Reinforcement Learning-based Multiple Camera Collaboration Control Scheme

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***Abstract*—This paper proposes a reinforcement learning-based multiple camera control scheme to accurately monitor an object of interest or abnormal behavior. The proposed scheme recognizes the object information such as object coordinates and size using an object detection deep learning model or CCTV controller selection. The recognized object information is mapped with the cameras to be linked, and PTZ camera control values are generated and transmitted to the video surveillance system. The video surveillance system performs PTZ control according to the PTZ camera control value. The multiple camera-based collaboration control scheme can support monitoring from various angles in CCTV cameras. In addition, the accuracy of video analysis can be improved by using videos obtained from various positions or angles.

Keywords—reinforcement learning, multiple camera collaboration, video surveillance.

I. Introduction

Video surveillance systems are being installed and used by local governments and the private sector for crime prevention, traffic monitoring, and facility management. Recently, the introduction of an intelligent video surveillance system to which deep learning technology is applied is spreading [1]. To improve the performance of the intelligent video surveillance system and increase the monitoring efficiency of the CCTV controller, it is necessary to provide the object information in the video input from multiple cameras in the center of the image frame [2-3]. However, existing systems perform video analysis such as object and event detection independently without interworking multiple cameras. As a result, when an abnormal event or object of interest occurs, CCTV controllers cannot accurately monitor it [4-5].

This paper proposes a reinforcement learning-based [6-9]multi-camera collaboration control scheme for accurately monitoring objects of interest or abnormal behavior. The proposed scheme recognizes object information using a deep learning-based object detection model. Thereafter, camera control values for each camera are generated to simultaneously control multiple cameras.

The remainder of this paper is organized as follows: Section 2 describes the multiple camera collaboration control scheme. In Section 3, we describe the implementation results. Finally, Section 4 presents our conclusion.

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II. Multiple Camera Collaboration Control Scheme

The camera collaboration control scheme enables CCTV controllers to closely observe objects of interest and abnormal behavior. In addition, when performing intelligent video analysis, various types of object information can be used, so that the accuracy of video analysis performance can be improved. This technology displays various types of object images through cooperative interlocking control between the object of interest and adjacent cameras. To perform camera collaboration control, the information about the object must be obtained. It recognizes object information using a deep learning-based object detection model. The recognized object information is mapped with the camera to collaborate to generate a PTZ camera control value, and transmit it to the video security system. The video security system performs PTZ control based on camera ID and displays the video in real-time through screen division.

A. Object Information Recognition

To recognize object information such as object coordinates (x, y) and size (width, height), an object is detected using YOLOv3[10-11]. YOLO is one of the best performing object detection models. It has high object detection accuracy and high speed, so it is widely used in real-time applications. s shown in Figure 1, when an object is detected, the object information is transmitted to the intelligent video surveillance system to calculate camera control information.

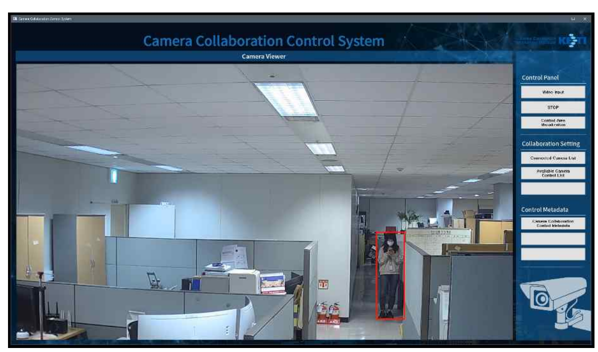

Fig. 1. Acquisition of object information using YOLOv3.

B. Multiple Camera Collaboration Engine

The multiple camera collaboration engine creates a reinforcement learning-based PTZ control model to calculate the control value for PTZ camera control using the received context information such as object coordinates and size. To train the PTZ camera control model, we collected several PTZ camera control action values of about 6000. We generate the random number of events or objects based on a predefined camera preset so that the position of events or objects can be randomly generated. It randomly assigned 500 locations for each preset to collect about 6000 training data from a total of 12 presets.

The proposed method fine-tunes DDQN(Double Deep Q Network) architecture as shown in Figure 2 [12-13]. It does not use the image as input data but uses x, y, width, and height information of events or objects. The collaboration engine generates control values of the PTZ camera using the movement direction and action value determined according to the current position of the object or event. As shown in Figure 3, the collaboration control engine performs coordinate calibration to collaborate with an adjacent camera based on the acquired PTZ value. The coordinate values to be moved for each camera are finally derived. Using this value, the VMS(Video Management System) controls PTZ cameras.

