RESEARCH ON OPTIMIZATION OF AGRICULTURAL MACHINERY FAULT MONITORING SYSTEM BASED ON ARTIFICIAL NEURAL NETWORK ALGORITHM
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基于人工神经网络算法的农业机械视频监控体系优化研究

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ABSTRACT
Aiming at the demand of mileage statistics, work area statistics, fault site return and related data automatic retention in the current agricultural machinery reliability appraisal process, the optimization of agricultural machinery video monitoring system based on artificial neural network algorithm was studied. Together with the new video monitoring technology, the agricultural machinery GPS, GSM and fuel consumption recorder technology are combined to realize the functions of real-time data transmission, monitoring, analysis and statistics. Aiming at intelligent fault analysis, a real-time online detection mechanism is proposed, and a cloud collaborative detection mechanism is proposed to solve the problem of inaccurate offline model detection. Use plane map or satellite map to browse. Thus, an online monitoring and visual testing platform for agricultural machinery faults without real-time monitoring records is established. Finally, the test platform is tested and applied. Test results show that the algorithm can greatly shorten the training time and improve the accuracy of training model detection. With the increase of online training iterations, it is helpful to improve the detection accuracy of the generated model. In a word, the system service platform can provide scientific and transparent data for agricultural machinery fault identification, ensure the scientific, open and fair principles of agricultural machinery fault identification, and greatly improve the efficiency of agricultural machinery management.

摘要
针对当前农机可靠性鉴定过程中里程统计、工区统计、故障点返回及相关数据自动保存的需求，研究了基于人工神经网络算法的农机视频监控系统的优化。结合新的视频监控技术，将农机 GPS、GSM 和油耗记录仪技术相结合，实现实时数据传输、监控、分析、统计等功能。针对智能故障分析，提出了实时在线检测机制，并针对离线模型检测不准确的问题，提出了云协同检测机制。使用平面地图或卫星地图浏览。建立了无实时监测记录的农机故障在线监测与可视化测试平台。最后，对测试平台进行了测试和应用。实验结果表明，该算法可以大大缩短训练时间，提高训练模型检测的准确性。随着在线训练迭代次数的增加，有助于提高生成模型的检测精度。总之，该系统服务平台可以为农机故障识别提供科学、透明的数据，保证农机故障识别的科学、公开、公平原则，大大提高农机管理效率。

INTRODUCTION
In recent years, our country has paid more attention to the research and development of new agricultural machinery technologies and tools. It is easy to identify whether the performance and economic indicators of newly designed agricultural machinery meet the design requirements, but it is difficult to evaluate whether its reliability meets the requirements *(Bajaj J. et al., 2020)*. With the dramatic increase of video data generated by camera equipment, how to deal with these data has become a thorny problem. In the process of agricultural machinery work, the traditional video surveillance needs supervisors to pay attention to the front surveillance picture all the time, but it is limited by human physiology. The supervisors cannot concentrate on the picture all the time. It is very easy to omit important monitoring information and cannot accurately obtain sensitive information *(Caixal G. et al., 2021)*.

The number of channels of monitoring equipment is proportional to the number of monitors needed. While the number of video channels increases, it needs to increase the huge human cost. In addition, in order to understand the occurrence process of the event after the monitor omitted some important real-time images, it is necessary to filter and interpret the massive video data manually. In this process, it also requires a lot of physical work and time *(Gandjbakhch E. et al., 2020)*. From this, we can see that the traditional video surveillance equipment only has the function of video playback and storage, and does not have the ability of video analysis and processing. In the process of using, it needs a lot of manpower and material resources, and pays a great cost. It has been difficult to meet the needs of modern society for security equipment. In this context, people pay more and more attention to the active security system equipment based on intelligent video surveillance *(Hassan M. M. et al., 2020)*.

Combining with the transcoding process of video stream, three schemes of capturing video frames from video stream are proposed, and the capturing time of three schemes is compared. The experimental results of three schemes are given under the multi-channel fast detection mechanism. Based on the artificial neural network algorithm, the process and principle of cloud cooperative detection mechanism are elaborated in detail. The pedestrian detection technology of HOG + SVM is analysed. The principle and process of off-line learning and on-line learning of agricultural machinery are introduced. Finally, the experiment verifies that the model learning efficiency is higher and the model detection effect is better by using the cooperative detection mechanism of agricultural machinery cloud.

