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The Adaptive Approach to Abnormal Situations Recognition Using Images from Condition Monitoring Systems

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Abstract—Decision support in equipment condition monitoring systems with image processing is analyzed. Long-run accumulation of information about earlier made decisions is used to realize the adaptiveness of the proposed approach. It is shown that unlike conventional classification problems, the recognition of abnormalities uses training samples supplemented with reward estimates of earlier decisions and can be tackled using reinforcement learning algorithms. We consider the basic stages of contextual multi-armed bandit algorithms during which the probabilistic distributions of each state are evaluated to evaluate the current knowledge of the states, and the decision space is explored to increase the decision-making efficiency. We propose a new decision-making method, which uses the probabilistic neural network to classify abnormal situation and the softmax rule to explore the decision space. A modelling experiment in image processing was carried out to show that our approach allows a higher accuracy of abnormality detection than other known methods, especially for small-size initial training samples.

Keywords: maintenance decision support systems, image recognition, abnormal states classification, contextual multi-armed bandit problem, probabilistic neural network (PNN)

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1. INTRODUCTION

Improving the efficiency of automated monitoring systems is still a topical issue for such complex facilities as cellular telephone network equipment, public transport, gas pipelines etc. [1, 2]. Objects under monitoring usually include sets of various data, e.g. photos of a part of an object, video data, fragments of vibration monitoring signals, etc. After a potential emergency (abnormal situation) is detected, a decision-making person (DMP) should take preventive measures. It is obvious that when a problem has many possible solutions, the DMP can miss the most effective one, especially under time pressure [3]. This is a reason why in recent developments of technical diagnostics systems much attention has been paid to automated detection of potential emergencies. Information about earlier emergency occurrences is used to learn such systems [1]. Unlike conventional classification problems [4], available historical data often lacks the information about the action needed to prevent the earlier experienced emergency; rather it evaluates the reward of preventive actions. Moreover, the initial amount of empirical data is usually insufficient to support the decision-making. That is why the effective decision-making algorithm should use not only accumulated historical data (e.g. images of an object under observation), but also examine the decision space. The latter is particularly important at early stages of system operation [5].

Let us consider the solution of the problem using conventional methods of reinforcement learning, e.g., Q-learning, [6] given a countable set of states [7]. Such methods use the Markov decision process, in which the application of a particular action to a current state brings the system to a new state fully defined by the previous state and this action [6]. It is this property that makes it possible to use dynamic programming to evaluate the optimal reward of applying a decision-making strategy. In our problem of decision support with image recognition we assume that an action brings the system to a terminal state that should correspond to particular efficiency estimation. For this reason the use of Q-learning methods does not look sensible.

Let us consider a contextual multi-armed bandit model [8, 9], e.g., the UCB (upper confidence bound) method [10]. For the feature vector of abnormal state these algorithms predict the reward of each decision by using, e.g., the generalized regression neural network (GRNN) [11]. Unlike the typical applications of contextual multi-armed bandit models [9], in the condition monitoring problem the efficiency of an action is supposed to be binary: the action can be either success or failure. The goal of this paper is to find the ways to implement the multi-armed bandit algorithm for recognition of abnormal situations described by images of the observed object [12]. We propose a new decision-making method that uses images of objects to detect potential emergencies. The method is based on the probabilistic neural network (PNN) [13] and softmax search strategy [14]. The latter is used for making the final decision in exploration of unknown states when the available information about an object under monitoring is not enough.

The rest of the paper is organized as follows. The emergency detection problem is set in Section 2. Section 3 gives the solution of the problem using the PNN-based classification algorithms [13]. Section 4 elaborates on the state space exploration strategies developed earlier within the scope of the multi-armed bandit model of the UCB [10] and softmax [14] types and presents the final decision-making algorithm. The modeling results for simulated patterns are presented in Section 5. The conclusions and future works are given in the last section.