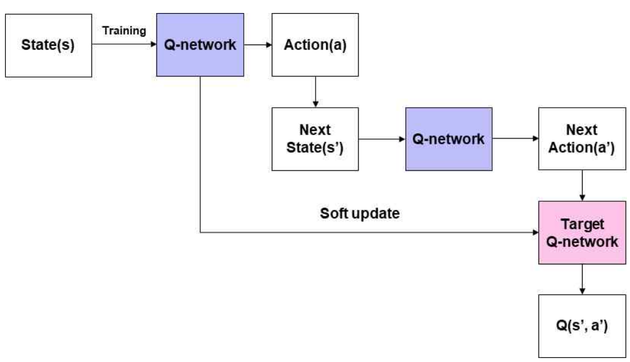

Fig. 2. DDQN model for controlling PTZ camera.

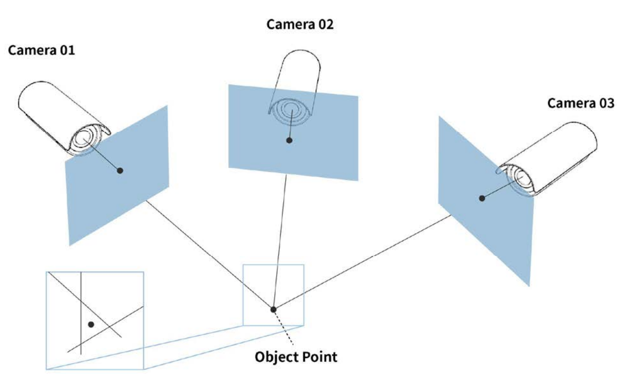

Fig. 3. The camera collaboration for coordinating calibration among PTZ cameras.

We update the network parameters to minimize the error difference between the current and predicted Q values. We train PTZ camera control value using modified DDQN. All tested network configurations were trained for 210 epochs with fixed learning rates, as shown in Table 1, with no early stops applied.

TABLE I. HYPER-PARAMETERS VALUES EXPLORED

Hyper-parameters	Vales explored
Optimizer	Adam
Loss function	MSE(Mean Square Error)
Activation function	ReLU(Hidden layer)
	Linear(Output layer)
Learning rate	0.02
Batch size	128
Epochs	210

III. IMPLEMENTATION RESULTS

To evaluate the reinforcement learning-based camera collaboration scheme, we use the programming language of Python 3.6. The proposed scheme received the position and size of the object and event from the intelligent video analysis system. Fig. 4 shows the implementation results of the proposed system when the object appears. The proposed scheme can position the object in the center of the camera regardless of the position of the object in the camera. The proposed scheme can automatically track the object by controlling the PTZ camera. Through this experiment, it is possible to improve the accuracy of video analysis by appropriately adjusting the position and size of the object using the proposed method.

We also measured the camera control accuracy. For the camera control model evaluation, 10 self-evaluation datasets on the position and size of variously changed objects in the image frame of the camera were acquired. The camera control accuracy is measured by comparing the position and size of an object or event in the moving camera image frame with the Ground Truth(GT). After operating the proposed camera control scheme, it was calculated using Equations (1) to (4). As a result of performing camera control based on the test dataset, an accuracy of about 89.4% was achieved.

x_{error} represents the error rate for the distance from the current location ($x_{current}$) of the object and event to the x-axis screen center (x_{center}), and y_{error} represents the distance from the current location ($y_{current}$) of the object and event to the y-axis screen center (y_{center}). s_{error} represents an error rate for the optimal object and event size (τ) determined by the administrator from the current size ($s_{current}$) of the object and event.

$$accuracy = 100 - \frac{|x_{error} + y_{error} + s_{error}|}{3} \quad (1)$$

(a) Object position (b) Before camera control (c) After camera control

Fig. 4. The test results of camera collaboration control.

$$x_{error} = \frac{|x_{error} - x_{current}|}{x_{center}} \times 100 \quad (2)$$

$$y_{error} = \frac{|y_{error} - y_{current}|}{y_{center}} \times 100 \quad (3)$$

$$s_{error} = \frac{|\tau - s_{current}|}{\tau_{center}} \times 100 \quad (4)$$

IV. CONCLUSIONS

This paper proposes the reinforcement learning-based camera collaboration control scheme to accurately monitor an object of interest or abnormal behavior or support improving the accuracy of video analysis. The goal of the proposed scheme is to automatically and smoothly control PTZ camera to minimize the distance between the event position and camera center position and adjust the size of objects properly. Through experiment results, the proposed scheme automatically and smoothly regulates the location and size of the object by controlling the PTZ camera based on the modified DDQN algorithm.

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