The aim of the experiment has been to acquire thermographic signals. As a result of diagnostic experiments series of thermograms recorded during object operation in different technical states have been obtained.

Thermographical images have been acquired during thermovision observation every 30 seconds period. The total number of recorded images was 840. The machine was working with rotation speed equal to 1150 rmp. The following technical states were simulated during machine operation:

S1 – machine without faults – 240 images,

S2 – 50% throttling of air pump – 120 images,

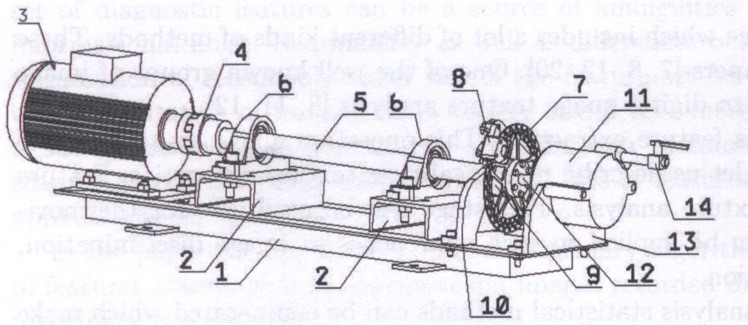
S3 – 90% throttling of air pump – 120 images,

S4 – 90% throttling of air pump + clearance of second bearing mounting – 120 images,

S5 – load of disk brake – 120 images,

S6 – faulty bearing no 2 – 120 images.

a)



1 – frame, 2 – bearing support, 3 rotor, 4,9,12 – couplings, 5 shaft, 6 – bearing set, 7 – disk of brake, 8 – brake clamp, 9 – coupling, 10 – brake support, 11 – air pump, 13 – pump support, 14 – throttle valve

b)

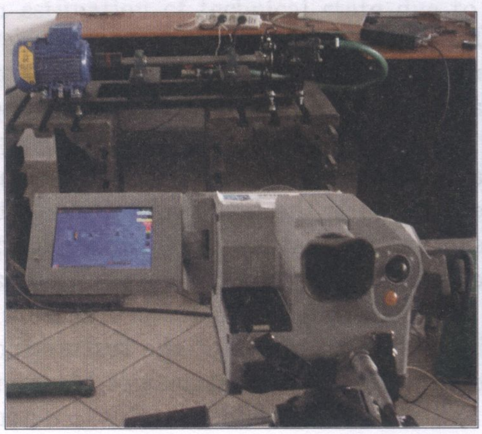


Fig. 2. Investigated object a) and laboratory stand b)

2.4. Estimated features of thermographic images

Recorded thermovision images have been analyzed with the use of selected statistical texture analysis methods. In this case specialized software MaZda dedicated to calculation of texture parameters (features) in digitized images has been applied. MaZda was originally developed in 1996 at the Institute of Electronics, Technical University of Lodz (TUL), Poland for texture analysis of mammograms [17].

The software is able to analyze gray scale digital images with separated regions of interest and extract up to 259 different statistical parameters (features).

In case of thermogram analysis it was necessary to separate regions of interest (ROI) in the images. Five regions of interest have been defined:

ROI 1 – motor,

ROI 2 – coupling,

ROI 3 – bearing no 1,

ROI 4 – bearing no 2,

ROI 5 – pump.

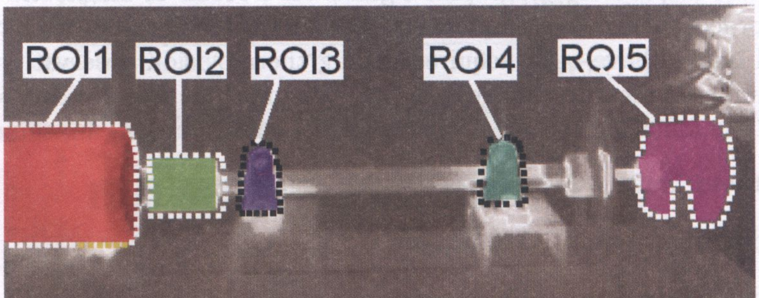


Fig. 3. Exemplary thermographic image with selected regions of interest (ROI)

For each region of interest (ROI) of every recorded image 259 features have been extracted. The following features [8, 11] have been taken into consideration:

- 9 features on the basis of histogram of the image (mean, variance, skewness, kurtosis and five histogram percentiles for 1%, 10%, 50%, 90%, and 99%),
- 5 features on the basis of gradient matrix (absolute gradient mean, variance, skewness, kurtosis, and percentage of non-zero gradients),
- 220 features on the basis of co-occurrence matrix. (11 features defined in calculated for matrices constructed for five distances between image pixels (d = 1, 2, 3, 4 and 5), and for the four directions as in the case of run-length matrix features),
- 20 features on the basis of run length matrix (short run emphasis inverse moment, long run emphasis moment, gray level nonuniformity, run length nonuniformity and fraction of image in runs, separately for horizontal, vertical, 45° and 135° directions)
- 5 features on the basis of autoregressive model parameters (θ_i, $i = 1, \ldots, 4$ selected pixel-to-pixel relationship, noise standard deviation)

Figure 4 presents an exemplary plot of a diagnostic signal of mean temperature estimated for selected ROI's . Values of selected feature are functions of numbers of consecutive recorded images. In the plot limits of technical states have been indicated. It can be observed that in some cases e.g. ROI 5 identification of changes of technical state is possible.

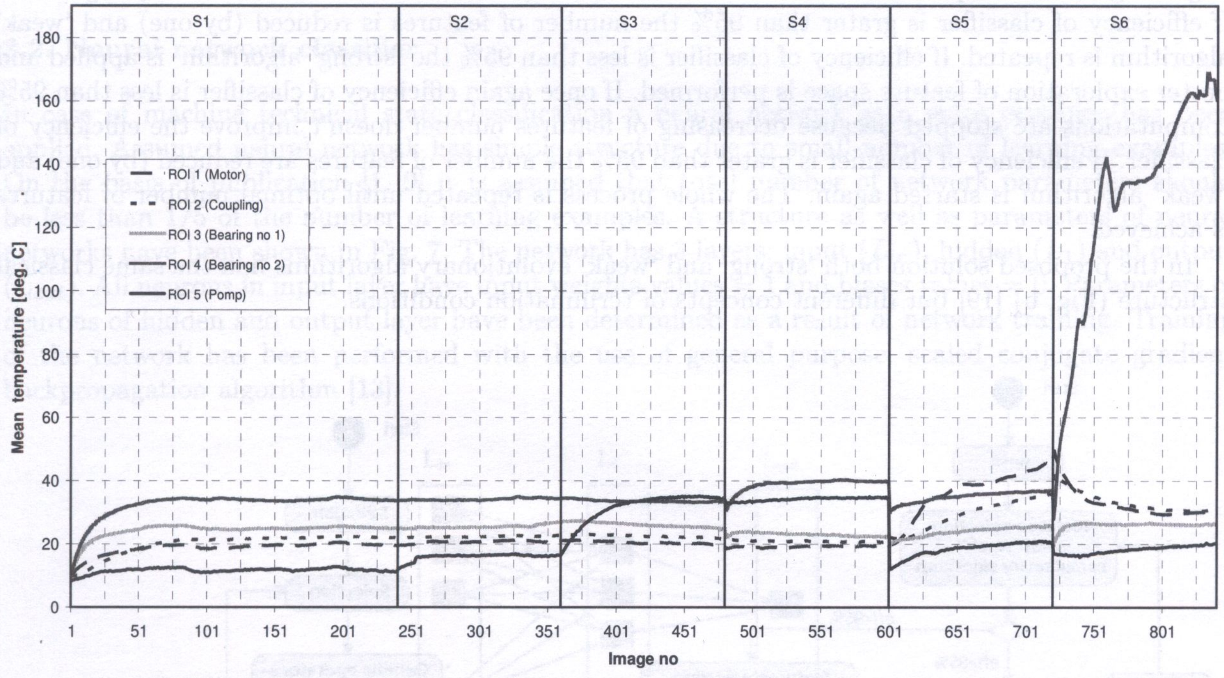


Fig. 4. Plot of diagnostic signal of mean value extracted from all considered region of interest as a function of numbers of consecutive recorded images

3. Methods of features set limitation

On the basis of the results of the research reported in literature [5, 9, 19] it can be stated that an excessive number of input data entails that noise increases and efficiency of the classifier decreases. Hence, limitation of dimensions of the feature value space is necessary.

