The use of neural networks for testing and failure analysis of electronic devices

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Abstract. The paper deals the problem of remote technical diagnostics of complex objects. This allows detecting failures not only during testing of equipment, but also during operation. One effective way of non-contact measurement of technical state of the test object is to obtain a thermogram their surface. The article describes the structure of the information-measuring system, which includes a measuring channel with a thermal imager. Method thermography analysis using the comparison of measured data with the calculated temperature fields is proposed. To solve the incorrectness of the inverse heat conduction problem, it was suggested to use a two-branch artificial neural network. The structure of such a convolutional neural network is described. The influence of neural network parameters on the quality of detection of defective thermograms was studied. It is shown that such a technique allows increasing the detection accuracy of failures and defects of electronic devices during remote monitoring.

1. Introduction

Technical diagnostics of complex objects develops in the direction of operational control of technical states using remote measuring instruments. This allows detecting failures not only during testing of equipment, but also during operation. In many cases, controlled technical objects have a set of measurable parameters that can identify their technical state [1]. However, it is not always possible to build measurement channels for continuous monitoring of these parameters. Often, access to measurement is impossible due to closed design, restrictions on the weight and volume of the object to be monitored. Furthermore, the measuring procedure may contributions distortion in the object operation process. In this connection, the methods of contactless remote monitoring with the help of infrared thermography are promising [2, 3].

In this case, a channel for remote measurement of the temperature field of the object should be organized, including a thermal imager, a thermogram processing unit and a temperature field analysis unit, in which a decision is made on the operability of the object, and the failure facts are differentiated.

The problem of technical diagnostics using thermograms is as follows:

- The set of obtained thermograms of the object and the set of inoperative states do not have a one-to-one correspondence. Different faults and inoperative states can correspond to the same temperature distribution on the object surface. Essentially, we are incorrect inverse heat conduction problem, which is necessary to find the location and intensity of the internal heat sources in the test object.
- A large number of thermograms that are to be analyzed leads to complex algorithms for selecting the desired thermal images of the object.

In the report, to solve this problem, it proposed to use a hybrid intellectual model based on a convolutional neural network and a fully connected neural network.

2. The information-measuring system for remote technical diagnostics

In [4, 5], an information-measuring system IMS for remote monitoring of electronic devices in ground tests have been described. Figure 1 shows a block diagram of a system that consists of measuring channels:

- Determining environmental parameters via Termohigrometr Poly MI 6401;
- Measuring of the temperature field of the surface based on the thermal imaging NEC R500;
- Measuring of the device electrical parameters using a digital oscilloscope GDS-2104.

Control of test modes of devices is carried out using a computer and SPS-3610 and FPGA XC3S500E units.

The main idea is based on a set of mathematical models of the thermal state of the device corresponding to the failures in it. Classes, corresponding to different defects in the electronic device, differentiate these models. In this case, the decision on the operability of the electronic device was made by comparing the measured thermogram with the set of calculated thermograms obtained with the help of mathematical models. However, as noted above, it was not always possible to classify the inoperative state due to the incorrectness of the inverse heat conduction problem.

