Multi-intruder Tracking and Classification of Visual Surveillance in Net Cage System

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Abstract

Ocean farming in net cages is becoming more popular. The security of net cages is one of key problems in application and popularization of net cages. In this paper, visual surveillance system is proposed in net cages to obtain multi-intruder tracking and classification. The proposed visual surveillance system is a four-phase scheme. The first phase scheme is the procedure of background and foreground detection. The second phase scheme is the procedure of intruder extraction, and intruder tracking is in the third phase scheme. Finally, the fourth stage scheme is the procedure of intruder classification. Using the proposed visual surveillance system would greatly reduce the loading of surveillants and obtain automatic detection, tracking and classification of multi-intruder, thus this research is very important.

Keywords: visual surveillance, net cage, classification.

1. Introduction

Visual surveillance has become an interesting research for the last decade after 9/11 event. Visual surveillance has a wide range of potential applications, such as event detection or understanding [1, 2], multi-object tracking [3, 4], people or vehicles counting [5, 6], vehicle navigation, etc. Analyzing these researches, the interesting targets are almost overland objects, such as people, vehicles, etc. Therefore, the research of visual surveillance on the sea would be an interesting issue.

The fish is an island country's important source of income, and also another main source of the animalistic protein. Ocean fishing has gradually been replaced by ocean framing in the past two decades because of diminishing fishery resources in the ocean. Ocean farming in net cages is becoming more popular because of the decline in wild fish stocks. Most of fishes in net cage have high economic value, such as jewfish, cobia, yellowtail fish, etc. However, the fishes in the net cage will be usually filched, which will be a great loss to fishers. Therefore, security of net cages is one of key problems in application and popularization of net cages.

Digital video recorder (DVR) is usually used in the security of net cages. DVR can overcome the shortcomings of the video cassette recorder (VCR) [7] and also have the advantage of remote monitoring. However, the loading of surveillants for 24hr watching is high in DVR. Therefore, the intelligent visual surveillance is necessary to obtain the automatic detection, tracking and classification of intruders to reduce the loading of surveillants.

Fig. 1. The experimental platform of net cage.

Fig. 2. DVR system in experimental platform.

The experimental platform of National Penghu University (as shown in Fig. 1) is used to simulate the proposed visual surveillance system. This experimental platform is the DVR system, as shown in Fig. 2. The diagram of the proposed visual surveillance system in the current net cage is shown in Fig. 3.

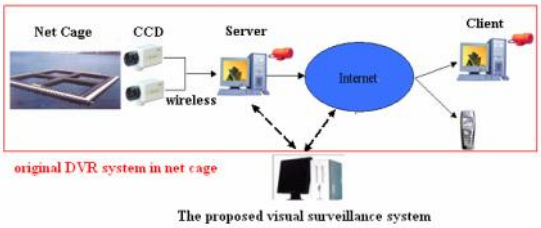


Fig. 3. The diagram of the proposed visual surveillance system.

The proposed visual surveillance is a four-phase scheme and it can obtain automatic detection, tracking and classification of intruders (primarily ship). The first phase scheme is the procedure of background and foreground detection. The second phase scheme is the procedure of intruder extraction. The third phase scheme is the procedure of intruder tracking, and the procedure of intruder classification is in the fourth phase scheme. Therefore, using the proposed visual surveillance system would obtain the automatic detection, tracking and classification of multi-intruder to greatly reduce the loading of surveillants.

In the remainder of this paper, the background and foreground detection are presented in Section 2. The intruder extraction, intruder tracking, and the intruder classification are described in Section 3~5, respectively. Section 6 presents experimental examples and evaluations of the results. Finally, conclusion is made in Section 7.

2. Background/Foreground Detection

The first stage scheme is the procedure of background and foreground detection. The first stage scheme consists of background initialization, foreground detection, and background updating.

It is very important that complete foreground region is obtained based on good background initialization. The background image can be divided into static and dynamic pixels [8]. Because the background in net cage is dynamic, the statistical method is used to obtain background initialization. The median method is used to construct background image from the past and consecutive n frames.

