Design and Study of Mechanical Monitoring Terminal Monitoring System Based on Reel Neural Network

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Abstract. With the development of the times, the society is slowly progressing, the era of information technology has come. With the research of computer technology and the development of artificial intelligence technology, various algorithms have been put forward and popularized. Among them are widely used expert algorithms, genetic algorithms, and a special co product neural network algorithm. In this paper, the mechanical monitoring terminal monitoring system is designed by using the reel neural network. After consulting a large number of literatures at home and abroad and watching the relevant models and starting to model them simply, this paper uses the existing resources of the laboratory to apply distributed network control through the use of multiple computers to assemble the central control system, so as to carry out experimental simulation, and get the analysis results. The final experimental results show that the co product neural network algorithm has better application in the monitoring system than other algorithms, and the data capture speed is faster and the analysis is more accurate.

Keywords: Reel Neural Networks, Modeling, Mechanical Monitoring, Program Optimization

1. Introduction.
The target detection algorithm based on deep convolution neural network brings a new research direction for mechanical detection, and leads the development progress of mechanical detection [1]. Therefore, after investigating the current social environment, we finally choose the target detection algorithm based on deep convolution neural network as our experimental algorithm after verifying a variety of algorithms and comparing and analyzing the various performance of mechanical monitoring.

Because in the current social environment, the advent of the information age is inevitable, in the future, people's dependence on computers and information technology will be more and more serious [2]. However, based on the current situation, the benefits of informatization for human society are greater than the harm, because informatization can use data collection, analysis and other means to replace manual for better services [3]. For example, in today's industrial era, people can use a variety of intelligent mechanical means instead of manual to deal with some dangerous things and manufacturing machinery industry, and save resources and liberate labor force to cope with other
situations while ensuring a high success rate. Moreover, the advent of the information age has also played a good role in social progress [4]. For example, in the past, it was difficult to find out the culprit once the theft broke the law. But now, after comprehensive monitoring, we can use information comparison, head image recognition and a variety of high-tech methods, such as DNA verification, to find out the real prisoners [5]. Therefore, based on the above situation, we believe that the industrial age has entered the era of information, information will inevitably penetrate into all walks of life. Therefore, based on the purpose of this paper, we have launched a set of mechanical monitoring terminal monitoring technology in the machinery industry according to the informatization, so as to monitor the problems and performance of mechanical products more conveniently [6].

In recent years, with the development of science and technology, especially the microelectronic information technology has been a huge breakthrough, so that the condition monitoring and fault diagnosis technology has been a huge development [7]. Since the 1980s, China has started the research on condition monitoring and fault diagnosis technology, and so far, a relatively complete technical system has been established [8]. For the object of this study, there are usually a variety of technologies to choose from, but there are two most commonly used technical means. One is based on the traditional transfer function diagnosis technology; the other is based on the popular artificial intelligence diagnosis technology. According to the object we want to study, we finally choose the diagnosis technology based on artificial intelligence. But the detection technology is not only using artificial intelligence technology, but also using some other auxiliary methods for auxiliary monitoring [9]. For example, the use of Bayesian method, time series method and other mathematical methods, because it needs to form a set of basic monitoring methods, and expert system, neural network and other major system design. The purpose of this paper is to use neural network as the main monitoring means and other methods as auxiliary monitoring means to design the whole mechanical monitoring system [10].

2. The Target Detection Algorithm

2.1 Loss Function

The SSD loss function is divided into two parts: position loss and confidence loss. Confidence loss uses SoftMax loss function to calculate the probability that the algorithm classifies correctly. Position loss uses the SmoothL1 loss function to calculate the error between the real box and the coordinates of the prediction box. The loss function is expressed as

$$L(x, c, l, g) = \frac{1}{N}L_{conf}(x, c) + \alpha L_{loc}(x, l, g)$$  

(1)