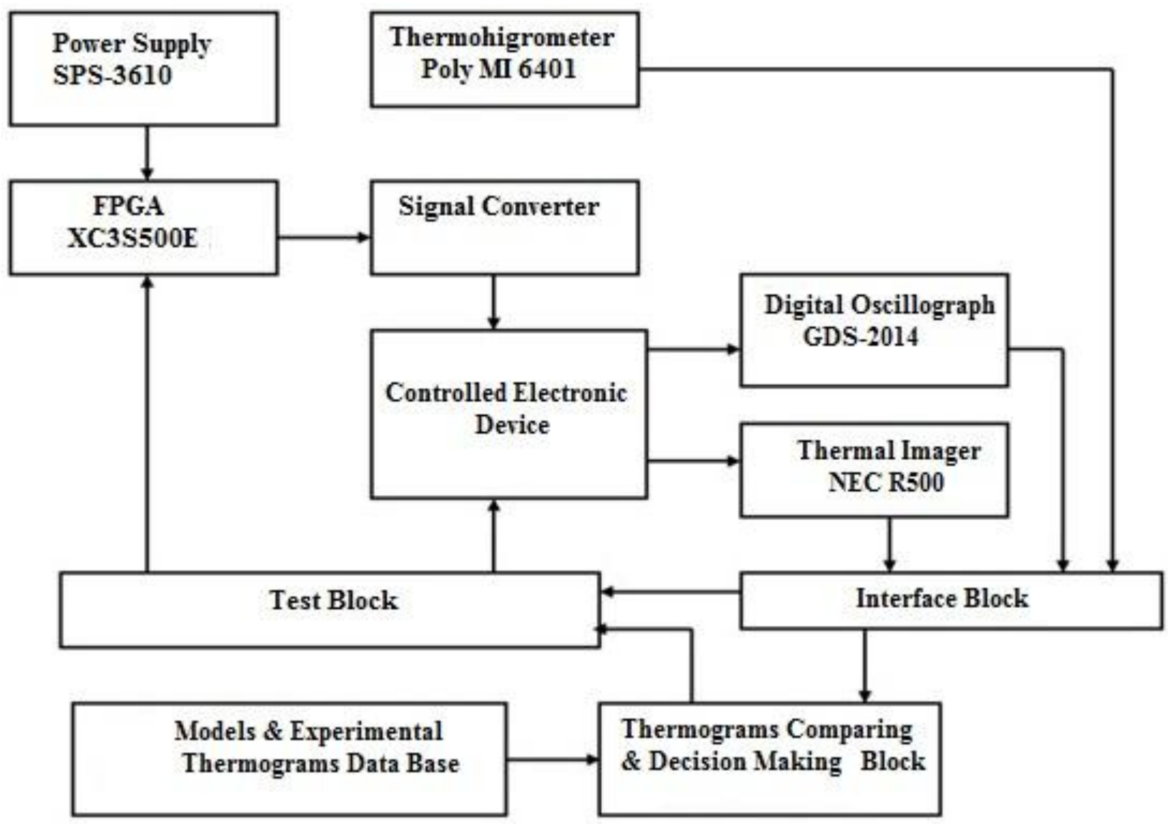

Figure 1. Structure of information-measuring system for electronic devices testing.

To solve this problem, the development of this approach with the use of intelligent tools for measuring information analysis is proposed.

3. Hybrid intelligent model

It is known that the artificial neural network ANN effectively recognize complex images [6, 7]. There are a large number of ANN applications for analyzing information under uncertainty [8, 9]. In this report, we propose an approach to the regularization of incorrect inverse problem of recognition of diagnostic images, which is based on the combined use of two neural networks.

For each type of technical object, mathematical models of the thermal state of its surface are developed depending on the behaviour of internal heat sources:

$$T_i^M = F_i(x, y),$$

when $i \in I$; $I -$ an index set of technical states corresponding to various defects and failures.

The developed mathematical models of the thermal state and history of previous tests of objects are used to form the fact base and the rule base that are components of the knowledge base. They are used in the expert system with a forward chaining on the production rules.

Thermal states of technical objects are characterized by thermograms obtained with the thermal imager $T_j(x, y),\ j = \overline{1, J}$, $J -$ number of thermograms in the knowledge base of IMS. Standing heat sources $Q_i(x, y),\ i = \overline{1, I}$, $I -$ number of sources inside the object is used to determine the object's performance. We define the set of states $D_n(x, y)$, $n = \overline{0, N}$ in which a technical object can be located (one of failures or a working state). In this case, we assume that to all serviceable states there will correspond one state D_0 . Figure 2 shows a graph model of the technical object states.

