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Real-Time Production Monitoring approach for Smart Manufacturing with Artificial Intelligence techniques

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Abstract—Production monitoring in real-time is a very important problem in smart manufacturing. It helps enterprises to timely detect abnormalities in the production process and then guarantee the product quality and reduce waste. In this paper, we develop a novel method to monitor the real-time production based on the Convolution Neural Network and the Support Vector Data Description algorithm. The numerical result shows that our proposed method leads to high efficient on the testing data.

1. Introduction

In recent years, industrial manufacturing processes are undergoing drastic changes towards "smart manufacturing" based on the rapid development and wide applications of advanced technologies. In the smart manufacturing, manufacturers are enabled to create and use data throughout the product life cycle with the goal of optimizing the manufacturing processes and responding rapidly to changes in the production and in the market demand [1, 2].

Among several stages in the smart manufacturing, production monitoring in real-time is a very important task. By detecting timely abnormalities in production lines, the production monitoring allows enterprises to ensure the production quality and reduce waste. Traditional methods like statistical process control (SPC) are usually used to monitor the production process [10]. In the SPC, for example, a set of samples is collected in a given time to measure the statistic that represents the characteristic of interest. When the value of this statistic exceeds a threshold, the process is said to be out-of-control. Otherwise, the process is still in-control. However, these classical methods are no longer efficient for monitoring many production process because of the real-time data created in the smart manufacturing based on the application of Industrial Internet of Things technologies for the large production lines operating continuously. Therefore, advanced models to monitor data in real-time are required.

With the high requirement in the smart manufacturing, the monitoring models should have the ability of not only timely determining when a production process is deviating from the normal conditions but also predicting when the process might start deviating from accepted conditions.

Artificial Intelligent (AI) algorithms provide powerful tools to design such monitoring models. In particular, machine learning algorithms have been recently proposed for use within Statistical Process Monitoring (SPM), which has been shown to effectively detect a variety of abnormal conditions. This approach turns the monitoring problem into an outlier detection problem or a supervised classification problem which classifies future observations as either in or out-of-control situations. Moreover, the data from smart manufacturing environment are not instance, necessarily quantitative. For instance, in many manufacturing processes, the data are collected by continuously taking pictures of products. Detecting abnormal products from these data is then the problem of concern.

By this context, we suggest in this paper a new method to monitor a real-time production process based on a conventional neuron network (CNN) and a support vector data description (SVDD) algorithm. The CNN is applied as a feature extractor to extract the core information from data in image formats [8], while the SVDD is used as a classifier to detect outliers. We apply our proposed method on data extracted from images of the steel nut to detect the defected ones. The obtained result shows that our proposed method can detect all the defected nut images in the tested dataset. The rest of the paper is organized as follows. In Section 2, we briefly present the convolution neural network learning and Support Vector Data Description algorithm. The real-time Production Monitoring approach is described in Section 3. Section 4 is devoted for an illustrative example. Some concluding remarks are given in Section 5.

2. Methodologies

Convolutional Neural Network: Convolutional neural network (CNN) is a type of feed-forward artificial neural network in which the connectivity pattern between its neurons is inspired by the organization of the animal visual cortex [6]. A convolutional neural network consists of several feature extraction stages and a classifier. The classifier of CNN generally uses a back-propagation (BP) network [7] and a radial basis function (RBF) network. In each feature extraction stage, a higher level of features is obtained through convolution operations. Each feature extraction stage includes a convolution layer and a sub-sampling layer. In particular, a convolution layer contains a series of feature maps, each of which is connected to one or more of the feature maps in the previous layer by a convolutional kernel. The convolutional kernel of size $(K \times K)$ defines the connection weights. Each neuron in the convolution layer extracts the local features at the same position in the previous part of the feature map by convolution. The convolution operation of the j^{th} feature map of the i^{th} convolution layer is calculated as

$$o_{ij}(x, y) = \tanh \left[b_{ij} + \sum_{k \in K_{ij}} \sum_{r=0}^{R_i-1} \sum_{c=0}^{C_i} w_{ijk}(r, c) o_{(i-1,k)}(x+r, y+c) \right],$$