There are some ways of limitation of a set of feature. One of the effective but time consuming method is comprehensive searching. Good results in optimization of feature space can be obtained on the basis of discriminant analysis, and particularly extended Fisher's criterion [5, 16]. Another way which gives very good results is the application of evolutionary algorithms [6, 19]. As opposed to known feature selection methods, evolutionary algorithms are able to search for optimal set of features among the whole feature set. The advantage of this strategy is that features are estimated in global manner which allow to consider relationship between features [19].

3.1. Application of evolutionary computation

The evolutionary algorithms have been applied to optimize features set extracted from thermal images recorded during machine operation. In Fig. 5 the way of searching for relevant features is presented. To reduce the time of computation concepts of two kinds of evolutionary algorithms: 'weak' and 'strong' have been used. Maximization of efficiency of state classifier has been used as an optimization criterion. Classification of technical state has been performed with the use of neural networks implemented in the algorithm.

The main goal of this computation was to limit this size of features set as much as possible with the assumption that classifier efficiency (Section 3.2) for optimal set of features should be grater than 95%.

It has been assumed that optimal set of features should include not more than 10 features. At the beginning of the computation 10 features are selected by 'weak' version of evolutionary algorithm. If efficiency of classifier is grater than 95% the number of features is reduced (by one) and 'weak' algorithm is repeated. If efficiency of classifier is less than 95% the 'strong' algorithm' is applied and better exploration of feature space is performed. If once again efficiency of classifier is less than 95% computations are stopped because decreasing of features number doesn't improve the efficiency of classifier. If efficiency of classifier is grater than 95% the number of features are reduced (by one) and 'weak' algorithm is started again. The whole process is repeated until optimal number of features is achieved.

In the proposed solution both 'strong' and 'weak' evolutionary algorithms had the same classical structure (Fig. 6) [19] but different concepts of termination conditions.

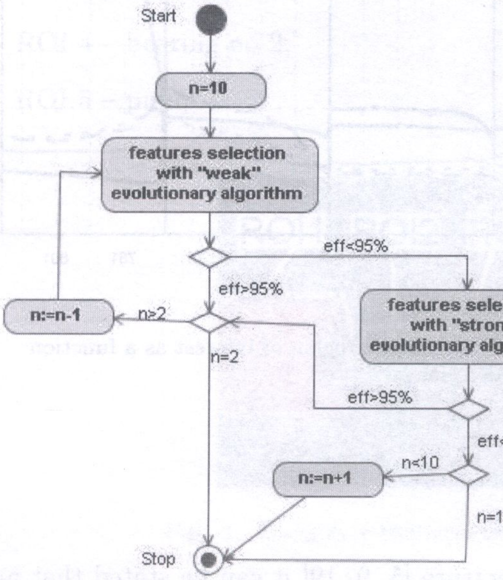


Fig. 5. A way of searching for relevant features

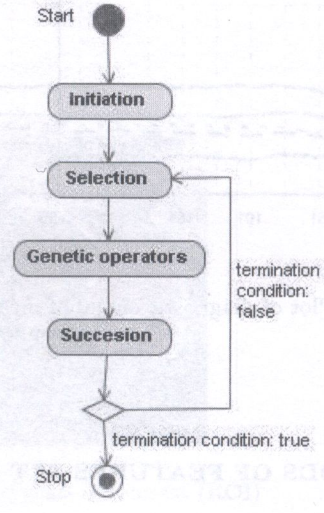


Fig. 6. Scheme of the evolutionary algorithm

Optimal number of selected features n is a parameter of the algorithm. It has been assumed that the population consists of 20 individuals. The genotype of an individual is a row vector with n numbers (identifiers) of randomly selected features. The phenotype of the individual is the classifier identified for features whose identifiers are in the genotype. The classifier is neural network (Section 3.2)

The value of a fitness function for an individual is an efficiency of the classifier.

The algorithm uses four operators [2, 6, 14]:

- proportional selection,
- two-point crossover (features replacement),
- uniform mutation,
- elitist succession.

Also, a 'repair' operator that prevents features repeating in a genotype is used.

In case of the 'weak' algorithm one termination condition has been defined – achieving 5 generations. For 'strong' algorithm the following two termination conditions have been determined:

- achieving 100 generations or,
- achieving 20 generations without increasing the value of fitness function.

