International Journal of Engineering & Technology, 7 (4.3) (2018) 157-161

SPC

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Design of Algorithm for Identification of Locomotive Electrical Machine Unit During Repair

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Abstract

The purpose of this article is the design of an algorithm for identification of locomotive electrical machine unit by robotic cleaning facility during repair. The recognition and identification of objects is affected by several random factors and is the probabilistic process. the Johnson criterion was used as the criterion that allows making decision on fulfilment of the identification task with the specified degree of reliability. The diameter of locomotive fuel and oil pump motor fittings was adopted as the critical minimal dimension of the object to be identified. It was calculated that for identification of locomotive electrical machine unit the digital image should have dimensions of 80x80 pixels. The identification of 80x80 two-dimensional vector requires larger memory space and longer system learning time. The decrease of input data amount is possible by image additional processing. In order to decrease the unit identification system input data amount the algorithm foreseeing input vector of values generation using summarization of pixel binary codes over lines was developed. The unit identification system was built on the basis of the multilayer perceptron and was modeled in Neural Network Toolbox MATLAB package. The best learning error magnitude result was shown by the network with 40 hidden layers.

Keywords: *Electrical Machine Units, Leaning, Neural Network, Repair Works, Unit Identification.*

1. Introduction

During the locomotive unit and assembly repair works on their disassembling, resource evaluation, reconstruction or replacement, assembling and testing are carried out. The peculiarities of repair foresee the use of manual labor. For a long time it was stemmed from the complexity of automation facilities' use in repair works and existing ratio of labor force and hardware value. The modern Robotized Technological Complex (RTC) can be programmed using the learning method and has the bevy of process self-diagnostic and control features, while the manual labor value increases. At the moment robotized complexes get extension in the sphere of control and maintenance of technical objects [1-3]. It allows expecting the use of automation and robotization facilities in repair works in the immediate future.

Railway locomotive and wagon manufacturing works possess the positive experience of production lines' use [4, 5]. The widest extension got production lines for repair of bogies, railway motors, mounted wheels and axle boxes, shells and reducers of traction gears, diesel engines, connecting rod and piston group and radiator sections [6]. It is reasonable to use the RTC in repair works for performance of the most large-scale processes: cleaning, technical evaluation, reconstruction, unit and component painting.

The key aspect of the RTC independence is a computer vision [7, 8]. Its' availability has been already technically practicable. The use of computer vision is known in spheres of activities related to the security. In terms of repair works and in order to form the optimum technology for reconstruction, the process complexes have to possess the information about unit or detail type, its technical condition.

The locomotive unit and detail reconstruction during the repair is carried out in accordance with the operation process order. The cleaning of units and details during the repair is the demanding stage, the quality of which affects the efficiency of further process operations [9]. The quality of automated cleaning depends on the correct identification of unit or detail.

Electrical machines most complicated are for cleaning among all locomotive units and components, because each locomotive uses several electric machine types with different weight and dimensional characteristics, modes and conditions of operation. It determines their different types of contamination. The situation is complicated by the necessity of individual selection of cleaning methods for external and internal surfaces that differ by their physical properties and contamination form. In the electrical machine internal cavity are located insulated windings that can adsorb moisture during the cleaning or can be damaged by mechanical impact. The design of anchors of direct current electric machines includes copper collectors, which are subject to mechanical damage and oxidation.

2. Purpose

The purpose of this article is the design of algorithm for identification of locomotive electrical machine unit by robotic cleaning facility during repair.

3. Main Body

Locomotives use different electric machines: traction generators, auxiliary generators, starter-generators, traction electric motors, exciters and sub-exciters, electric motors of different mechanisms (fuel, water and oil pumps, vents, etc.). Locomotive motors operate in the most severe operating conditions, because they are not protected by the body which would keep water and dust out. The magnetic frames of auxiliary electric machines (starter-generators, electric motors of fuel, water and oil pumps) are contaminated by lubrication. The surface of motor fittings and machine DC poles are contaminated by wear particles of brushes and copper plates.

The locomotive electric machine degree of contamination is affected by several factors of probabilistic nature: serviceability of the machine itself, operation season and region, locomotive mode of operation. In order to effectively clean electric machine elements the robotized system shall have properties for cleaning technology adaptation depending on machine type, unit type and degree of their contamination as shown in Figure 1.