where \tanh denotes the hyperbolic tangent activation function, b_{ij} denotes the bias parameter of the feature map, K_{ij} denotes the set of feature maps in the $(i-1)^{th}$ layer connected to o_{ij} , w_{ijk} denotes the convolution kernel between the feature map o_{ij} and the feature map $o_{(i-1,k)}$, R_i and C_i denote the number of rows and the number of columns of the convolution kernel correspondingly. The sub-sampling layer uses the region filter to reduce the resolution of the feature map in the convolution layer. The sub-sampling operation can extract the important features for classification and ignore the useless details and noise. The sub-sampling operation of the j^{th} feature map of the i^{th} convolution layer is calculated as

$$o_{ij}(x, y) = \tanh \left[b_{ij} + g_{ij} \sum_{r=0}^{N_i-1} \sum_{c=0}^{N_i} o_{i-1,j}(xN_i+r, yN_i+c) \right], \quad (1)$$

where g_{ij} denotes the gain parameter of the feature map o_{ij} , N_i denotes the sub-sampling rate of the i^{th} layer.

The CNN obtains the mapping relationship between input and output through learning. This mapping relationship is finally reflected in the network weight, which makes CNN to have the ability to extract features of input data layer by layer [5, 13]. The sum of squared the output errors is used as the system error function. The weights are updated during the training process to achieve the best performance.

Support Vector Data Description: Support vector data description (SVDD) is a technique related to One-class SVM [12]. Instead of finding a maximum margin hyperplane in feature space that best separates the mapped data from the

origin as One-class SVM, the object of SVDD is to find the smallest hypersphere with center \mathbf{c} and radius R that covers the normal instances in the training data-set [11]. SVDD is a useful method for outlier detection and has been applied to a variety of applications. Denote $\mathbf{x}_k \in \mathbb{R}^n, k = 1, \dots, N$ as a set of training data. The SVDD is equivalent to solving the following *primal optimization*:

$$\begin{aligned} & \text{Minimize } R^2 + C \sum_{k=1}^N \xi_k \\ & R, \mathbf{c}, \xi \\ & \text{subject to } \|\phi(\mathbf{x}_k) - \mathbf{c}\|^2 \leq R^2 + \xi_k, \quad \xi_k \geq 0 \quad k = 1, \dots, N, \end{aligned} \quad (2)$$

where $\phi(\cdot)$ is a function mapping data to a higher dimensional space, the parameter $C > 0$ is used to control the influence of the slack variables ξ_i . After the optimization problem is solved, a hyper-spherical model is characterized by the center \mathbf{c} and the radius R . A testing instance \mathbf{x} is detected as an outlier if

$$\|\phi(\mathbf{x}) - \mathbf{c}\| > R^2. \quad (3)$$

3. Real-Time Production Monitoring approach

In this section, we propose a novel approach for real-time production monitoring using the CNN-SVDD method. In the CNN, after extracting features from input data, the classifier like SoftMax regression is applied to classify the input. However, in this method, it is necessary to label all the possible classes for the object of interest. This requirement might be difficult to meet in many practical manufacturing processes, since in these processes the practitioners can not predetermine what kind of failures could be possible. Instead, the manufacturing data are mainly collected under normal operation condition. Therefore, we suggest to use the SVDD algorithm to classify the abnormal product from the normal one based on the features extracted from the CNN. By this method, the real-time monitoring problem is transferred to the one-class classification. In particular, the method is implemented as follows. Suppose that we have enough normal samples to train the model. Firstly, we use the CNN to extract features of the input data. The extracted features are then used as the input to train the SVDD model, i.e, to calculate the centre and the radius of the hypersphere in the SVDD. After training, the parameters of the CNN and the SVDD can define the normal class. Secondly, in real-time monitoring, images of the product are taken continuously from the process. These images are fed to the trained model to define if they belong to the normal class or not.

In practice, this proposed method can be also applied for the sampling monitoring scheme. There are several manufacturing processes where the real-time monitoring is not necessary. They could be the manufacturing processes of products that are not expensive. In these cases, monitoring in real-time is even more expensive because of the problems related to sampling and storing data. For this situation, the methods of SPM can be combined to monitoring the manufacturing process. For example, after extracting the features of input from the CNN,