3.2. Neural network classifier

In case of machine technical state classification a neural network as a state classifier has been applied. Assumed neural network has simple structure due to small number of learning examples. On the basis of publication [1, 9] it is assumed that total number of network parameters should be less than 1/5 of the number of learning examples. A structure as well as parameters of neural networks have been shown in Fig. 7. The network has 3 layers: input (L_{in}), hidden (L_1) and output (L_{out}). All neurons in input layer have input weights values = 1 and biases values = 0. Parameters of neurons of hidden and output layer have been determined as a result of network training. Training of the network has been performed with the use of general purpose, scaled conjugate gradient backpropagation algorithm [13].

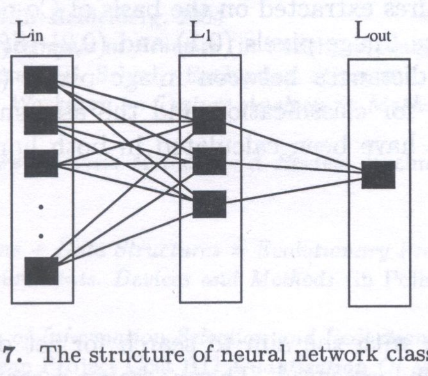


Fig. 7. The structure of neural network classifier

Table 1. Parameters of neural network

layer	L_{in}	L_1	L_{out}
number of neurons	n (optimal number of features)	3	1
transfer function	linear	log-sigmoid	log-sigmoid

The efficiency of the classification has been assessed by means of calculation of a relative number of correctly classified examples

$$eff = \frac{l_1}{l_w} \cdot 100\% \tag{1}$$

where l_1 – number of correctly classified examples, l_w – number of all classified examples.

4. Results of the research

As a result of searching of relevant features two features for each region of interest have been extracted. The classifier for each of 5 regions of interest (ROIs) has been identified on the basis of selected optimal diagnostic features of thermographic images. The selected optimal features as well as values of classifiers assessment is shown in Table 2.

Table 2. Optimal features and obtained classifiers efficiency

	Optimal feature Id	Relevant Feature Names	Classifier efficiency
ROI 1 (rotor)	63 250	S(2,0)DifVarnc GrMean	100.00%
ROI 2 (coupling)	27 156	S(0,1)SumVarnc S(0,4)SumOfSqs	97.68%
ROI 3 (bearing no 1)	71 217	S(0,2)SumVarnc S(5,5)DifVarnc	99.46%
ROI 4 (bearing no 2)	7 176	Perc. 50% S(4,-4)Contrast	100.00%
ROI 5 (pump)	51 253	S(1,-1)Entropy GrKurtosis	100.00%

The obtained results show that it is possible to classify the state of a technical object with very high efficiency by means of statistical parameters of thermographic images. In case of 3 from 5 regions of interest classifier efficiencies have been 100%, in case of the region of interest no 3 the efficiency was very close to 100%. Only in the region of interest no 2 (the area of coupling) the efficiency was approximately equal to 98% which is also a very good result.

It may be observed that features extracted on the basis of Co-occurrence matrix, especially sum of variance for distances between image pixels (0,1) and (0,2) (S(0,1)SumVarnc, S(0,2)SumVarnc) and difference of variance for distances between image pixels (2,0) and (5,5) (S(2,0)DifVarnc, S(5,5)DifVarnc) are very useful for classification and the assessment of machine technical state. Distances between image pixels have been calculated in both horizontal and vertical direction of image.

5. Conclusions

In the paper results of research with the aim to search for set of optimal diagnostic features of thermographic images have been presented. Thermograms recorded during an active diagnostic experiment have been analyzed with the use of different methods of statistical texture analysis. As the result of the analysis a set of 259 diagnostic features for each region of interest of each of 840 recorded images have been obtained. Five regions of interest have been considered. In order to search relevant features an evolutionary algorithm has been applied. The assessment of feature relevance has been performed on the basis of classification results and a simple neural network classifier has been applied. It has been assumed that the procedure of searching for the set of features is being performed until two optimal features are found. The optimal feature set is such a set which can be characterized by a value of classification efficiency that is grater than 95%.

The result of the research shows that it is possible to find relevant features of thermographic images which can be used to identify technical state of a machine with very high efficiency. The usefulness of the application of evolutionary algorithms as one stage of this procedure has been proved.

The analysis of determined diagnostic signals indicates possibilities of the application of statistical methods of thermogram analysis for determination of one dimensional diagnostic signal. The proposed concept can be used for identification of changes of technical states during machine operation.

Considering the discussed results it can be stated that continuation of the research in this area is necessary. Further research should be focused on verification of other methods of image processing that could be useful for identification and calcification of machine technical state.

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