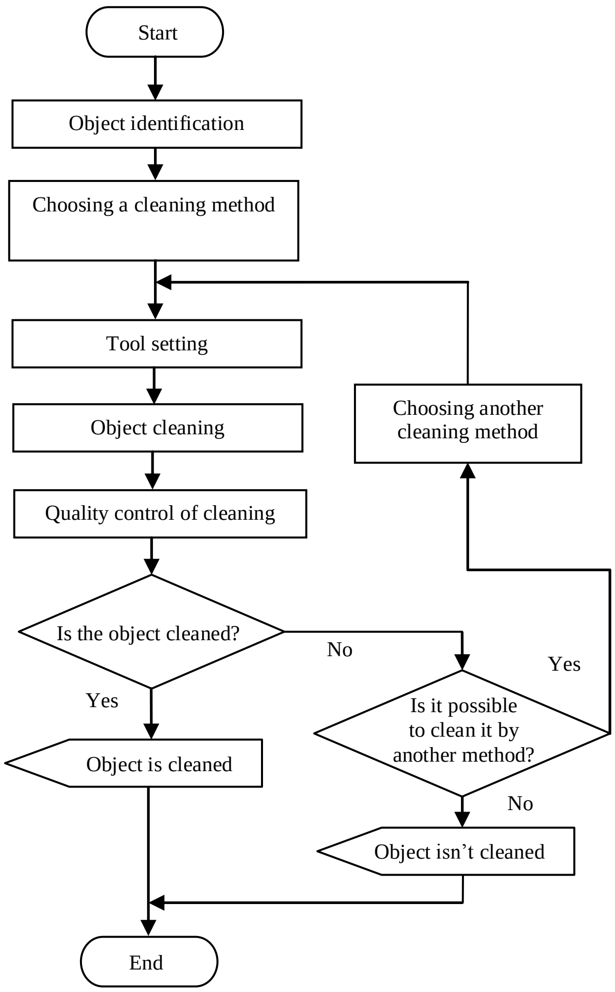

Fig. 1: Algorithm of adaptive technology for cleaning units of electric machines of diesel locomotives

The analysis of modern studies in sphere of intelligence systems [10-12] indicates that at the moment artificial neural networks are the most effective toll for image identification.

In order to identify different image categories in vision systems of robotic systems are widely used multi-layer perceptrons learning using back-propagation method [8, 13, 14].

During the development of multi-layer perceptron for electric machine unit identification it is required to determine its' parameters and carry out the corresponding learning.

The process for recognition and identification of objects is affected by several random factors and is the probabilistic process. It needs the criterion allowing to make decision on identification task execution with the specified degree of reliability. As such criterion the Johnson criterion was used [15]. It represents the relationship between the number of resolved periods of equivalent test image N in critical size of the object to be observed and the probability of observation task resolution. The critical size is the size along which the object image analysis is carried out in order to recognize its' attributes. If we take that the one period of equivalent test image equals two pixels, then the Johnson criterion for resolution of computer vision tasks with 50 % probability will amount to:

2 – Detection;
3 – Orientation;
6…8 – Recognition;
12 – Identification.

On this basis the quantity of pixels on which the image for transfer to neural is broken up can be calculated:

$$P = \frac{L^b N}{L^s}. \qquad (1)$$

Where, L^b is the dimension of the biggest sample, L^s is the dimension of the smallest sample.

We assume the locomotive traction motor frame (height -827 mm) as the biggest sample. The smallest sample is the locomotive fitting of fuel and oil pump motor (diameter – 82 mm). In order to recognize objects with dimensions in the range 82-827 mm according to (1), the image shall be divided into pixels and have dimensions of 80x80. In terms of one-dimensional vector of the two-dimensional matrix of such image in neural network it is required to provide 6400 input neurons. With the same number of hidden layer neurons, the number of intercommunications and weights will amount to 40960000. The network with such characteristics requires the larger memory space, longer learning time and sufficient amount of learning selection. The decrease of input data amount is possible due to the image additional processing. The electric machine elements (frames and fitting) have numerous distinctive features that shall be concentrated in the vector of the smallest possible dimension. For this purpose it is offered to convert the two-dimensional image matrix into special histogram, each column of which reflects the number of dark pixels of corresponding line (Figure 1). As electric machine elements are rotary bodies, and then in their correct positioning (front control); matrix columns and lines histogram will be nearly identical. It allows using one histogram parameters as input data without loss of basic information about element features. As shown on Figure 2, histograms adequately reflect elements' features (the vertical dimension corresponds the number of histogram columns; the element type is reflected in the form of histogram).