Background subtraction is a popular method and it is normally used to obtain foreground detection [9]. The moving object is detected by taking the difference between the current image and reference background image in a pixel-by-pixel fashion. However, the sway of the CCD generated by wind and wave in the sea would bring the noise, and it is difficult for moving object recognition. Therefore, the modified background subtraction [10] is used to reduce the influence of the sway of the CCD. The pixel p in foreground image is calculated by equation (1), where N is the total number of $k \times k$ window centered in the pixel p, where D_t, I_t and B_t are the foreground image, current image and background image, respectively.

$$D_t(p) = \min_{i \in N} \left| I_t(p) - B_t(i) \right| \tag{1}$$

Finally, the history map based on learning function [11] is used to update background image in background updating. The learning function of history map is estimated by equation (2).

$$h_t(x,y) = \begin{cases} h_t(x,y) + A, \text{if } (x,y) \text{ is foreground} \\ h_t(x,y) - D, \text{if } (x,y) \text{ is background} \end{cases} \tag{2}$$

However, the learning curve $h_t(x,y)$ is very influenced by wave, thus the modified learning curve $h_t(p)$ is proposed to reduce the influence of wave. The modified learning function of history map is estimated by equation (3), where $D_t(p)$ is calculated by equation (1). When h_t is equal to a specified threshold, the background image is updated by using these past and consecutive frames based on the median method.

$$h_t(p) = \begin{cases} h_t(p) + A, \text{if } D_t(p) \geq T \\ h_t(p) - D, \text{if } D_t(p) < T \end{cases} \tag{3}$$

3. Intruder Extraction

The second stage scheme is the procedure of intruder extraction. The second stage scheme consists of median filter, shadow removing, morphological processing, connected components labeling, the hole filling, and the minimum bounding rectangle finding.

When foreground detection is obtained, the intruder extraction is performed. In intruder extraction, $n \times n$ median filter [12] is first used to reduce the noise, and then shadow removing [13] is used to remove the shadow. The shadow removing method is briefly described as follows.

First, the foreground pixel and corresponding background pixel are regarded as vector in RGB color space, as shown in Fig. 4, and the chromaticity distortion measurement is calculated by equation (4). The foreground pixel is categorized as candidate shadow pixel while $\cos\theta$ is greater than specific threshold. Next, the foreground pixel is categorized as candidate shadow pixel while the brightness difference between foreground pixel and corresponding background pixel is greater than a specific threshold. And according to observation, the shadow pixel has a lower gray value than the background pixel in individual RGB channels. When three cases mentioned above are suited, the foreground pixel is regarded as shadow pixel.

$$\cos\theta = \frac{\overrightarrow{Foreground} \bullet \overrightarrow{Background}}{\left|\overrightarrow{Foreground}\right|\left|\overrightarrow{Background}\right|} \quad (4)$$

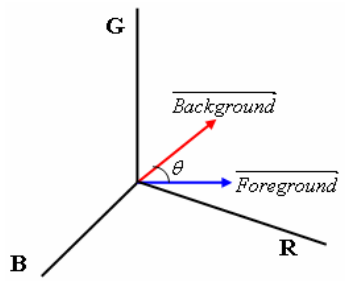


Fig. 4. Chromaticity distortion measurement.

After removing the noise and shadow, the automatic selection of threshold [14] is used to obtain binary image.

After the above processing, the intruder region may be very coarse and not precise. Therefore, the close operation of morphological processing [15] is used to make the shape of intruder region better.

When the morphological processing has been finished, 8-adjacent of the connected components labeling [16] is applied on the initial objects to label each isolated region. The size of each isolated region in the symbolic image is calculated and the isolated region is removed with the area being smaller than the given threshold.

After using the connected components labeling, the object would be divided into the isolated regions. Therefore, the hole filling is used to obtain the complete object under the isolated regions belong to the same object. The isolated regions will be merged when the distance between one and another is smaller than the given threshold. In the hole filling, the first and last points are found by scanning the row of isolated regions which will be merged. Finally, the points are filled by each found pair of first and last points in the row. The same processing is applied in the column again, and then the holes in the isolated regions would be filled

Finally, the minimum bounding rectangle is used to mark the intruder. The minimum bounding rectangle can be determined by computing the maximum and minimum value of x and y coordinates. The left-top corner coordinates of bounding box is the minimum value of x and y coordinates, and the right-bottom corner coordinates of bounding box is the maximum value of x and y coordinates.

