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Decision support in intelligent maintenance-planning systems based on contextual multi-armed bandit algorithm

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Abstract

In this paper we focus on two essential problems of maintenance decision support systems, namely, 1) detection of potential dangerous situation, and 2) classification of this situation in order to recommend an appropriate repair action. The former task is usually solved with the known statistical process control techniques. The latter problem can be reduced to the contextual multi-armed bandit problem. We propose a novel algorithm with Bayesian classification of abnormal situation and the softmax rule to explore the decision space. The dangerous situations are detected with the Shewhart control charts for the distances between the current and the normal situations. It is experimentally shown, that our algorithm is more accurate than the known contextual multi-armed methods with stochastic search strategies.

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Keywords: maintenance decision support system; pattern classification; statistical process control; contextual multi-armed bandit.

1. Introduction

Improving the efficiency of maintenance decision support systems is an acute problem in monitoring of mobile network equipment, public transport, pipeline control, etc.[1,2]. Such operations support system typically sequentially solves two tasks: 1) detection (or prediction) of potential emergencies, and 2) classification of the discovered dangerous situations in order to provide a schedule for future repair. Our experience in development of the gas pipeline monitoring[3] and NetBoss XT operations support system has demonstrated the following observation.

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Though the rules to discover emergency and recommend appropriate repair action can be provided by the specialists based on the data gathered by the monitoring subsystem, the decision-maker can miss the most effective action, especially under time pressure and when a problem has many possible solutions. That is why much attention in recent developments has been paid to automatic detection and classification of potential emergencies. Historic data about earlier faults is used for learning[2]. Unlike conventional classification task[4,5], available data often do not include the correct action; rather the result of recommended action (positive or negative) is only available. Moreover, the failures are quite rare events, so the training data is usually very small and online learning should be applied[6]. Hence, an effective decision-making algorithm should use not only available historic data, but also explores the decision space. In fact, it is the special case of reinforcement learning scheme with exploration-exploitation dilemma[7].

In this paper we propose a decision-making algorithm in intelligent maintenance-planning systems, which can be successfully used even for small-sample-size problem[6]. At first, the potential emergencies are detected with the known statistical process control techniques, namely, Shewhart control charts for the distances between situations[8,9]. When the dangerous situation is detected, the repair action is recommended by using the empirical Bayesian classifier[4]. If the size of the training sample is rather small, the softmax (Boltzman) stochastic strategy is used to increase the search diversity[10].

The rest of the paper is organized as follows. In Section 2 we remind several methods for statistical process control and contextual multi-armed bandit problem[11]. In the last part of this section the complete maintenance-planning algorithm is presented. In Section 3 experimental study is shown for synthetic data generated by the Bayesian network. Finally, concluding comments are given in Section 4.

2. Materials and Methods

2.1. Statistical process control in maintenance-planning systems

Let the intelligent maintenance decisions support system periodically observes the states of $L \geq 1$ objects, e.g., segments of gas pipeline[3,12]. The state of the l-th segment at time $t=1,2,\ldots$ is described by a feature vector $\mathbf{x}_l(t)$ of dimensionality M. As it was stated in introduction, the first task is to detect as soon as possible the segment l^* and time t^*, at which the state of this segment becomes potentially dangerous. In this paper we do not deal with fast destructions and predictions of robustness after natural catastrophes[12]. We will primarily focus on maintenance planning for rather *slow* degradation of the observed object, e.g., corrosion or geometrical distortions of the gas tube. In such case, the most obvious way to solve the task is to apply well-known statistical process control techniques[9]. If only $M=1$ feature is observed, then the most widely used approach is the Shewhart individual control chart[8]. According to this method, an average state $\bar{\mathbf{x}}_l(t) = \frac{1}{t-\Delta t}\sum_{t'=1}^{t-\Delta t} \mathbf{x}_l(t')$ and moving range $\overline{\Delta \mathbf{x}}_l(t) = \frac{1}{t-\Delta t-1}\sum_{t'=2}^{t-\Delta t} \left|\mathbf{x}_l(t') - \mathbf{x}_l(t'-1)\right|$ are estimated. Here $\Delta t>0$ is a time delay, which guarantees that only non-dangerous situations are aggregated. Finally, the statistics $\left|\mathbf{x}_l(t) - \bar{\mathbf{x}}_l(t)\right| / \overline{\Delta \mathbf{x}}_l(t)$ for the current state $\mathbf{x}_l(t)$ is computed. If it exceeds a certain threshold (usually, 2.66), the situation at the segment $l^*=l$ in the moment $t^*=t$ is defined as potentially dangerous.

There are certain variations of the described procedure. For instance, if $M>1$ features are analyzed, the multivariate statistical process control is implemented[13] with, e.g., the Hotelling's T^2 statistic[8,14] is compared with a threshold. However, this method assumes the multivariate normal distribution of the observed feature vectors. This assumption is not usually valid. Hence, in this paper we propose a slight modification of the Shewhart chart, which does not require the data to be normally distributed. Similarly, we specify a dissimilarity measure $\rho(\ldots)$ between feature vectors. For example, the Eucliden metric is usually an appropriate choice. Next, we compute an average distance to the normal situation