2. CLASSIFICATION OF ABNORMAL STATES

Let us consider an intelligent system that can recognize the state of an observed object by processing an image of the whole object or its part. Let the system detect an abnormal object state, which should be classified. We can describe the state of the object with a feature vector $\mathbf{x}$ of fixed dimensionality M. Features $\mathbf{x}$ are defined as a result of image processing with respect to the given domain. Specifically, in the case of heavily blurred images the use of mathematical morphology operations [16] and computation of elementary geometric characteristics such as the area, perimeter, center of gravity, various moments [12, 17] give good results [15].

The goal is to assign an abnormal condition described by a feature vector $\mathbf{x}$ to one of A ($A \geq 2$) possible preventive actions. For simplicity let us assume that these actions are statistically independent. Let there be a training set (historic data) of N 3-tuples $X_N = \{(\mathbf{x}_n, a_n, r_n)\}, n = \overline{1, N}$, where $\mathbf{x}_n$ is the feature vector of the n-th abnormal state, $a_n \in \{1, ..., A\}$ is the action taken to correct the n-th abnormal state, $r_n \in \{0, 1\}$ is the reward (efficiency) of action a_n which can be either success ($r_n = 1$) or failure ($r_n = 0$). Let us use the pattern recognition methods [4] to solve this problem.

The initial training sample of size $N_0 \geq 0$ is formed before the decision support system is introduced. After decision a is made and a corresponding action is taken, the reward r of the action is evaluated by the DMP, and the $(N + 1)$-th item is added to the training sample. Thus, new events are gradually added to the training sample in operation of the system. The problem is that the number of possible actions A is usually fairly large, and the same action can be applied successfully in different situations. Moreover, the amount of available historic data about failures can be insufficient to apply complicated algorithms of machine learning.

It should be noted that this task differs from a conventional classification problem [3, 4] where the class label of each reference instance from the training sample is known (i.e. $r_n = 1, n = \overline{1, N}$). The presence of the negative decisions whose class is unknown ($r_n = 0$) restricts the possible solutions. As was mentioned in the introduction, multi-armed bandit algorithms can be used in this case. Unlike the conventional problem of multi-armed bandit for which the optimal algorithm (in the sense of highest hit ratio) is known (e.g. using Gittins indexes [7]), the presence of a context (description of situation $\mathbf{x}$) complicates the decision [10, 18]. Within the framework of exploitation-exploration dilemma [6] the solution usually comes down to a successive iterative two-stage procedure. At the first, exploitation, stage a decision-making strategy optimal for an available training sample is used, and at the second, exploration, stage the state space is examined to refine the chosen strategy. Let us look at each stage in more detail.

3. THE OPTIMAL DECISION-MAKING STRATEGY

The condition of the highest expected reward of action a under conditions $\mathbf{x}$ can be used in the exploitation stage [19]:

$$a^* = \underset{a \in \{1, \dots, A\}}{\arg\max}\, \overline{r}(a, \mathbf{x}) \tag{1}$$

where $\overline{r}(a,\mathbf{x}) = E\{r|a,\mathbf{x}\}$ is the conditional expectation of the reward for action a. Given known probabilities $p(r = i|a,\mathbf{x}), i = \overline{0,1}$, we get the following estimate for yes-no reward $r_n \in \{0, 1\}$:

$$\overline{r}(a,\mathbf{x}) = p(r = 1|a,\mathbf{x}). \tag{2}$$

In practice $p(r|a,\mathbf{x})$ is unknown, and expected reward $\overline{r}(a,\mathbf{x})$ for each action $a \in \{1, ..., A\}$ can be evaluated using machine learning algorithms based on training samples $X_N(a) = \{(\mathbf{x}_n, r_n)|(\mathbf{x}_n, a, r_n) \in X_N\}$ of size $N(a)$. It is obvious that $\sum_{a=1}^{A} N(a) = N$. In the case of the yes-no reward the training sample $X_N(a)$ is divided into two sub-samples: a positive sub-sample $X_N^+(a) = \{\mathbf{x}_n|(\mathbf{x}_n, a, 1) \in X\}$ of size $N^+(a)$ and a negative sub-sample $X_N^-(a) = \{\mathbf{x}_n|(\mathbf{x}_n, a, 0) \in X\}$ of size $N^+(a) = N(a) - N^+(a)$. If the PNN classifier is utilized, the following expression can be used to evaluate conditional probability $p(r = 1|a,\mathbf{x})$ in (2):