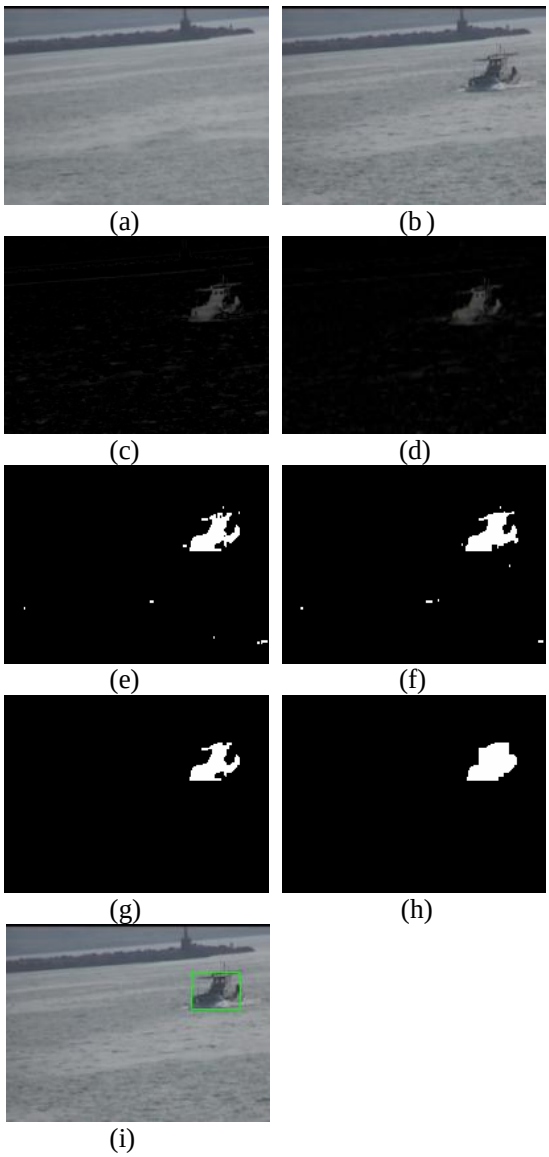


Fig. 5. The processing of intruder extraction.

Fig. 5 is the processing of intruder extraction, where Fig. 5(a) is background image, Fig. 5(b) is the current frame, Fig. 5(c) is foreground detection, Fig. 5(d) is the result of removing the noise and shadow, Fig. 5(e) is the binary image, Fig. 5(f) is result of the close operation of morphological processing, Fig. 5(g) is the result of the connected components labeling, Fig. 5(h) is the result of hole filling, and Fig. 5(i) is the minimum bounding rectangle of the intruder.

4. Intruder Tracking

Once the bounding box of the intruder is obtained, the object tracking is applied. The object tracking can be categorized as region-based tracking, active contour-based tracking, feature-based tracking, and model-based tracking [17]. The block matching is a popular method of region-based tracking. Motion estimation plays an important role in block matching. Many methods of motion estimation were proposed, such as full search algorithm [18], three-step search algorithm [19], four-step search algorithm [20], etc. In these methods, using the full search algorithm can obtain more accurate result, but the computational cost is very high. Therefore, the modified full search algorithm is proposed to greatly reduce the computational cost.