Considering the offered approach on the network input vector dimension, the electric unit machine identification algorithm will include the following operations:

1. The unit monochrome image acquisition $F(i)$ coming into the cleaning position.
2. The image adaptive binarization $F(i) \rightarrow F^B(i)$, ("1" – black color of pixel, "0" – white color of pixel) is carried out by the following rule:

$$F^B = \begin{cases} 1, if\ F(i) \le \varphi(i) \\ 0, if\ F(i) > \varphi(i) \end{cases} \qquad (2)$$

Where: $\varphi(i)$ is the threshold level.

3. The input vector of values generation using summarization of pixel binary codes over lines as in [16]:

$$F_n^S(i) = \sum_1^m F_n^B(i). \qquad (3)$$

Where, m is the number of columns in two-dimensional digital image matrix, n is the number of lines in two-dimensional digital image matrix.

4. The ritualization of image input vector.
5. The feeding of standardized values of image vector to the artificial neural network inputs.
6. The assignment of fed image vector to one of the artificial neural network outputs (recognition of electric machine unit).

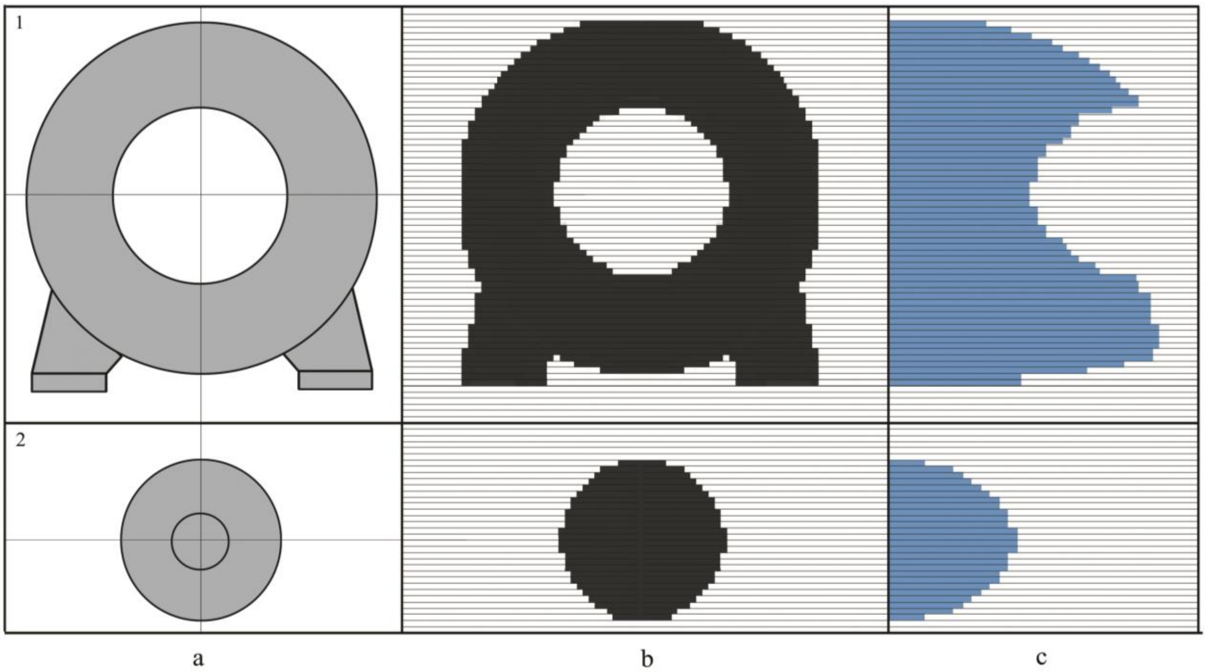

Fig. 2: Locomotive auxiliary generator image conversion. 1 – frame, 2 – fitting, a – initial image, b – digital image, c – image histogram.

Such approach allows decreasing the size of input vector and upper network layer to 80 neurons. The number of output layer neurons was adopted to be equal to the nominal range of electric machine units – 8. The number of hidden layer neurons depends largely on the type of task to be solved and parameters of learning selection. There is a range of heuristic rules for determination of perceptron hidden layer number of neurons. In this work the approach of their number optimization according to modeling results was used. On the initial stage, the perceptron with the known insufficient capacity of hidden layer (20 neurons).