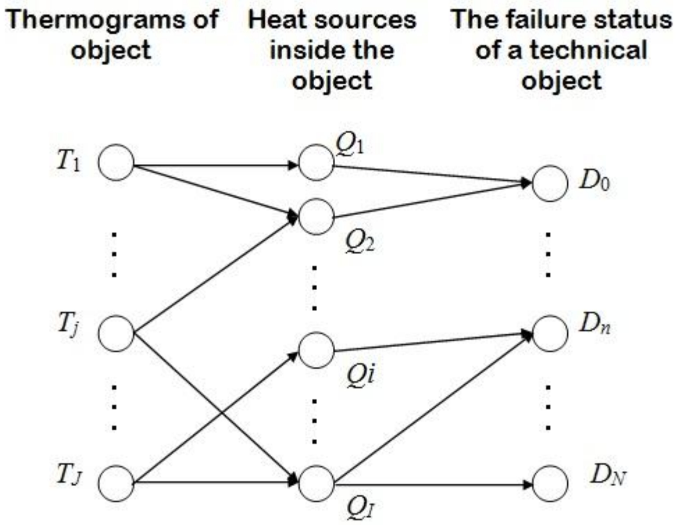

Figure 2. Graph model of the technical object states.

In general, we have incorrect inverse problem, since the same surface thermograms may correspond to multiple heat sources states. Consequently, the one-to-one mapping of thermograms and inoperative states of the object is violated. We use an additional vector of measured process parameters, where V_m, $m = \overline{1, M}$, $M -$ is the number of parameters monitored by measuring means. This may be, for example, input and output voltages of the electrical signals, supply voltages, frequency, and phase of the signals, and others. We carry out a regularization of the problem using more information on the connection of electrical parameters with thermal conditions. Thus, the inverse problem becomes correct by narrowing the infinite set of solutions to finite compact sets corresponding to the chosen defects.

We require the following condition: for any pair of classes T^l and T^k, $l, k \in \{1, 2, ..., N\}, l \neq k$, there is at least one pair of elements $T_j^l \neq T_i^k$, $j \in J_l$, $i \in J_k$ or $V_m^l \neq V_r^k$, $m \in M_l$, $r \in M_k$.

Consequently, the separation of thermograms with the help of the vector V into subsets $T^n(x,y,V) \to D_n$ puts them in a one-to-one correspondence with the inoperative states of the controlled object. Thus, the set of classes is formed: $T^n = (\{T_j^n\},\{V_m^n\}),\ j \in J_n;\ m \in M_n,\ n = \overline{0,N},$ where J_n and M_n - index sets of thermograms and vectors of the object parameters included in the n-th class (Figure 3).

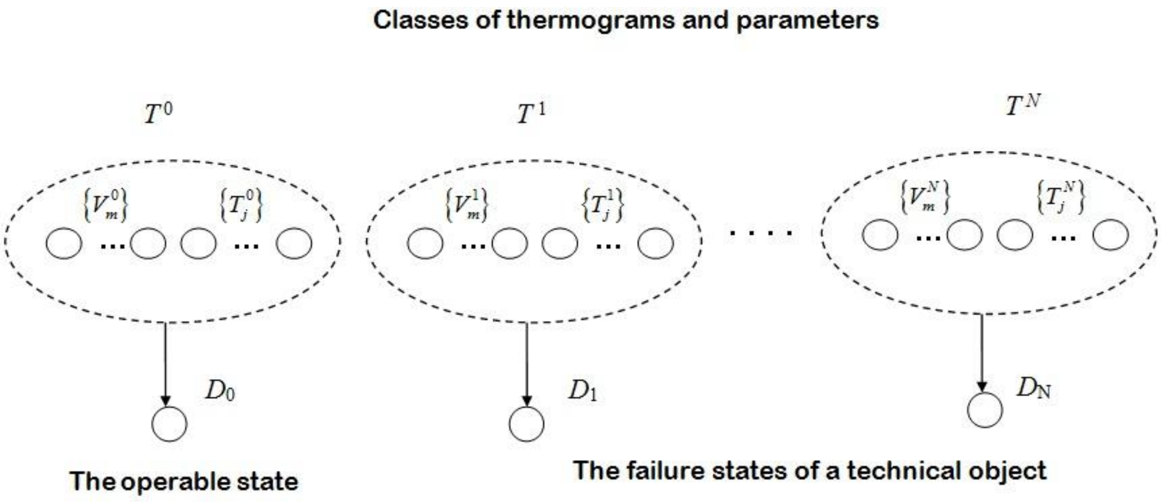

Figure 3. Separation signs of inoperability classes.