$$\hat{p}(r = 1|a,\mathbf{x}) = \frac{\sum\limits_{\mathbf{x}_n \in X_N^+(a)} K(\mathbf{x},\mathbf{x}_n)}{\sum\limits_{\mathbf{x}_n \in X_N^+(a)} K(\mathbf{x},\mathbf{x}_n) + \sum\limits_{\mathbf{x}_n \in X_N^-(a)} K(\mathbf{x},\mathbf{x}_n)} = \frac{\sum\limits_{\mathbf{x}_n \in X_N^+(a)} K(\mathbf{x},\mathbf{x}_n)}{\sum\limits_{\mathbf{x}_n \in X_N(a)} K(\mathbf{x},\mathbf{x}_n)}. \tag{3}$$

Here $K(\mathbf{x}, \mathbf{x}_n)$ is the kernel function determining the dissimilarity of vectors $\mathbf{x}$ and $\mathbf{x}_n$, e.g. Gaussian Rosenblatt–Parzen kernel [13]:

$$K(\mathbf{x},\mathbf{x}_n) = \frac{1}{\left(2\pi\sigma^2\right)^{M/2}} \exp\left(-\frac{1}{2\sigma^2}(\rho(\mathbf{x},\mathbf{x}_n))^2\right), \tag{4}$$

where $\rho(\mathbf{x},\mathbf{x}_n)$ is the Euclidean distance between vectors $\mathbf{x}$ and $\mathbf{x}_n$, σ is the smoothing parameter.

Making sufficiently accurate evaluations (3) for all $a = \overline{1,A}$ requires large ($N_0 \gg 1$) representative initial training samples $X_N(a)$, which hold examples of using each action in different conditions. However, the initial sample are usually small [20], and the number of reference instances $N(a)$ for each action is not sufficient to make an accurate estimation (3). As a result, the effectiveness of decision rule (2)–(4) may be low, especially in the starting stages of its operation. The following method of evaluating the probabilistic distribution of states (2) is proposed to increase the effectiveness of the decision-making system. The method uses a united sample that combines all possible classes (actions) [20, 21]. It should be noted that in the case of yes-no reward there is probability $(A - 1)^{-1}$ that actions $i \in \{1, ..., A\}$ from the negative training sample $X_N^-(i)$ may be positive examples for an action $a \neq i$ and instances from the positive sample $X_N^+(i)$ will be negative examples for an action $a \neq i$. Let us reduce the problem of choosing action $a \in \{1, ..., A\}$ to generating A binary classifiers—one for each action. Then either conventional support vector machines [24] or (when the short training time is needed) simpler methods (e.g. the PNN [13]) can be used. In view of the assumption that any other action $i \neq a$ may prove right for negative examples from set $X_N^-(i)$ with equal probability $(A - 1)^{-1}$, we propose to modify expression (3) in the following way:

$$\hat{p}(r = 1|a,\mathbf{x}) = \frac{\sum\limits_{\mathbf{x}_n \in X_N^+(a)} K(\mathbf{x},\mathbf{x}_n) + \sum\limits_{\substack{i=1\\i\neq a}}^{A}\left(\frac{1}{A-1}\sum\limits_{\mathbf{x}_n \in X_N^-(i)} K(\mathbf{x},\mathbf{x}_n)\right)}{\sum\limits_{\mathbf{x}_n \in X_N^+(a)} K(\mathbf{x},\mathbf{x}_n) + \sum\limits_{i=1}^{A}\left(\sum\limits_{\mathbf{x}_n \in X_N^-(i)} K(\mathbf{x},\mathbf{x}_n)\right)}. \tag{5}$$