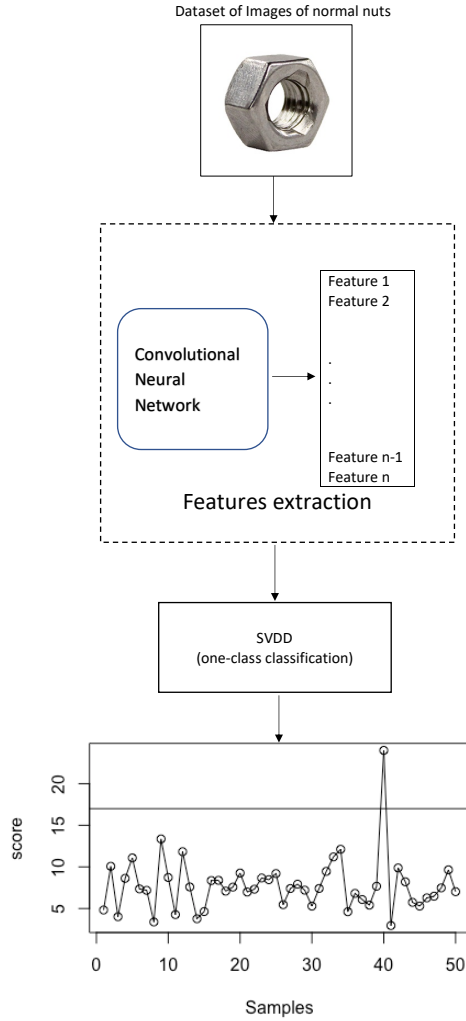


Fig. 1: Procedure of real-time monitoring scheme for detecting the defected nut.

the SVDD algorithm can be integrated with a cumulative sum control chart (CUSUM) in SPM to provide an explicit graphic for monitoring. More details of the CUSUM control chart can be seen in [10].

4. Illustrative example

In this section, we illustrate an example of our proposed method for the detection of defected nuts with their captured images. In this example, a dataset containing 100 images of normal nuts is considered as the one-class training set. Since the data is not enough to train the model, we use a transfer learning method, which is the method of storing knowledge gained while solving one problem and applying it to a different but related problem. In particular, we use the pre-trained CNN AlexNet [9]) to extract the feature vectors at the 'fc7' layer.

The pre-trained CNN AlexNet is trained on 1.2 million

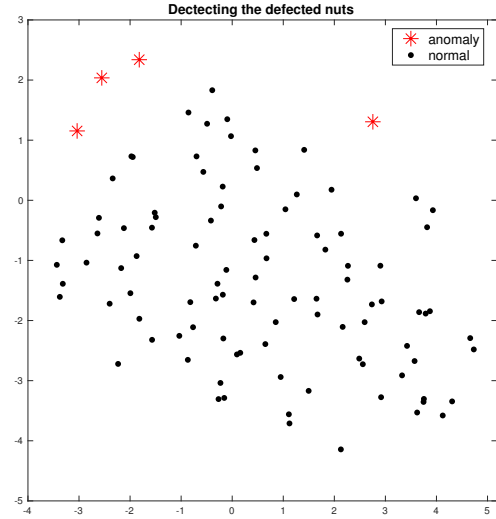


Fig. 2: The defected nuts detected with CNN-SVDD.

images and can classify images into 1000 object categories [6]. It consists of 8 weight layers including 5 convolutional layers and 3 fully-connected layers, and three max-pooling layers are used following the first, second and fifth convolutional layers. The first convolutional layer has 96 filters of size 11×11 with a stride of 4 pixels and padding with 2 pixels. The stride and padding of other convolutional layers are set as 1 pixel. The second convolutional layer has 256 filters of size 5×5 . The third, fourth and fifth convolutional layers have 384, 384 and 256 filters with size of 3×3 respectively.

The feature vectors extracted using Alexnet will be trained using SVDD. In [4], the kernel method with one-class SVM and pre-trained AlexNet was developed for Image anomaly detection for production line. However, as described in Sec. 2, the SVDD algorithm solves for the optimal hyper-spherical to cover the origins. In the real-time monitoring, the advantage of SVDD compared to One-class SVM is that SVDD can be applied to develop a method in quality control, which requires the existence of the control limits. Moreover, after the process was running for a long time, we can collect the dataset of the images of defected nuts. The updated dataset can be used retrain the feature vector for the system. Fig. 1 presents the scheme of the detection system.

Fig. 2 shows the results of detecting the images of defected nut. According to experimental results, 100% of defects can be detected effectively. The model can be combined with the machine vision system to realize the real-time intelligent monitoring of production line [3].

5. Conclusion

In this paper, we have presented a new approach using convolution neural network and support vector data description for real-time monitoring in smart manufacturing. The proposed

method is tested with the images of steel nuts, which shows a promising result. However, more experiments are required to evaluate the performance of the proposed method. Moreover, a study on developing an application of this method on statistical process control is being executed.

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