The implementation of the proposed approach is to build a convolutional neural network ANN 1, which is trained on a set of calculated thermograms, obtained using mathematical models. Another network ANN 2 is a fully connected neural network that processes the vector of additional parameters. In figure 4 the structure of the hybrid intellectual model is shown.

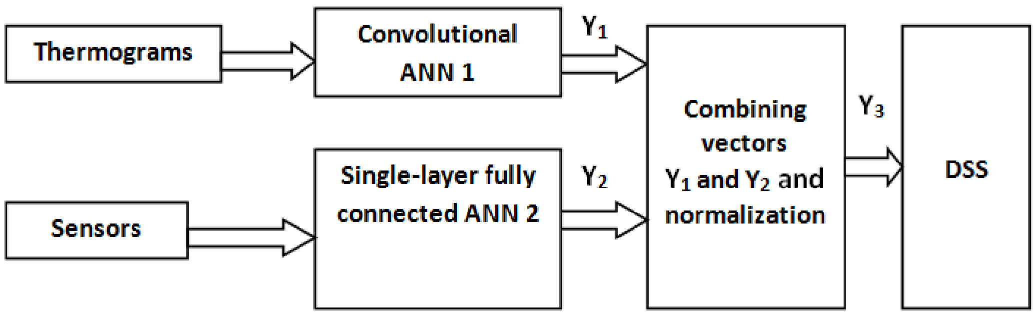

Figure 4. Structure of the hybrid intellectual model.

4. A measuring channel with a convolutional neural network

The thermal imager and the convolutional neural network ANN 1 form the main measuring channel. The organization of the convolutional network is based on the Y. LeCun approach [6] also combines some feature which were introduced in [10, 11] and is presented in figure 5. The network uses batch normalization, which was first introduced in [12].

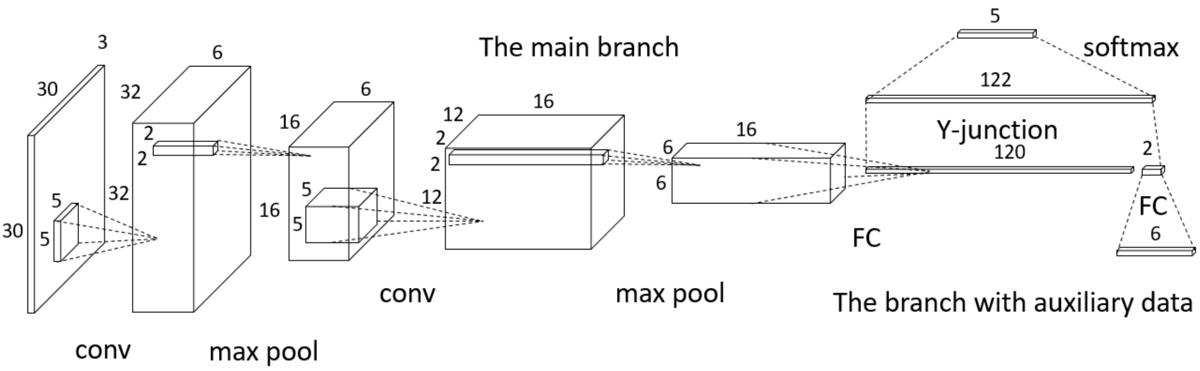

Figure 5. Neural network with two branches used in the experiments.

Proposed artificial neural network consists of two branches. The main branch is well known convolutional neural network. It consists of several convolutional layers united in feed-forward neural network. Thermograms are used as input for this branch.

Thermograms as any other image can be presented as an 3D array in which every value represents colour of the corresponding pixel. The width and height of the array is the same as width and height of the image (in pixels) and the depth of the array is 3, one for each of three (red, green, blue) channels. The size of thermograms used in our experiments were 30x30 pixels.

The first convolution layer's receptive field size is 5x5, padding is 3 and stride 1 pixel. The number of feature maps produced with the layer is equal to 6. The output of the first convolution layer is fed to max pooling layer with receptive field 2x2 and stride 2. This layer's output conveyed to the input of another convolutional layer which receptive field size is 5x5 and the stride is equal to 1. At this layer number of produced feature maps is 16. After the layer max pooling layer is used. The receptive field of the layer is 2x2 and stride is equal to 2. This reduces size of the feature maps with factor of 2. The output is fed to the third convolutional layer with receptive field of 6x6. Because size of the feature maps used as input for the layer is also 6x6 this layer can be considered as fully-connected. The output of this layer is vector which length is 120. Output of this convolutional layer is output of the whole first branch.