In so doing we expect that due to adding abnormal states from samples $X_N^-(i), i \in \{1,\ldots,a-1,a+1,\ldots,A\}$ to the training set the evaluation of the probability density will prove far more accurate than with conventional approach (3). It is especially the case with initial training samples of small size N_0 [20]. At the same time the heuristic assumption that using examples from sample $X_N^-(i)$ as positive examples for action a makes, according to (5), an identical contribution to estimated conditional probabilities for all actions $a \neq i$.

4. ADAPTIVE EXPLORATION OF THE STATE SPACE

It is known that the best characteristics for the multi-armed bandit problem [7, 8] are provided by the methods that not only use the optimal criterion (1), (2) with density estimations (3) or (5), but also explore the state space for improving of the current decision-making strategy. Developed in the UCB method [10, 12], interval-based strategies of choosing action a^* are used in this case. The regression model [4] is used to predict the decision-making effectiveness. Instead of criterion (1), the upper confidence bound is used to choose the necessary strategy. Note that in our case of the yes-no result of an action PNN-based expression (3) agrees with non-parametric Nadaraya-Watson regression [22], which underlies the GRNN [11].

$$\overline{r}_{GRNN}(a,\mathbf{x}) = \frac{\sum\limits_{(\mathbf{x}_n,r_n)\in X_N(a)} K(\mathbf{x},\mathbf{x}_n)\cdot r_n}{\sum\limits_{(\mathbf{x}_n,r_n)\in X_N(a)} K(\mathbf{x},\mathbf{x}_n)}. \tag{6}$$

Then the use of the asymptotic distribution of a dependent random variable in GRNN [22] with the UCB gives the following criterion:

$$a^* = \underset{a\in\{1,\dots,A\}}{\arg\max}\left(\overline{r}_{GRNN}(a,\mathbf{x}) + z_{1-\alpha/2}\cdot\hat{\sigma}_{GRNN}(a,\mathbf{x})\right). \tag{7}$$

Here $z_{1-\alpha/2}$ is a $(1-\alpha/2)$ quantile of the normal distribution, which is dependent on significance level α (e.g. when $\alpha = 0.05$, the normal-distribution tables give $z_{1-\alpha/2} \approx 1.96$); $\hat{\sigma}_{GRNN}(a,\mathbf{x})$ is the estimation of the standard deviation, which in the case of Gaussian Parzen kernel takes the form:

$$\hat{\sigma}_{GRNN}(a,\mathbf{x}) = \frac{\sqrt{\dfrac{\pi}{2N(a)}\sum\limits_{(\mathbf{x}_n,r_n)\in X_N(a)} K(\mathbf{x},\mathbf{x}_n)\cdot\left(r_n - \overline{r}_{GRNN}(a,\mathbf{x}_n)\right)^2}}{\sum\limits_{(\mathbf{x}_n,r_n)\in X_N(a)} K(\mathbf{x},\mathbf{x}_n)}. \tag{8}$$

The range of the confidence interval is proportional to $\hat{\sigma}_{GRNN}(a,\mathbf{x})$ and can be used as a criterion of how well a particular action a is explored. According to (7) least investigated actions (which have greater upper confidence bounds) are used most often [10].