In the consecutive frames, the block matching is to find the motion vector in the search region, as shown in Fig. 6. The full search matches all possible candidate blocks within the search region in the reference frame to find the block with the minimum distortion. The search region is defined as equation (5), where W_p and H_p are the width and height of the minimum bounding rectangle of the intruder, respectively, as shown in Fig. 7.

$$S_R = \alpha W_p + \beta H_p \tag{5}$$

The Mean Absolute Difference (MAD) is used to find the block with the minimum distortion within the search region. In the equation (6), (x, y) is the candidate motion vector, and $f_k(\cdot,\cdot)$ and $f_{k+1}(\cdot,\cdot)$ refer to the template block in the current frame and tested block within the search region. The best motion vector can be obtained from equation (7).

$$MAD(x,y) = \sum_{j=0}^{H_p-1} \sum_{i=0}^{W_p-1} \left| f_{k+1}(i+x, j+y) - f_k(i,j) \right| \tag{6}$$

$$(x_{best}, y_{best}) = \arg \min_{(x,y)\in S_R} MAD(x,y) \tag{7}$$

The modified full search algorithm is built on the coarse-to-fine scheme of search region. That is, the coarse search region S_R is first defined, and the background subtraction is used with the region S_R and the corresponding region of background image. Next, schemes of the median filter and binary image are used to obtain regions of moving object. Finally, the fine search region S'_R is obtained from the minimum bounding rectangle of the possible regions of moving object. Therefore, the equation (7) is changed as equation (8) in the finding of best motion vector. Fig. 8 is the result of intruder tracking, where Fig. 8(a) and Fig. 8(b) are the kth frame and $(k+60)$th , respectively, based on the video in 10 fps.

$$(x_{best}, y_{best}) = \arg \min_{(x,y)\in S'_R} MAD(x,y) \tag{8}$$

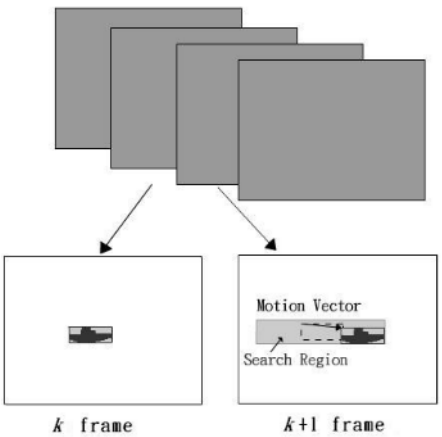
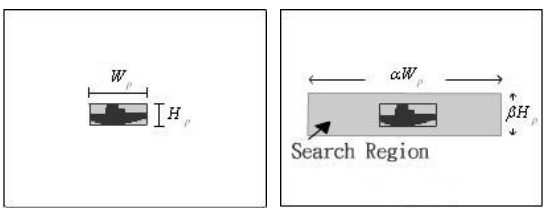


Fig. 6. The block matching in consecutive frames.



(a) (b)

Fig. 7. Definition of the search region.

(a) (b)

Fig. 8. Intruder tracking.

5. Intruder Classification

After the intruder extraction and intruder tracking, feature extraction and intruder recognition are applied to obtain the aim of intruder classification in the fourth phase scheme.

The moment invariants are widely used as features of intruder in feature extraction. The 2D moments of a $M \times N$ image that has gray function $f(x,y)$ are given as

$$m_{pq} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} x^p y^q f(x,y) \quad p,q = 0,1,2,3,... \quad (9)$$

The central moments are defined as equation (10), where $\bar{x} = m_{10}/m_{00}$ and $\bar{y} = m_{01}/m_{00}$.

$$\mu_{pq} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} (x-\bar{x})^p (y-\bar{y})^q f(x,y) \quad (10)$$

When a scaling normalization is applied, the central moments change as

$$\eta_{pq} = \frac{\mu_{pq}}{\sqrt{\mu_{00}^{p+q+2}}} \quad (11)$$

Seven famous moment invariants [21] computed by normalizing central moments through order three are given as

$$I_1 = \eta_{20} + \eta_{02} \quad (12a)$$

$$I_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \quad (12b)$$

$$I_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \quad (12c)$$

$$I_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \quad (12d)$$

$$I_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \quad (12e)$$

$$I_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \quad (12f)$$

$$I_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \quad (12g)$$

Classification is the important stage of image processing system where each unknown pattern is assigned to a category. In the intruder recognition, the Back-Propagation Neural Network (BPNN) [22] is used to obtain the aim of intruder classification based on seven moment invariants. The BPNN consists of the input layer, hidden layer, and output layer. The intruders in net cage would be people and ship. Therefore, the intruders are divided into four categories: people, bamboo raft, dory, and dinghy. Therefore, the structure of BPNN adopted in this paper is designed as 7-5-4 network, as shown in Fig. 9. The weights of among the input layer, hidden layer, and output layer are obtained by the training process and testing process. The training process of BPNN is described as follows.