As easy to see, parameters of the convolutional layers, such as receptive field, stride and padding, were chosen so that with application to the given size of thermograms output of the last convolution layer is a vector.

In order to take into account signals from the controlled unit's build-in sensors an auxiliary branch of ANN was introduced. This branch consists of fully connected neurons layer. Input for the branch is a vector with normalized data from the sensors which length is equal to 6. Output of the layer is also a vector of length 2. The vector is merged with output vector of the main branch and result vector gotten after the merge is passed in as input for neurons layer that performs softmax or two-staged linear [13] normalization. This layer is the output layer of the whole ANN and performs categorization of failure in controlled unit.

ANN was used for categorization of four major and critical failures in controlled device. Therefore, output layer contains five neurons (one per each failure category and one corresponds to the normal condition of the unit).

Additional details of the network, such as number of trainable params per layer and some additional information, is presented in table 1.

Table 1. Neural network's summary.

Type	Input height/ width	Recept ive field	Stride	Padding	Output height/ width	Neurons	Depth per layer	Feature maps	Weights	Params
					the main branch					
conv	30	5	1	3	32	6144	1	6	25x6	156
max pool	32	2	2	0	16		1	6		
conv	16	5	1	0	12	2304	6	16	150x16	2416
max pool	12	2	2	0	6		1	16		
conv	6	6	6	0	1	120	16	120	576x120	69240
					the auxiliary branch					
fc						2			6x2	14
					the common part of neural network					
Y-junc-tion										
fc						3			122x5	615
						Total 8570				**Total 71826**

Some recent papers [14] consider in details application of some architectures that allow emulating sparsity in connections in neural networks. In our experiments we didn't use some of those techniques and used sparsity explicitly in similar manner as it was used in [6], retrieving different sub-set of feature maps for input of the third convolution layer. And as for neurons in convolutional layer each of them connected to the input within its receptive field.

Considering the fact that the main branch of our neural network is widely used convolutional network the weights for the layers can be initialized with weights of some pre-trained convolutional network which parameters compatible with our network. Although we didn't use this approach and initialized all the parameters with random value from range (-2, 2) and trained the network from scratch. But using pre-trained weights can reduce the training time in cases when it's important.

In our experiments we trained our network using back-propagation technique [15] with learning rate 0.001 using 100 epochs. Achieved precision of thee network is 99%. For training we used model thermograms generated programmatically for each of classified failure and for case when controlled unit is operating normally.

Although traditionally neural networks are trained on dataset that comprises subset of samples which network will process during its exploitation we trained the network on model thermograms, not on thermograms taken from some controlled unit. In our case we considered the problem from metrological point of view. Similar to any other metrological instrument it first passes its calibration on standard data in laboratory and then it is used in field. In similar manner we collected network's training dataset from thermograms that were generated programmatically based on mathematical model of surface temperature field of our control device. In practice even thermograms of two unit of the same model can differ slightly. By mean of using model thermograms we reduce influence of such variations.

Some sample thermograms used in network's training are shown on figure 6.

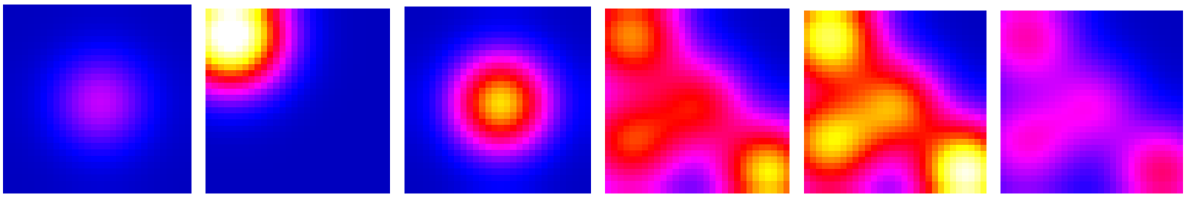

Figure 6. Some of the thermograms used in the experiments (best viewed in electronic version).