Another exploration method is the random decision-making strategy based on the simulated annealing [14]. In this case reaction a to situation $\mathbf{x}$ is chosen using the following rule:

$$a^* = \underset{a\in\{1,\dots,A\}}{\arg\min}\ \mathrm{sgn}\left(\sum_{i=1}^{a}\pi(i,\mathbf{x}) - p\right)\mathrm{sgn}\left(\sum_{i=1}^{a-1}\pi(i,\mathbf{x}) - p\right), \tag{9}$$

where $p \in [0, 1]$ is an uniformly distributed random variable, and distribution function $\pi(a, \mathbf{x})$ is the chance of choosing action a to situation $\mathbf{x}$, which is determined for criterion (1) with the softmax rule (or Boltzmann exploration) [14]

$$\pi(a,\mathbf{x}) = \frac{\exp(-\hat{p}(r=1|a,\mathbf{x})/T)}{\sum\limits_{i=1}^{A}\exp(-\hat{p}(r=1|a,\mathbf{x})/T)}. \tag{10}$$

Here T is the "temperature" that falls with time following the rule chosen experimentally according to the precise context.

Our experiments [23] showed that even in the simplest model conditions the use of realizations (6) and (7) of the UCB method is effective only when size N_0 of the initial training sample is large enough, while the softmax rule usually gives satisfactory accuracy even without a priori information about a right reaction ($N_0 = 0$). Moreover, unlike the UCB (7), this approach can be used not only for the conventional density estimation (3) and (6), but also for modified estimation (5). For this reason it is the softmax rule (9) (10) that was realized in the proposed decision-making algorithm (table). The algorithm can be readily generalized for video data processing with the aid of still-to-still recognition algorithm [25] and aggregation of recognition results (table) for each frame by using a collective decision rule such as simple voting [4].

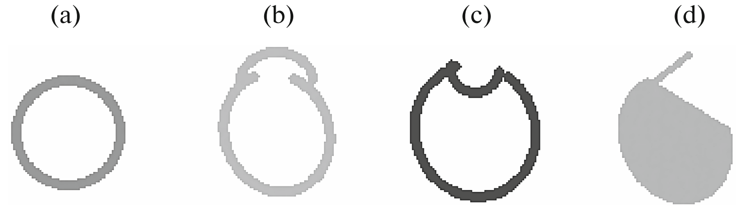

Fig. 1. Model states: (a) normal state; (b) bulge; (c) dent; (d) separation.

5. EXPERIMENTAL RESULTS

We took some generated images (Fig. 1) that resemble typical cross sections of gas pipelines [1, 26] to carry out modeling of the proposed decision-making algorithm. The state of gas pipes can be classified in the following manner [27]:

(1) normal state (Fig. 1a);

(2) a departure of the pipe axis from the designed position: floated pipe segments, pipe bulges (Fig. 1b);

(3) geometrical distortions of the pipeline cross-sections: out-of-roundness, dents (Fig. 1c);

(4) defects of pipe walls and welds, etc. (Fig. 1d).

So, we should choose one of $A = 4$ actions to remove a corresponding effect.

Special software[1] has been developed using MS Visual C++ 2013 Express Edition to experiment with the decision-making algorithms. OpenCV library was used in the experiments. Images of each class are generated in the following manner. The cross-section of a pipe is represented as an ellipse whose center and semi-axes vary uniformly over the range [28, 32] according to a particular state of the pipe (Fig. 1a). In the image of the first defect (Fig. 1b) the cross-section of a pipe is represented as a segment of an ellipse whose start and end angles vary in equal increments over the ranges [105°, 125°] and [40°, 60°], respectively. The pipe bridging (Fig. 1b) is modeled with a segment of an ellipse whose semi-axes and subtending angle vary uniformly in the ranges [13, 17] and [170°, 190°], respectively. The image for the third state of the pipe (Fig. 1c) is generated similarly except that the ellipse of the dent is turned by 180°. The images of the last defect (Fig. 1d) are showed as a segment of an ellipse whose start and end angles vary uniformly over the ranges [170°, 190°] and [–10°, 10°], respectively. The breaking is represented as a straight line segment whose length vary uniformly over the ranges [25, 35] and inclination to a randomly chosen end of the arc of the main cross-section makes 45°.