The innovation of the research is to build an efficient video stream transponder for agricultural machinery and a platform for intelligent detection. It provides an application interface for other video surveillance processing algorithm models, facilitates the combination of machine learning model and video server, and improves the accuracy of the model through manual feedback and online incremental training. At the same time, while reducing the cost of manpower and material resources brought by agricultural machinery monitoring system, it also improves the monitoring efficiency of the monitoring system, and lays the foundation for the construction of an active monitoring mode which integrates pre-prevention, real-time response and assistant decision-making.

The optimization of agricultural machinery video surveillance system is studied based on artificial neural network algorithm. Based on the artificial neural network (ANN) algorithm, three schemes of capturing video frames from video streams are proposed. Then the proposed method is simulated on VS2010 IDE. The results of traditional SVM training model and incremental SVM training model are compared. The experimental results show the superiority of the design system.

Kariki O et al.'s research shows that during the actual use of agricultural machinery, if there is a certain deviation between the actual construction state and the original design state, a failure will occur, and the entire machine cannot continue to work or some functions cannot be realized. This will affect its actual production to a certain extent *(Kariki O. et al., 2020)*. However, in the process of actual work, it is inevitable that certain wear and circuit problems will occur between the machines. The long-term component friction will cause the gap and position between the different components to be misaligned, resulting in the fact that the machine cannot be used normally. *Kayraklioglu E et al.* pointed out that according to the current actual use of agricultural machinery, the most common failure causes in the current use of common agricultural machinery are: illegal work by operators, wear and tear of mechanical parts, corrosion and aging, and wear of parts, and electrical fault lights of agricultural machinery *(Kayraklioglu E et al., 2021)*. *Luz E et al.* introduced intelligent algorithm into equipment management of production workshop. Infrared monitoring system was installed to effectively supervise the use status and lease of equipment. Good results were achieved and work efficiency was greatly improved. *(Luz E. et al. 2021)*. *Mohibi S. et al.* pointed out that although video surveillance technology has made great progress, there are still many defects in traditional closed-circuit video surveillance system and digital surveillance system. The most notable one is that many incidents occur in video pictures, which require people to review videos afterwards, investigate and collect evidence, make detailed judgments, and fail to give full play to the initiative of video surveillance *(Mohibi S. et al., 2020)*. Pesut B. pointed out that intelligent video surveillance system, as a higher-end video surveillance application, can solve a series of problems such as management, forensics and so on. It combines machine vision algorithm with traditional video surveillance system by virtue of computer's powerful computing ability and data processing ability, thus improving the intelligent processing ability of surveillance system *(Pesut B et al., 2020)*. Pi J. et al. pointed out that in the development of agricultural remote monitoring; video technology plays a direct role in determining the quality of monitoring.

Applying Internet of Things technology to it can effectively improve the efficiency of video technology *(Pi J. et al., 2021)*. *Provvidenza C et al*. applied video surveillance coefficients to the supervision of factory robots. The application of far infrared technology can play a good supervisory role for robots within 100 meters from the camera, which is a breakthrough in the application of video surveillance in production *(Provvidenza C. et al., 2020)*. *Romney W et al*. pointed out that although the current video surveillance technology has made some progress, it is easy to be affected by the changes of the environment in the process of outdoor surveillance, applying wireless sensor technology to it, effectively reducing the impact of the surrounding environment on the quality of video surveillance *(Romney W. et al., 2020)*.

From this point of view, scholars have rich research on video surveillance, the development of video surveillance provides great convenience to people, and there is an urgent need for its development. However, the current research on video surveillance of agricultural machinery is still less, there is a certain theoretical blank, so based on the previous research, this paper studies it.