All information that the neural network has about the task shall be contained in the learning selection massive. For this reason the quality of neural network learning hinges on the number and quality of examples in learning selection. The extent to which such examples completely describe the subject domain is essential.

When developing the neural recognition system the creation of learning selection covering the set of natural data to the fullest extent is the priority. When recognizing electric machine units during repair it is highly conceivable that the unit fault image can be obtained due to impact of several factors. Primarily such factors are unit setup tolerance against the camera. Photometric brightness, background characteristics and premise dust concentration are also important. In the article the volume of learning selection is accepted as the relationship of network weight number and error magnitude:

$$n \geq \frac{\omega}{\varepsilon} \tag{4}$$

Where, n is the scope of learning selection; ω is the network weight number; ε is the limiting network error.

With the limiting network error taken is a ε=0.1, the number of network learning selection examples' shall be 10 times bigger than weight number. Considering the assumed initial network structure as 80x20x8, the volume of learning selection shall not be less than 12800 examples. The origination of such data volume from natural images is connected with certain difficulties. In order to decrease time and resource expenses the method of artificial generation of learning examples was used. For this purpose, several images of locomotive electric machine units were taken at the repair facility. For each angle the most successful (ideal) snapshot was selected. Obtained images were processed in accordance with the developed algorithm. In the result, for each image an ideal numerical vector was obtained. For each value of obtained vector tolerances (±10%) were calculated. These values were used as limiting in artificial generation process (function *randn* (…) was used, MATLAB environment). Implementing such approach allowed to obtain the required volume of learning selection by each electric machine unit (Table 1).

The neural network was modeled using Neural Network Toolbox MATLAB package. The network learning was carried out using the algorithm based on Levenberg–Marquard method. It is based on reaching the least mean-root square error. The network learning is interrupted, when its' decrease stops. Among advantages of this learning method is the promptness of learning and relatively low mean-root square error. For the network learning 80 % of source information was used.

The learning control was carried out on the basis of 20% of source information that was used in the learning. The best learning error magnitude result was shown by the network with 40 hidden layers (Figure 3).

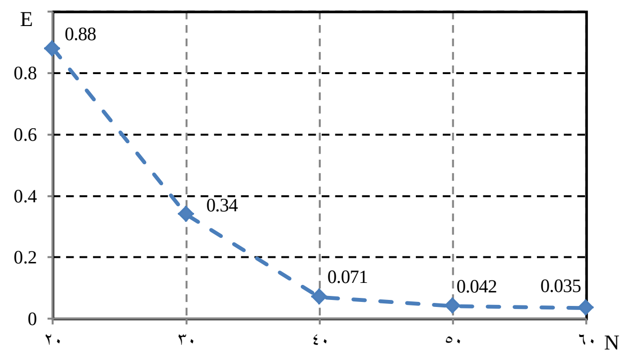

Fig. 3: Dependence of network error magnitude E on hidden layer neuron number N.

Table 1: Fragment of the source information array for recognition of diesel locomotive nodes