A noise-resistant algorithm used for video detection of a fork-lift truck [15] was taken to extract features $\mathbf{x}$: the Otsu binary thresholding algorithm was applied to an input image, and contours were detected, big adjacent contours being connected with a line segment linking their neighbor ends. Convex envelopes were generated for open contours [12]. All resulting contours were filled using the flood fill algorithm. Then the morphological erosion using a disk structuring element 10 pixels in diameter was applied to filter the image [16]. After the Canny edge detection the final contour of the object was determined. The features of the object were the area, perimeter and position of the center of gravity [17] relative to the expected normal state (Fig. 1a)—a circle 60 pixels in diameter. The results of image preprocessing (Fig. 1) are shown in Fig. 2. Additionally, morphological opening using a disk element 56 pixels in diameter [16] was performed, and the area of the resulting shape was computed. Besides, vector $\mathbf{x}$ was supplemented with a binary feature indicating whether the contour of the selected form is convex (Figs. 2a, 2b, 2c) or not (Fig. 2d). Thus the resulting vector $\mathbf{x}$ consists of $M = 6$ features. The Euclidean metric was used to compute the dissimilarity $\rho(\mathbf{x}, \mathbf{x}_n)$ of feature vectors in Gaussian kernel function $K(\mathbf{x}, \mathbf{x}_n)$ (4).

In the test we ran the following procedure successively. First we set a training sample of size N_0 for each situation $\mathbf{x}_n$ for which the correct action a_n is supposed to be known. Next we repeatedly ($N - N_0$ times) choose action $a \in \{1, ..., A\}$ at random. A new image answering to this action and having features $\mathbf{x}$ is generated. Each of the decision-making methods (GRNN (1), (3), (4); UCB (7); PNN (1), (2), (5); GRNN + softmax (3), (9), (10); PNN + softmax (5), (9), (10)) are tried to determine recommended action a^*. For softmax rule (10) the initial temperature T is set to 0.2, it lowers (the current value of T is multiplied by 0.9 for every four new situations) until it reaches 0.01. If $a^* \neq a$, the decision is considered wrong. As a result, the average error rate is computed for each method. The whole testing process is repeated 100 times.

[1] https://sites.google.com/site/andreyvsavchenko/MaintenanceDSS.zip

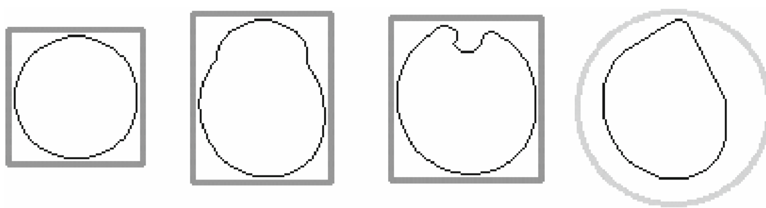

Fig. 2. Images of the model states after preprocessing.

Figure 3 shows the mean error rate as a function of size N_0 of the initial sample, in which the correct action is known for each situation. Here the testing sample contains $N = 1000$ images for each of which the reward r of the action chosen by the system is known.

We see that given a small initial training sample ($N_0 \leq 9$), the conventional methods (GRNN, UCB, PNN) show low accuracy, while the use of the softmax rule (10) to explore the decision space gives a fairly high mean reward (1). In particular, when $N_0 = 8$, the proposed method (table) proved to be 9–15% more accurate than GRNN, UCB and PNN approaches. When N_0 is increased, the binary classification (1), (2), (5) gives the least error rate from the other conventional methods. However, even in this case our method (5), (9), (10) is 0.5–1% more accurate. Moreover, when $N_0 \leq 10$ and the softmax rule with binary classification (5), (10) is used, the error rate is 0.5–3% lower than that provided by the non-parametric regression (3), (10). When N_0 is large, the difference from the Boltzmann rule (9), (10) for GRNN (3) is statistically insignificant in terms of the McNemar's test with significance level of 0.05. It should be noted that as compared with other methods, our algorithm provides the accuracy whose standard deviation makes 0.5–1.5% and is almost independent of N_0. This standard deviation proves to be 1–3% lower than with the "GRNN + softmax" approach and 2–11% lower than that provided by the conventional methods. The latter is due to the fact that with our approach the greater part of the state space is explored in the beginning stage whatever the initial sample is. Moreover, the above-mentioned increase of the negative training sample size for each action results in still higher accuracy. That is why the effect of the initial sample representativeness is not so important for our method than for the others.