MATERIALS AND METHODS

Collaborative detection mechanism

Neural network is an operation model, which consists of a large number of nodes (or neurons) connected with each other. Each node represents a specific output function, called an excitation function. The connection between two nodes represents a weighted value for the signal passing through the connection, which is called the weight, which is equivalent to the memory of the artificial neural network. Based on the artificial neural network, the pedestrian detection algorithm is implemented in the system, which enables the camera to detect pedestrians or vehicles in the real-time video stream acquired in the deployment area. The accuracy and robustness of the detection algorithm are the bottlenecks restricting the overall performance of the system *(Shankar K. et al., 2020)*. To get rid of this bottleneck, cloud-based collaborative detection mechanism is adopted. As shown in Figure 1:

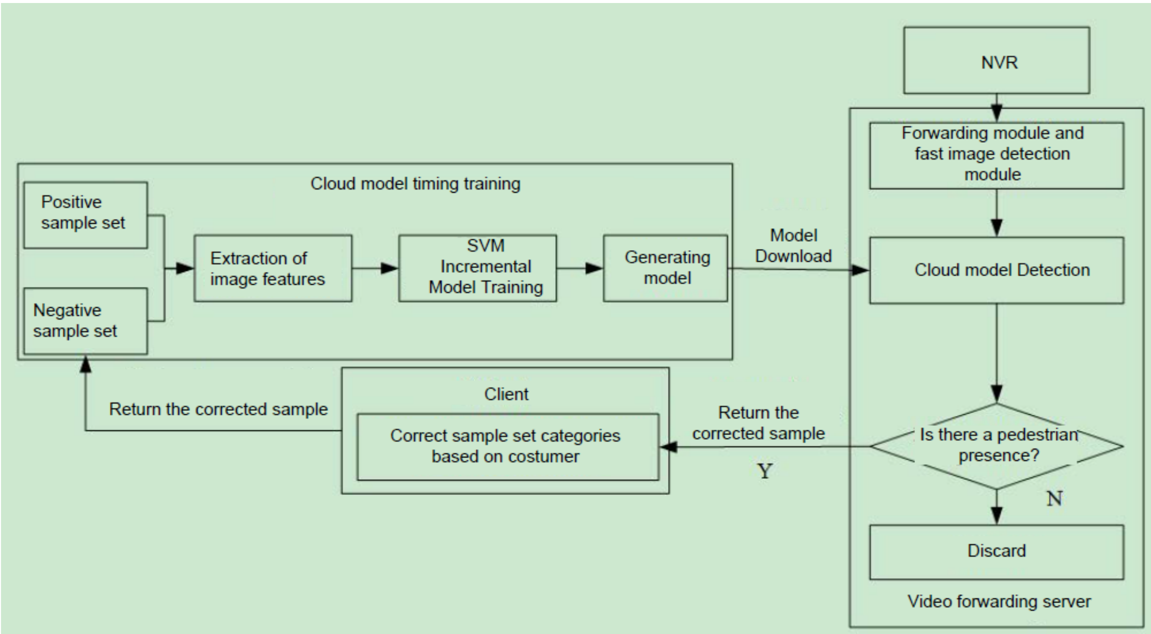

Fig. 1 - Flow chart of collaborative detection mechanism

When the video server starts to run, it will open the same number of video stream forwarding sub-threads according to the number of channels applied by the client. At the same time, the video server will also apply the corresponding sub-threads to capture the key frames in the buffer quickly by using the optimal scheme, and use the key frames as the effective pictures of the video to analyse whether there are any abnormalities. In this mechanism, the detection sub-threads and the completion of video stream forwarding sub-threads are independent of each other *(Warner E. et al., 2020)*. After the video server finishes capturing the video frames with potential abnormal behaviour, it extracts the features of the video frames by using the directional gradient histogram (HOG), extracts the video frames to be detected into vectors, and then detects them with the off-line training model, and sends the results to the client.

If the test result is abnormal, the client will remind and send the abnormal image to the customer, so that the customer can browse the abnormal conditions in the monitoring area. If the detection result is not abnormal, the detected image will be discarded. After the detection sub-thread completes these tasks, it will detect the image in the next detection time according to the response of the timer *(Zhao J. et al., 2020)*. The abnormal image sent to the client will be correctly labelled after the client has finished viewing, and then sent to the cloud server to update the sample set deployed on the server side. In this way, the sample set of the model will be continuously revised. After the change of the sample set, the mechanism will be applied to conceptual application of online learning. The server will train the existing model incrementally and regularly, and the completed model will be applied to the secondary detection of the video server. Through this model updating method, the accuracy and robustness of the system in specific scenarios can be improved.