Step 1: Design the input parameters of the network.

Step 2: Get initial weights W and initial θ values from randomizing.

Step 3: Input training data matrix **X** and output matrix **T**.

Step 4: Compute the output vector of each neural units.

(a) Compute the output vector H of the hidden layer.

$$net_k = \sum_i W_{ik} X_i - \theta_k \quad (13a)$$

$$H_k = f(net_k) = \frac{1}{1+e^{-net_k}} \quad (13b)$$

(b) Compute the output vector Y of the output layer.

$$net_j = \sum_k W_{kj} H_k - \theta_j \quad (14a)$$

$$Y_j = f(net_j) = \frac{1}{1+e^{-net_j}} \quad (14b)$$

Step 5: Compute the distances.

(a) Compute the distances of the output layer.

$$\delta_j = (T_j - Y_j) \bullet f(net_j) \quad (15a)$$

(b) Compute the distances of the hidden layer.

$$\delta_k = (\sum_j \delta_j W_{kj}) \bullet f(net_k) \quad (15b)$$

Step 6: Compute the modification of W and θ, where η is the learning rate.

(a) Compute the modification of W and θ of the output layer.

$$\Delta W_{kj} = \eta \delta_j H_k \quad (16a)$$

$$\Delta\theta_j = -\eta\delta_j \quad (16b)$$

(b) Compute the modification of W and θ of the hidden layer.

$$\Delta W_{ik} = \eta \delta_k X_i \quad (17a)$$

$$\Delta\theta_k = -\eta\delta_k \quad (17b)$$

Step 7: Renew W and θ.

(a) Renew W and θ of the output layer.

$$W_{kj} = W_{kj} + \Delta W_{kj} \quad (18a)$$

$$\theta_j = \theta_j + \Delta\theta_j \quad (18b)$$

(b) Renew W and θ of the hidden layer.

$$W_{ik} = W_{ik} + \Delta W_{ik} \quad (19a)$$

$$\theta_k = \theta_k + \Delta\theta_k \quad (19b)$$

Step 8: Repeat step 3 to step7 until convergence.

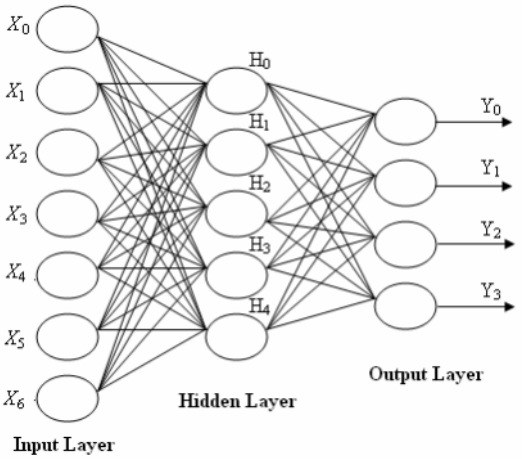


Fig. 9. The structure of 7-5-4 BPNN.

Next, the testing process of BPNN is described as follows.

Step 1: Input the parameters of the network.

Step 2: Input the W and θ.

Step 3: Input an unknown data matrix **X**.

Step 4: Compute the output vector.

(a) Compute the output vector H of hidden layer.

$$net_k = \sum_i W_{ik} X_i - \theta_k \quad (20a)$$

$$H_k = f(net_k) = \frac{1}{1+e^{-net_k}} \quad (20b)$$

(b) Compute the output vector Y of the output layer.