№	frame			fitting		
	1	2	3	1	2	3
1	0.7108	0.6760	0.6950	0	0	0
2	0.7432	0.7554	0.7388	0	0	0
3	0.7085	0.8282	0.7938	0	0	0
4	0.8412	0.7581	0.7445	0	0	0
5	0.8497	0.8554	0.7335	0	0	0
6	0.7916	0.8690	0.7400	0	0	0
7	0.7307	0.7748	0.7857	0	0	0
8	0.8710	0.8012	0.8022	0	0	0
9	0.7660	0.7463	0.8646	0	0	0
10	0.8305	0.7682	0.8452	0	0	0
11	0.8885	0.8831	0.8851	0	0	0
12	0.9089	0.9110	0.9155	0	0	0
13	0.9039	0.9204	0.9453	0	0	0
14	1.0000	0.9171	0.8920	0	0	0
15	0.8300	0.8211	0.9743	0	0	0
16	0.8518	0.8946	0.8474	0	0	0
17	0.8570	0.7327	0.7103	0	0	0
18	0.7923	0.6878	0.6980	0	0	0
19	0.7402	0.8079	0.7806	0	0	0
20	0.7276	0.7806	0.7291	0	0	0
21	0.6360	0.5906	0.7035	0	0	0
22	0.5890	0.6722	0.6114	0	0	0
23	0.5524	0.5712	0.6024	0.0200	0.0203	0.0210
24	0.4684	0.4567	0.4444	0.1446	0.1447	0.1551
25	0.4813	0.4414	0.4434	0.1875	0.1999	0.2185
26	0.4244	0.4538	0.3933	0.2407	0.2509	0.2463
27	0.4298	0.4232	0.4123	0.2704	0.2443	0.2710
28	0.3505	0.3804	0.4100	0.3224	0.3412	0.3348
29	0.3412	0.3457	0.3848	0.3613	0.3527	0.3109
30	0.3726	0.3404	0.3336	0.3539	0.3746	0.3744
31	0.3786	0.3480	0.3395	0.3974	0.3590	0.3471
32	0.3680	0.3475	0.3448	0.4310	0.3830	0.4242
33	0.3564	0.3388	0.3778	0.4200	0.4272	0.4113
34	0.4157	0.4140	0.4102	0.4021	0.4398	0.4245
35	0.4514	0.4589	0.3903	0.4012	0.4442	0.4091
36	0.4813	0.4140	0.4680	0.4464	0.4696	0.4489
37	0.4849	0.4360	0.4534	0.4851	0.4807	0.4375
38	0.6194	0.6052	0.6534	0.4575	0.4178	0.4926
39	0.6885	0.5760	0.6392	0.4815	0.4603	0.4503
40	0.6146	0.6377	0.5964	0.4368	0.4668	0.4545
41	0.7974	0.7145	0.6670	0.5057	0.4395	0.5238
42	0.7664	0.7939	0.7780	0.4697	0.5023	0.5144
43	0.8313	0.7721	0.8058	0.5256	0.4970	0.5138
44	0.7809	0.7617	0.7540	0.5300	0.4833	0.5428
45	0.8801	0.7562	0.8960	0.5109	0.5177	0.4757
46	0.8969	0.8492	0.8014	0.5436	0.5095	0.5102
47	0.9085	0.8572	0.9733	0.5193	0.5384	0.5205
48	0.9022	0.8773	0.8945	0.4961	0.5319	0.5101
49	0.9424	0.9824	0.9448	0.4931	0.4669	0.5247
50	0.9276	0.9370	0.9035	0.5368	0.4839	0.4958
51	0.8760	0.8496	0.7875	0.4573	0.5049	0.4665
52	0.7999	0.8725	0.8558	0.4759	0.4972	0.4920
53	0.7800	0.8379	0.8061	0.5229	0.4372	0.5172
54	0.7386	0.7357	0.8447	0.5050	0.5123	0.5003
55	0.8119	0.8601	0.7532	0.4936	0.5147	0.4588
56	0.8409	0.7752	0.7246	0.4414	0.4962	0.4732
57	0.7846	0.7018	0.7586	0.4683	0.4453	0.4995
58	0.7496	0.7786	0.7667	0.4745	0.4198	0.4541
59	0.8292	0.6831	0.8178	0.4465	0.4282	0.4056
60	0.7107	0.6788	0.7339	0.4180	0.3763	0.3917
61	0.6847	0.6826	0.7354	0.4301	0.3855	0.4011
62	0.4713	0.4567	0.4877	0.3678	0.3723	0.3575
63	0.4151	0.3787	0.4033	0.3735	0.3824	0.3472
64	0.3677	0.3981	0.3858	0.3802	0.3214	0.3699
65	0.3654	0.3182	0.3197	0.3433	0.3255	0.3302
66	0.3307	0.3257	0.3228	0.3131	0.3065	0.2993
67	0.2961	0.3425	0.3333	0.2792	0.2871	0.2456
68	0.3000	0.3476	0.3307	0.2474	0.2566	0.2714
69	0.3351	0.3448	0.3434	0.2137	0.2192	0.2132
70	0.2920	0.3491	0.3105	0.1315	0.1533	0.1505

4. Conclusion

Different characteristics of electric machine unit surfaces and probabilistic nature of their contamination force to use adaptive algorithms of their cleaning.
On the basis of the Johnson criterion use, electric machine unit dimensions it was calculated that for their identification the digital image shall have dimensions of 80x80 pixels.
In order to decrease the unit identification system input data amount the algorithm foreseeing the summarization of pixel binary codes over lines of digital image was developed.
The unit identification system was built on the basis of the multilayer perceptron and was modeled in Neural Network Toolbox MATLAB package. The best learning error magnitude result was shown by the network with 40 hidden layers. Modeling results has shown high locomotive electrical machine unit identification results of the neural network and confirm the adequacy of designed identification algorithm.

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