The next experiment (Fig. 4) demonstrates how the error rate depends on the number of images (N) in the testing sample. The size of the initial training sample is supposed to be fixed: $N_0 = 10$.

Here, as in the first experiment, our method (5), (9), (10) proved to be most effective. Note that all of the methods under consideration use the adaptive approach: for each situation the processed example is added to set X_N after recognition (see steps 6–8 of the algorithm from table). That is why the mean error rate falls with N for all the methods (Fig. 4). For the methods using GRNN, UCB and PNN large standard deviations result in noticeable fluctuations of the accuracy (differences in the accuracy for consecutive values of N are statistically insignificant). When $N \leq 1200$, our method (table) proves to be 0.9–3.2% more accurate than "GRNN + softmax" approach—the best of the other method. The experimental results allow a major conclusion that when initial training samples are small, the combination of the PNN

The decision-making method to recognize an abnormal situation using the probabilistic neural network and softmax rule

Input data: an image of an object, an initial training sample X_N, $N = N_0$

Output data: recommended action a^*

1. Computing the feature vector $\mathbf{x}$ for the input image
2. Repeating the evaluation of conditional probability $\hat{p}(r = 1 | a, \mathbf{x})$ (5) for each action $a \in \{1, ..., A\}$
3. Repeating the calculation of probability $\pi(\boldsymbol{a}, \mathbf{x})$ of making decision a (10) for each action $a \in \{1, ..., A\}$
4. Generating a random number $p \in [0, 1]$ and determining decision a^* according to randomized criterion (9)
5. Lowering temperature T
6. Asking the user for correctness r of decision a^* for situation $\mathbf{x}$
7. Adding new tuple ($\mathbf{x}$, a^*, r) to the historic data X_N
8. Assign $N = N + 1$
9. Recommending action a^* for eliminating the abnormal situation

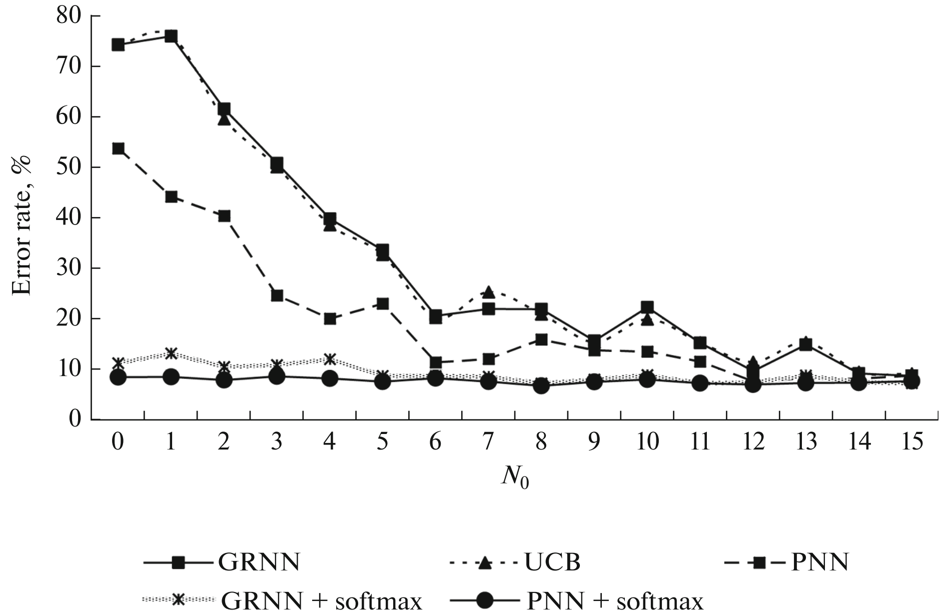

Fig. 3. The mean error rate (%) as a function of the initial training sample size N_0 for $N = 1000$ images.