In the pattern: for the total loss $L(x, c, l, g)$; for the confidence level $L_{conf}(x, c)$; for the prediction box $l$; for the real box $g$; for the weight $\alpha$; for the number of matches between the prediction box and the real box; when the intersection ratio is greater than the threshold $\delta = \{1, 0\}$ (take 0.5 in this article), the real box matches the prediction box, take it, otherwise $\delta = 0$. The position loss function is defined as

$$L_{loc}(x, l, g) = \sum_{i \in P} \sum_{j \in \mathbb{E}} \sum_{m \in \{c, c, c, c, w, h\}} x_{ij}^m \text{SmoothL1}(l_{ij}^m - \hat{g}_{ij}^m)$$  

(2)

$i \in P$ In the pattern: indicates that the first prediction box area is a positive sample, which represents a positive $k$ sample; $c$; the offset along and direction between the prediction box or the real box and the center of the default box $y_{ij}^m \in \{0, 1\}$ box, the difference between the prediction box or the true box and the width $i$ and height of the default box; and the category, otherwise when $j$ the first prediction box matches the first real $x_{ij}^m = 1$ box $x_{ij} = 0$ is $\hat{g}_{ij}$ the real box position parameter after encoding; $l_{ij}^m$ The SmoothL1 function is represented as

$$L_{conf}(x, c) = -\sum_{j \in \mathbb{E}} x_{ij}^m \log (\hat{c}_{ij}^m)$$  

(3)
In formula: \( i \in N \) indicates that the first prediction box area is a negative sample, representing a negative sample, \( N \) and for the probability of a correct \( \hat{c}_i^0 \) and category background prediction box, the probability \( \hat{c}_i^p \) value calculated using the SoftMax function can be represented as

\[
\hat{c}_i^p = \exp(c_i^p) \frac{\exp(c_i^p)}{\sum_p \exp(c_i^p)}
\]

(4)

3. Experiment.

3.1 Selection of Experimental Data
A random sample of 100 staff members of a laboratory who studied the reel neural network model in depth was asked to conduct a questionnaire. Two sets of questionnaires were used, the first set of questionnaires is about the use of old manual testing to deal with mechanical monitoring problems, and the second set of questionnaires is based on the study of deep learning reel neural models to solve mechanical monitoring problems.

3.2 The Experimental Process
In order to obtain more fair and reasonable data, we repeated the experiment several times and recorded the data, measured the average, relative deviation value, and then compared the scheme to show the advantages and disadvantages.

4. Evaluation Results

4.1 The Results of the Questionnaire are Displayed
The results of the feedback from the questionnaire are shown in Table 1, Figure1. Comparing the results data in Table 1 and 1, it is not difficult to find that the use of reel neural network models to solve mechanical monitoring problems is more popular than the use of traditional manual controls.

| Evaluation attitude | A new approach | Traditional methods | Total number of copies/servings |
|---------------------|----------------|---------------------|--------------------------------|
| Excellent.          | 120            | 25                  | 145                            |
| So so.              | 56             | 27                  | 83                             |
| Poor.               | 24             | 148                 | 172                            |
| Total number of copies/servings | 200            | 200                 | 400                            |

Table 1. On the evaluation of the co product neural network model by the mechanical plant staff

Through the data in Table 1, it can be found that the professional staff working in the machinery factory for a long time are biased towards using a new reel network to solve the image problem, we found that 60% of the work on the new method of praise, and for the traditional method the vast majority of people think that its eye injury is harmful to the body and feel that it is not possible. These data come mainly from professionals who have studied deeply and mastered the new reel neural network model, indicating that the new model is indeed more efficient and convenient than the previous model in terms of mechanical monitoring problems.
Figure 1. About the evaluation of the co product neural network model by the mechanical plant staff

On the basis of Table 1, we constructed a column chart, which shows the evaluation of the two methods by professional staff more intuitively through Figure 1, highlighting the advantages of the new model in dealing with problems.

After this questionnaire we mainly draw the professional staff involved in the further inquiry detailed attitude point of view to make an evaluation, to find a better way to solve the image problem and way out, but found that the results are still too one-sided, so we try to from other experts engaged in mechanical monitoring to draw some views, the results of the experiment as shown below.