The training process of the model is shown in the following figure: Firstly, the training sample is tailored to a suitable size, and the image is selected by directional gradient histogram (HOG). When feature selection is carried out, the detection sub-parameter file is generated according to the specific sample set, and the trained model is saved locally. According to the HOG feature extraction process, every picture in the sample set is extracted into one-dimensional vector. All the vectors generated by the image will participate in the training of SVM. Before the training of SVM, the corresponding parameters will be selected according to the actual needs. After setting the parameters, the training of SVM model will begin. The function flow chart of offline training module 2 shows:

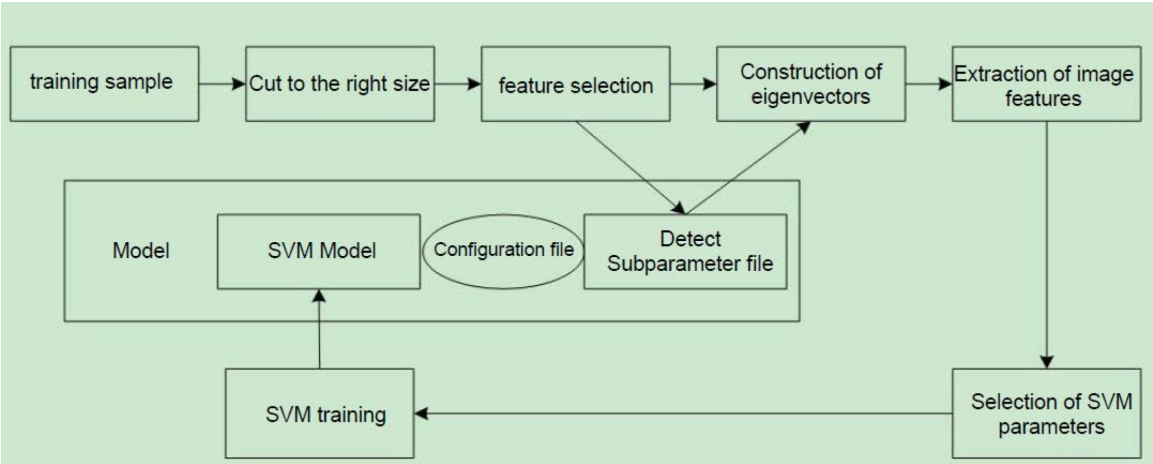

Fig. 2 - Flow chart of offline training module

The concept of online learning belongs to the category of incremental learning. The basic idea of online learning is to make the model perceive the environmental changes of the equipment deployment area by learning the image features of the new samples, to solve the disadvantage of the previous system algorithm model which is too single, and to improve the accuracy and robustness of the algorithm. Online learning is very suitable for the iterative updating of models in the case of continuous sample growth. Nowadays, most enterprises are applying off-line trained models and deploying them to predict or classify on-line. The model trains and learns the newly added data online. Only after collecting these new data in the background, the model integrates the new data with the original data before training. Compared with the incremental training method, this method not only wastes the storage space of the machine, but also wastes a lot of training time.