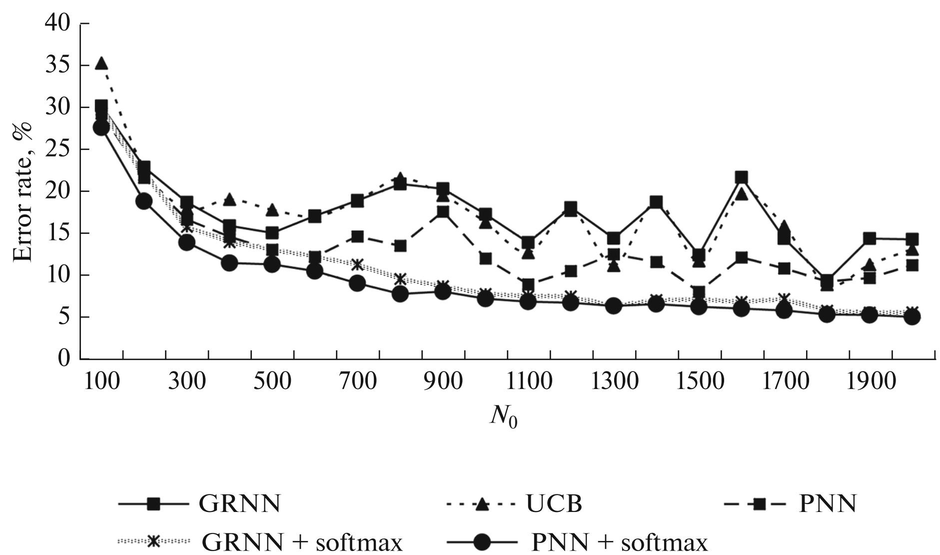

Fig. 4. The mean error rate (%) as a function of number of images N for initial training sample size $N_0 = 10$.

method (5) and the softmax rule (9) is the most favorable way to recognize abnormal states of an object even at the early stages of monitoring.

6. CONCLUSIONS

This paper deals with the maintenance decision support problem with the processing of images gathered by condition monitoring system. A new method is proposed (table) to recognize abnormal conditions. This method relies on historical data accumulated over time to increase the reliability of the decision-making (Fig. 4). Thus stated, the task is shown to differ considerably from the conventional classification problem in that the training sample holds situations the correct reaction to which (the class label) is unknown. In the proposed method when a binary classifier is built for each action, the training sample expands through negative examples of other actions, which lowers the error rate (Fig. 3). Using a simple modeling experiment, we showed that the approach allows higher accuracy even with a small size N_0 of the initial training sample (Fig. 3). It turns out that the accuracy of our method is 9–15% higher than that of conventional contextual multi-armed bandit algorithms and 0.5–3.2% higher than with the realization of the Boltzmann random strategy (3), (10) for nonparametric Nadaraya-Watson regression (4), (6).

The further research on the method can be outlined as follows:

(1) The use of the method for analysis of visual data in condition monitoring of real objects (e.g. main gas pipelines [1]). Here the primary attention should be payed to the complexity of available data and the reliability problem of decision-making in the absence of information about the right action in historical data.

(2) The use of adaptive versions of complex binary classifiers (e.g. support vector machine, relevance vector machine and its modifications [28], or k-nearest neighbors algorithm) instead of the PNN (5) at the second stage of the method (see table).

(3) The adaptation of the method to the case when an abnormal situation allows many possible reactions or a chain of consecutive actions.

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