4.2 The Views of Other Experts Involved in Mechanical Monitoring

Figure 2. On the views of other experts involved in mechanical monitoring

Data from Figure 2 show that most of the experts involved in the second survey, after seeing the new reel neural network model, thought that the model was performing well in the process of
processing and analysis, but there was room for improvement and that we could do better, so we thought we could improve it later to produce better experimental results.

4.3 Structural Characteristics of the Reel Neural Network Model
The reticulation neural network is a kind of neural network, which includes the reticulation calculation and other structures. In today's mechanical algorithms, it belongs to the learning algorithm and exists in deep learning, so we can also call it the deep co product neural network algorithm. Its essence is to make data processing simpler and more suitable for data processing in network models through multi-level distributed connections through multiple preceptors. It reduces the complexity of the model and reduces the risk of data fitting due to excessive data complexity. It extracts some data from a multi-layered network for better operation and accuracy, is a neural network based on supervised learning, and its core is in the hidden reel layer, extracting the characteristic information we need through multiple neurons and reel filters.

4.4 The Advantages of the Reel Neural Network Model
The difference between reel neural networks and other neural networks is that as the number of self-building layers increases, its model fits better and better, and its recognition and accuracy efficiency increase. However, its number of layers cannot be increased too much, because too much increase will make its convergence fitting more difficult, inefficient training. But if it has too few layers, its analog fit and recognition rate are also reduced, so it has a spike in existence. We need to perform data experiment simulations to ensure peak points in order to get the number of data fitted reel layers we need to optimize the experimental model. Because when we monitor machinery using models built by reel neural networks, we also image the machinery and then classify the images. We first preprocess the image, then input the entire image into the model and then output the classification. However, because individual images have small differences in the boundary is not easy to handle, so sometimes to blur resulting in image classification accuracy is not very high. Therefore, the reel neural network model designed in this paper has multi-region characteristics, which supports multi-directional design and input and output, ensuring that the function is more rich, complete, the experiment is more accurate, and has a high accuracy of image classification. And the reel neural network model we designed will follow the processing of experimental data and the analysis of images to self-monitor learning, because it belongs to artificial intelligence. It will continue to analyze and process similar content many times to obtain accurate results to ensure that the experiment is more and more perfect, more and more accurate.

4.5 Applications for Deep Learning
Deep learning is a new research direction of machine learning. His original goal was to use machine self-learning to achieve artificial intelligence similarity. However, most of the deep learning studied at present is based on the multiple analyses of big data samples to establish a database to compare and analyze the data, and get experimental results. Its ultimate goal is to give machines the same analytical and learning abilities as humans, and to recognize data such as text that is as self-thinking as the ultimate artificial intelligence.

4.6 Mechanical Monitoring
Mechanical monitoring is mainly to monitor the working condition of the whole or parts of the machinery and equipment in operation, to determine whether its operation process is normal or whether there are any other problems, or to analyze and deal with the abnormal situation, to predict whether its future trend is deteriorated or optimized. The purpose of mechanical monitoring is to grasp the normal information and abnormal information before the failure of the equipment, in order to deal with the situation in the future and reduce the occurrence of failure, thereby reducing the overall loss caused by mechanical abnormalities and improving the effective utilization of the equipment.
5. Conclusion.
In the post-industrial era and the era of large machines, information technology has become more and more important, because many processes are not manually able to complete, such as the precise analysis of large machine design (micron scale or even nanoscale), or like some data analysis statistics, such as 12306 ticketing system and so on. This is done either by precisely designing a large, redundant, non-human calculation of data, and by applying more extensively to artificial intelligence or computer technology, as we do when monitoring machinery. Because the entire machinery is made of integration or parts, each part has a part of the task, once a link error, will lead to the whole stagnation, which will cause a huge loss of economic benefits. So, in order to prevent this from happening, we designed a mechanical monitoring terminal monitoring system based on the real neural network to analyze the whole in real time, to ensure that we can quickly and accurately identify the problem and solve it, to ensure that the operation of the machine will not be affected, the overall task will not be delayed, to achieve our goal. In the existing environment, the real neural network is a good model, but in the future, we believe there will be better algorithms to apply it. So, looking forward to a better model is also our future wish.

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