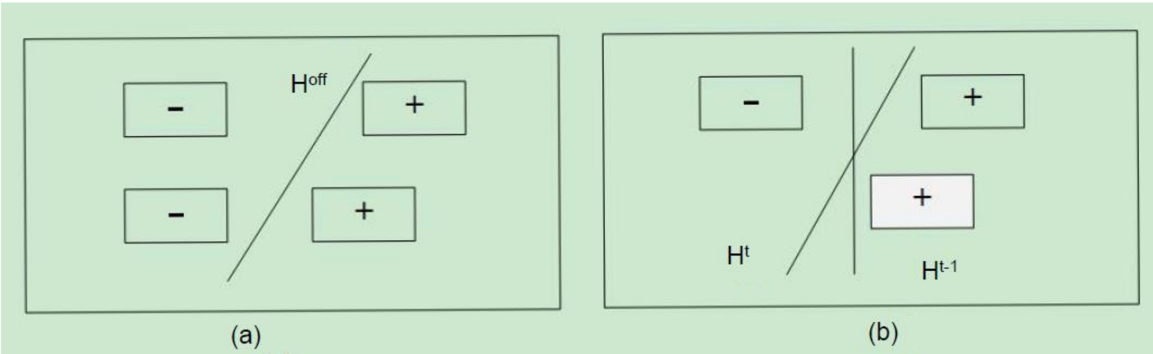

Fig. 3 - Principles of offline and online learning

The online learning process is shown in Figure 3. A chart shows the offline learning process and b chart shows the online learning process. The dotted line represents the initial classifier, in which the blue box represents the newly added samples for online learning. The newly added samples can be seen from the graph, and the classifier can be updated in real time. This process simulates the self-learning process of human beings and updates the decision-making power by constantly recognizing new things. In the online learning stage of the system, the video server sends the detected image to the client for alarm broadcasting. The client user determines the result. If the server judges the image without pedestrians as having pedestrians, then the client marks the image as a negative sample and sends it to the cloud server. When the cloud model is trained again, the information of the new sample set can be learned, and the pedestrian detection effect of the model under this background can be enhanced in continuous learning.

The online learning process is shown in Figure 4.

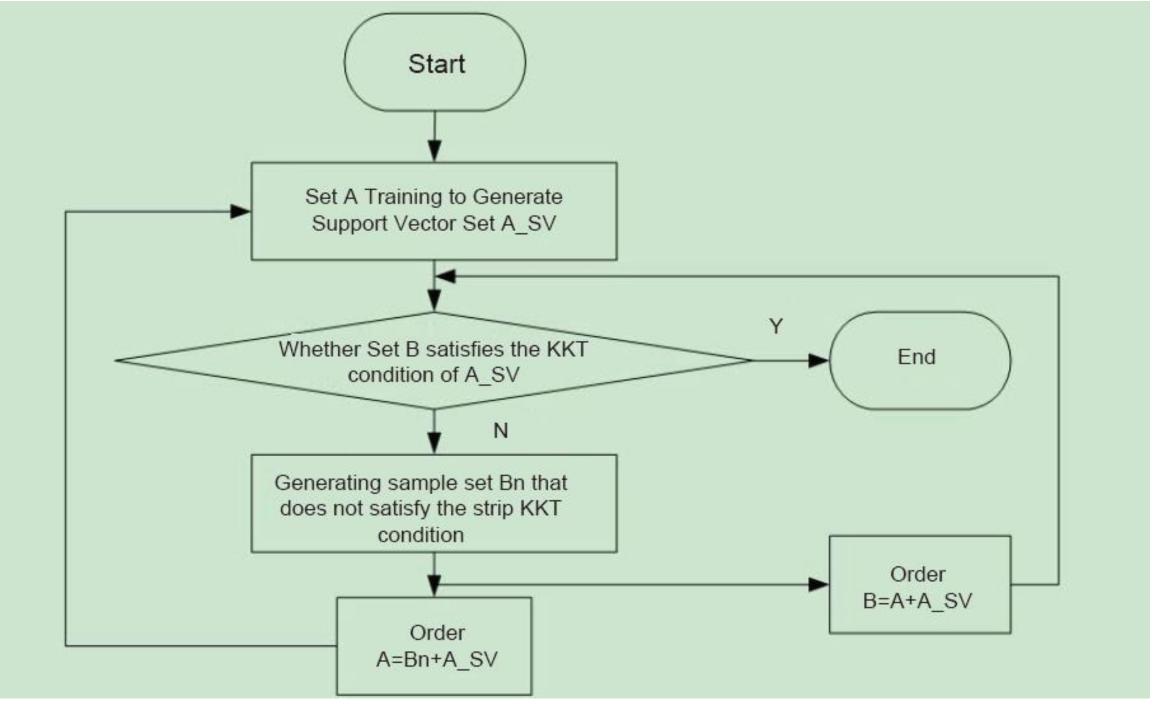

Fig. 4 - Incremental learning flow chart

The sample set of offline learning is A, the newly added sample set is B, the classifier trained by A is PA, and the support vector set of PA is SA_SV. The A_SV set satisfies the KKT condition. Sample B is validated according to the original KKT condition, and then the sample set B is divided into two categories according to satisfying KKT condition and not satisfying KKT condition, namely By and Bn; if Bn is empty, it ends. Otherwise, the union of A_SV and Bn is trained as a new training set, so that new model and new support vector set can be obtained; A_A_SV in A set is removed, and the remaining sample set in A is taken as a new sample set B1, so that B1 set is assigned to B, repeating the above steps; and the final result can be obtained by iterative training.