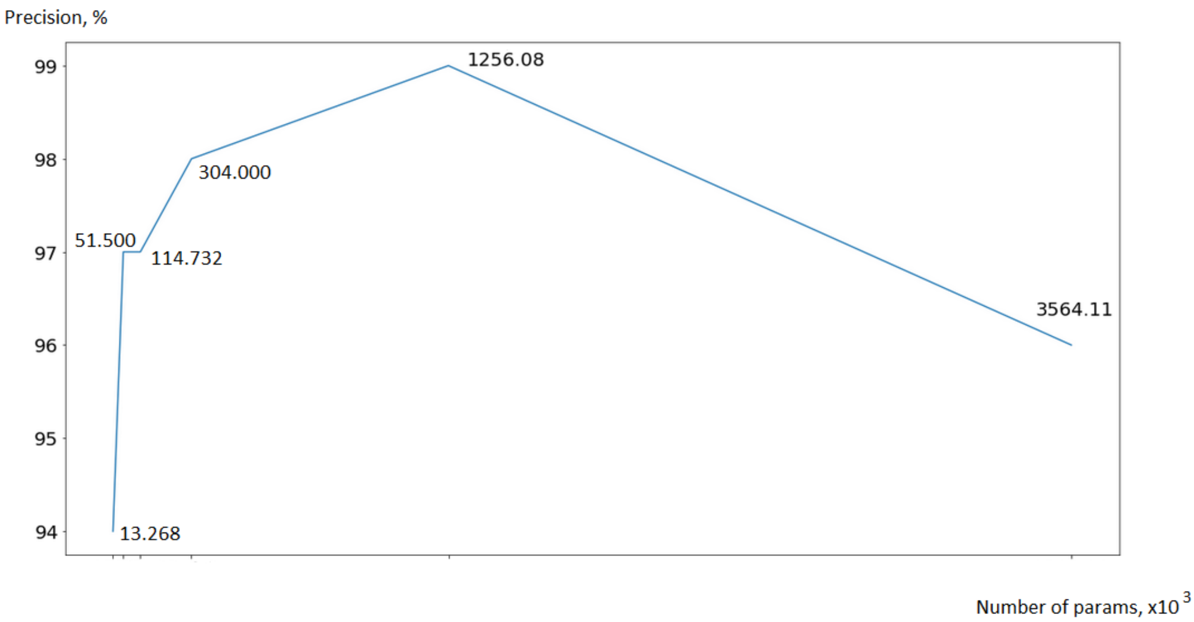

Figure 7. Dependency of networks' precision from number of parameters.

In addition to the experiments described above also some comparisons of precision of networks that differ in number of their params were made. Using conceptually the same network we vary number of used feature maps in convolutional layers and number of neurons in fully-connected layers. So that we achieved several networks with similar architecture but with different number of params. After we have trained each of them on the same dataset with thermogram we compared their precision. The discovered dependency of the networks' precision from number of their params is shown on Figure 7. The dependency is pretty much what would be expected to get: precision increases with number of params up to the certain point and after that point network tend to get overfit and precision decreases. In spite of that the dependency well known in case of metrology application this information can be used for sizing network by precision. It is essential that with number of parameters computation cost of feeding forward signal through network increases. In some cases calculation expensive network is not an option but refusing some amount of precision is allowed, so using diagrams similar to the one on figure 7 network sizing to some particular application can be performed.

5. Conclusion

Described approach can be easily generalized to application with wide range of units which technical state is controlled via thermograms and some auxiliary data. Using artificial neural network for interpretation thermograms and signals has many advantages. One of them is that even to unit of the same model can in practice have slightly different thermograms that corresponds to their state. Comparing (which is implicitly done during signal processing in network) thermograms of such unit with just canonical model sample not gives as good results as comparing thermograms taken from this particular instance of unit. And the latter is easily achievable with network fine-tuning on a given controlled unit. This kind of fine-tuning is nothing more like the same training with back-propagation but on thermograms from the given instance of controlled unit.

And the architecture of network can be easily corrected to take into account some additional signals as long as training dataset for the network is available.

6. References

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