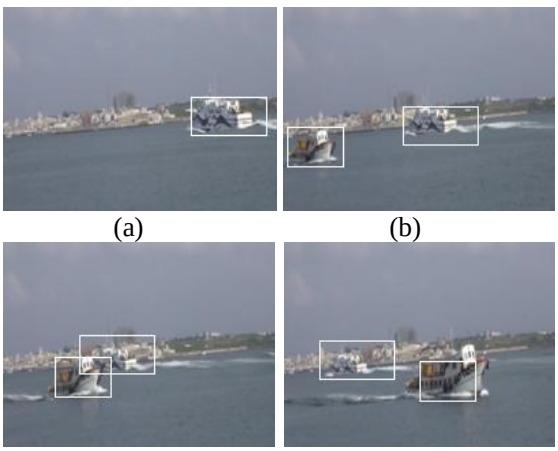
$$net_j = \sum_k W_{kj} H_k - \theta_j \quad (21a)$$

$$Y_j = f(net_j) = \frac{1}{1+e^{-net_j}} \quad (21b)$$

6. Experimental Results

In the following, the performance of the proposed visual surveillance will be demonstrated. Experiments are conducted on a computer with Intel(R) Core(TM)2 1.8 GHz CPU, 512MB RAM. We implement our algorithm in BCB (Borland C++ Builder) 6.0 program. In the BPNN, the number of examples in the training process is 195 and the learning cycles are 1000, where the training number of people, bamboo raft, dory, and dinghy are 42, 45, 54, and 54, respectively. Besides, the format of the video is 200×150 in 10 fps.

The first example demonstrates the performance of multi-intruder tracking of the proposed visual surveillance system. The parameters $\alpha = 1.5$ and $\beta = 1.5$ of the coarse search region S_R are selected to find the fine search region S'_R in the intruder tracking. Fig. 10(a) is the tracking result of the first ship that enters the surveillant window. Fig. 10(b) is the result of the first ship tracking, and the second ship that enters the surveillant window. Fig. 10(c) and Fig. 10(d) are the tracking results of two ships under surveillance.



(a) (b)

(c) (d)

Fig. 10. Results of multi-intruder tracking.

The second example is the complete procedure of the proposed visual surveillance system. In the proposed visual surveillance system, the scene is divided into two zones (tracking zone and alert zone) by setting one base line, as shown in Fig. 11. In Fig. 11, region R1 is tracking zone and R2 is alert zone, where $d1:d2 = 3:2$ is selected in this paper. In the tracking zone, the intruder is tracked from one frame to another, where the coarse search region S_R is set as $\alpha = 1.5$ and $\beta = 1.5$ in block matching. The alarm is sent to the surveillants while the intruder is in the alert zone, where background subtraction, intruder extraction, feature extraction, and intruder classification are employed in the coarse search region S_R which is set as $\alpha = 2.5$ and $\beta = 2.5$.

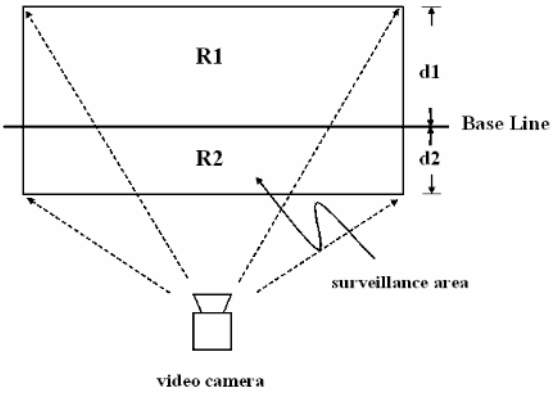


Fig. 11. Tracking zone and alert zone of surveillance.

Fig. 12 is the result of the complete procedure (from intruder detection to intruder classification) of the proposed visual surveillance system. Fig. 12(a) is the procedure of mail server connecting and BPNN training, and Fig. 12(b) is the background initialization. Figs. 12(c)~12(d) are the intruder tracking. Finally, the intruder is classified as the category of dory, and the alarm is sent to the surveillants, as shown in Fig. 12(e). The execution time is 156 ms.