HOG Image feature extraction algorithms

Histogram of Oriented Gradients (HOG) is a feature composed of the gradient direction of the local area of a statistical image, which is often used in object detection in computer vision and image processing. Compared with other features, HOG has many advantages. Firstly, HOG operates on the local square of the image and keeps good invariance to the geometric and optical deformation of the image. Secondly, pedestrians are allowed to take some minor actions under the conditions of spatial and directional sampling and normalization, without affecting the detection effect. In an image, the shape of the local object can be described by the gradient statistical information, so each image is extracted by HOG, and the gradient statistical information is represented by the generated vector. The process of HOG feature extraction is shown in Fig. 5. Firstly, the image is regarded as a three-dimensional image of x, y and z, and then the contrast of the image is adjusted by standardizing the colour space of the image with Gamma correction method, so as to reduce the influence of local shadows and changes of the image, and also to suppress noise interference.

The normalization formula is as follows:

$$I(x,y) = I(x,y)^{Gamma}, Gammatake 1/2 \tag{1}$$

In order to capture the contour information of the image and further weaken the interference of care, the gradient of each pixel is calculated. Among them, the gradient has a direction, and the calculation formula is as follows:

$$\begin{aligned} G_x(x,y) &= H(x+1,y) - H(x-1,y) \\ G_y(x,y) &= H(x,y+1) - H(x,y-1) \end{aligned} \tag{2}$$

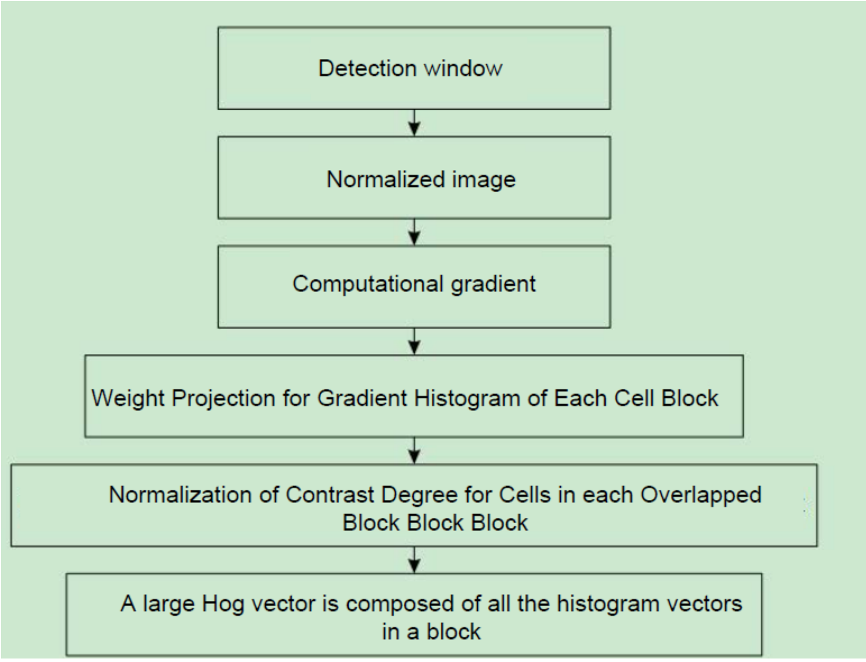

Fig. 5 - Flow chart of HOG feature extraction

Among them, $G_x(x,y)$ is the gradient of the pixels in the horizontal direction, $G_y(x,y)$ is the gradient of the pixels in the vertical direction. The formulas for calculating the gradient amplitude in the horizontal and vertical directions are as follows:

$$G(x,y) = \sqrt{G_x(x,y)^2 + G_y(x,y)^2} \tag{3}$$

$$\alpha(x,y) = \tan^{-1}\left(\frac{G_y(x,y)}{G_x(x,y)}\right) \tag{4}$$

Then the image is divided into small Cells (usually 6 x 6 pixels are a Cell); then the gradient histogram of each Cell under different gradient numbers is counted, i.e. the feature descriptor of each Cell is extracted; the fifth step is to make every three Cells into a block, and then connect the three Cell feature descriptors in series to get the block's feature descriptor. Then the HOG feature descriptors of all blocks in this graph can be connected in series to get the HOG feature of the target to be detected, which is the HOG feature vector to be extracted.

Neural network algorithms

For multi-layer artificial neural network, the interconnection mode formed by interconnection of many processing units in the neural network reflects the structure of the neural network, which determines the ability of the network. The stable structure of the nervous system stipulates and restricts the nature and information processing ability of the neural network, and limits the scope of the ability of the neural network system. At present, the structure of multi-layer neural network has been widely used because of its good performance, and the typical one is back propagation neural network (BP model).

In this kind of neural network model, the middle hidden neuron layer is introduced, so the standard BP model is composed of three neuron layers, the bottom layer is the input layer, the middle layer is the hidden layer, and the top layer is the output layer. There is a complete interconnection between neurons at all levels, and there is no connection between neurons at all levels, as shown in Figure 6.

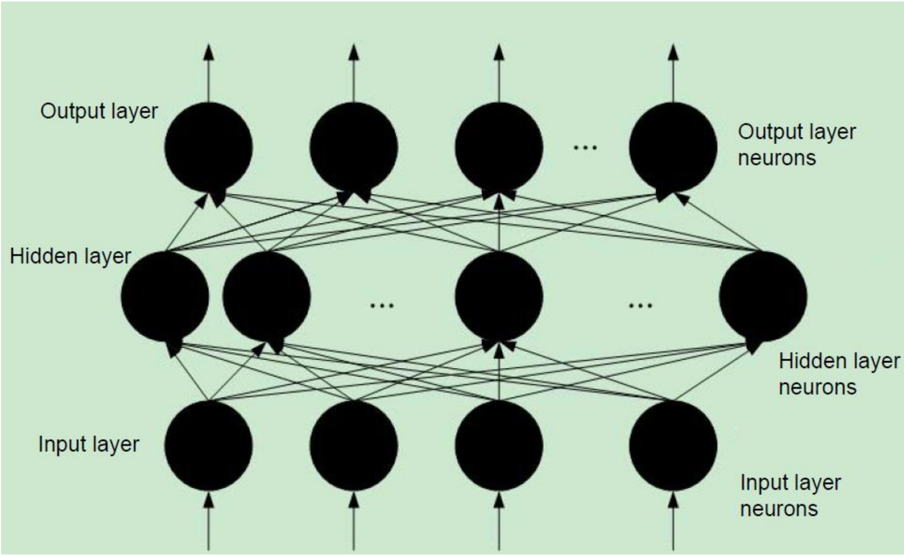

Fig. 6 - The structure of artificial neural network

The forward propagation of information and the reverse propagation of error constitute the core content of the learning process of BP model. The forward propagation here refers to the input data sample entering the network from the input layer, and then being processed by the weighted and hidden layer, the information is transmitted to the output layer for output. If the actual output information of the output layer does not match the desired output information, the learning and training process will turn to the back propagation stage of error information. In fact, the back propagation of errors is to transmit output errors in some form from hidden layer to input layer by layer, and distribute the error information to the neuron units of each layer network, and then obtain the feedback error information of each layer neuron, which can be used as the basic basis for correcting the weights of each unit. The process of information forward propagation and error back propagation as mentioned above and the process of adjusting the weights of each layer are carried out repeatedly in the learning and training stage. In summary, the continuous adjustment process of the weights between the layers has promoted the systematic training process, and finally the error of the network output falls within the allowable error range or meets other preset conditions, thus completing the training and learning process of network.

RESULS

Experimental environment

This experiment is simulated on VS2010 IDE. By comparing the effect of traditional SVM training model and incremental SVM training model, the performance of incremental SVM training results on pedestrian detection is verified, and it is suitable for use in the system. In this experiment, firstly, based on the off-line training model, its support vector set sets SA_SV, and then in the process of system operation, the image of the current person in the picture is captured, as a new sample B. For a 64*128 image, the practical process of extracting HOG features includes the following steps: after completing the above process, a 16*16-pixel block and an 8*8-pixel cell are set up in the 64*128 image window. Each block has four cells, and the number of gradient directions is bins=9. In each cell, the gradient directions of all pixels are histogram counted and a 9-dimensional feature vector is obtained. In this way, a 36-dimensional feature vector is obtained in each block, and then the sample image window is scanned by overlapping blocks. There are seven scanning areas in the horizontal direction and 15 scanning areas in the vertical direction. All the block features are connected. Finally, a 36*7*15=3780 dimension feature is obtained.

Analysis of experimental results

Off-line training module is a model generated by pre-training the sample set before the model goes online. The model generated by pre-training is not specific to specific detection scenarios. Before offline training of the algorithm, it is necessary to build an initial version of the sample library, including video frames (positive samples) containing pedestrians or other targets and video frames (negative samples) without people or other targets. In order to get a good classifier, a certain number and quality of samples are needed to represent the environmental characteristics of the monitoring equipment subordinate areas. These sample sets include as many states as possible. For example, negative samples use different illumination and angle images in the same area, while positive samples should collect pedestrian images of different ages, sexes and regions. In the off-line training module of cooperative detection mechanism, a more comprehensive INRIA pedestrian detection data set with illumination conditions and human posture in pictures is adopted, including 1218 negative sample pictures and 614 positive sample pictures. In this data set, each picture is calibrated for pedestrian area, and a rectangular frame is drawn to record the fixed point coordinates, rectangular length and width on the rectangular frame. In order to get better results when using INRIA data set, the original data is preprocessed, that is, 10 images of 64*128 size are randomly cut out from each original image, which not only increases the number of the original training set, but also increases the diversity of the original training set. The experimental results of sample distribution and iteration times are as follows:

Table 1

Comparison table of detection accuracy between traditional algorithms and online learning algorithms

Classification number	Training set	New Sample Set	Traditional algorithm		Online Learning Algorithms	
			Time /s	Accuracy rate	Time /s	Accuracy rate
2	Initial sample set	1832	976.5	83%		
	New Sample Set 1	100	1024.6	83.3%	18.3	83.3%
	New Sample Set 2	200	1119.1	84.2%	32.3	85.2%
	New Sample Set 3	200	1203.5	85.4%	31.2	85.9%
	New Sample Set 4	200	1312.3	85.6%	33.2	86.5%
	New Sample Set 5	200	1429.6	86.1%	34.3	86.7%

On-line training can adjust the number of iterations as needed. According to the experimental observation, the iteration times will affect the accuracy of the algorithm to a certain extent. The implementation of agricultural machinery fault monitoring is shown in Figure 7.

Fig. 7 - The implementation of agricultural machinery fault monitoring

The analysis of the above results is as follows: Online learning can greatly shorten the training time and effectively improve the accuracy of training model detection. With the increase of online training iterations, it is helpful to improve the detection accuracy of the generated model. The fault detection process of agricultural excavator is shown in Figure 8.

Fig. 8 - The fault detection process of agricultural excavator

The overall framework of cooperative detection mechanism, the process of cooperative detection, the process of feature extraction from HOG image and the problems needing attention in training are introduced. At the same time, the principle and overall process of cloud model off-line training and online incremental training are introduced. The simulation results show that online learning takes less time than traditional off-line training and has higher detection accuracy.

CONCLUSIONS

A video stream forwarding algorithm based on bidirectional ring buffer is proposed and implemented based on artificial neural network (ANN) algorithm and agricultural machinery video surveillance system. It realizes the efficient conversion of video frames compressed in H.264 encoding format to JPG format images captured by front-end cameras. After realizing the basic functions of traditional video surveillance, a cooperative detection algorithm based on artificial neural network is adopted. This algorithm takes the HOG+SVM pedestrian detection algorithm as the premise, applies the idea of online learning to the system, and then continuously updates the model on the iteration line, enhances the adaptability of the model to the environment and improves the accuracy of model detection. At the same time, the real-time on-line fast detection mechanism is adopted in this study. By shortening the program response time in two steps of acquiring video frames and detecting agricultural machinery video frames, the purpose of rapid detection is achieved, and valuable images are provided for subsequent detection, thereby improving the overall operational efficiency of the agricultural machinery system. Due to the limited time and laboratory conditions, some work needs to be further improved and expanded. Firstly, due to the limitation of the experimental equipment, there is no high-voltage test for the server under high concurrency. Secondly, in the online training of the model on the server, this part of the experimental process is carried out under the simulated experimental environment, because online training needs to continuously adjust the expert opinions of the test samples, and then return to the sample set on the remote server.

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