7. Conclusions

In this paper, the visual surveillance system in net cage is proposed successfully to obtain automatic detection, tracking and classification of multi-intruder. The proposed visual surveillance system is a four-phase scheme. In the first phase scheme, background initialization, foreground detection, and background updating are applied. In the second phase scheme, the median filter, shadow removing, morphological processing, connected components labeling, hole filling, and the minimum bounding rectangle finding are used to obtain intruder extraction. Next, block matching is used to obtain intruder tracking in the third phase scheme. Finally, feature extraction (using seven famous moment invariants) and intruder recognition (using Back-Propagation Neural Network) are applied to obtain intruder classification in the fourth phase scheme.

The good performance of the proposed visual surveillance system has been demonstrated in experimental results. The proposed visual surveillance system is very useful and helpful for security of net cage system. Therefore, using the proposed visual surveillance system would advance the application and popularization of ocean farming in net cages.

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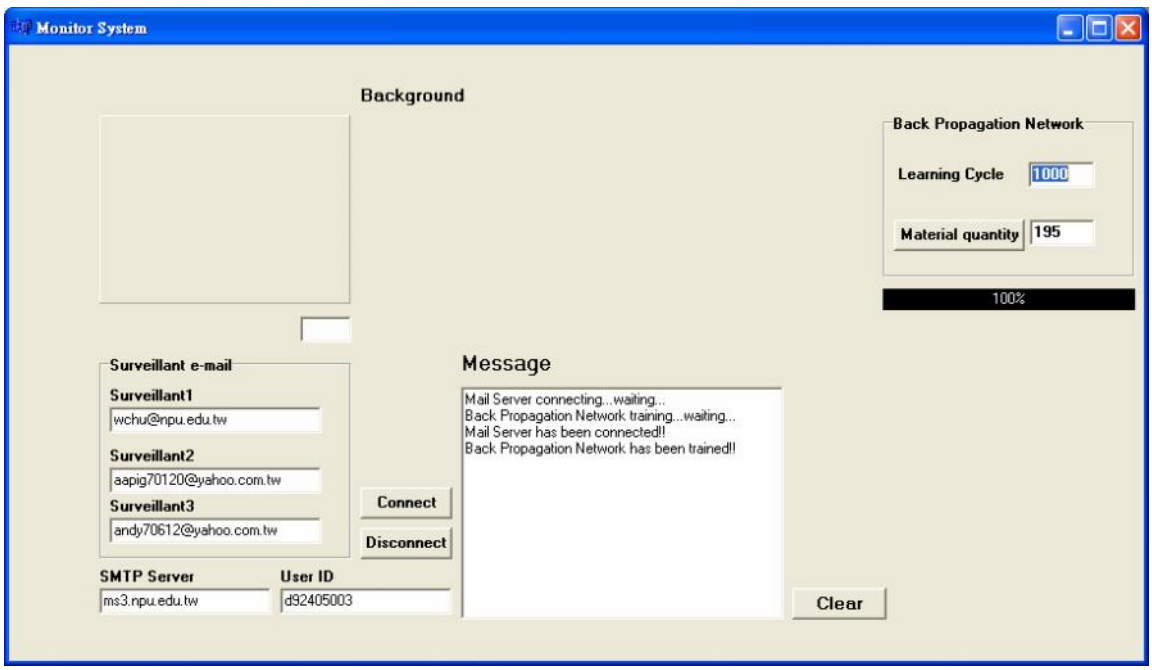
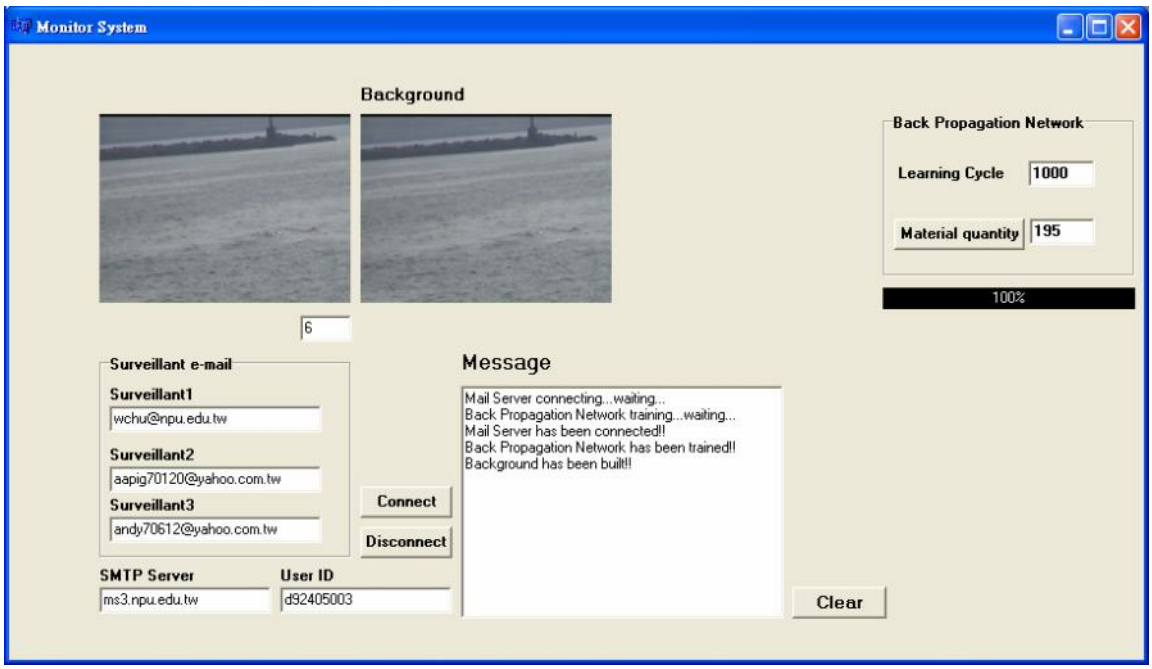
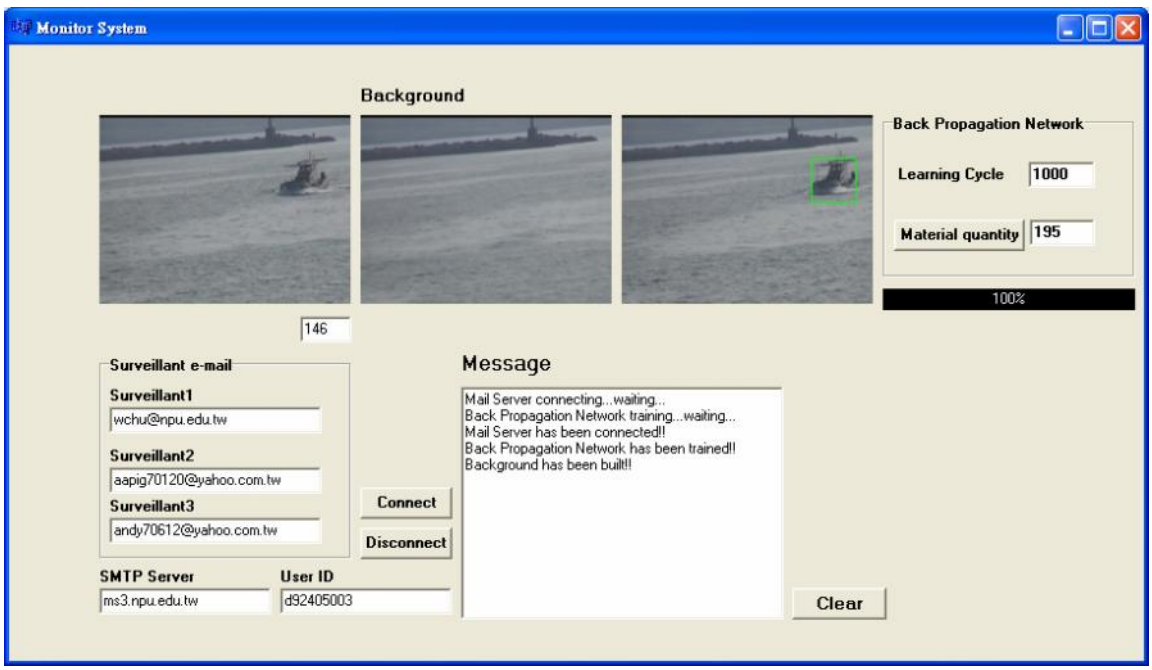


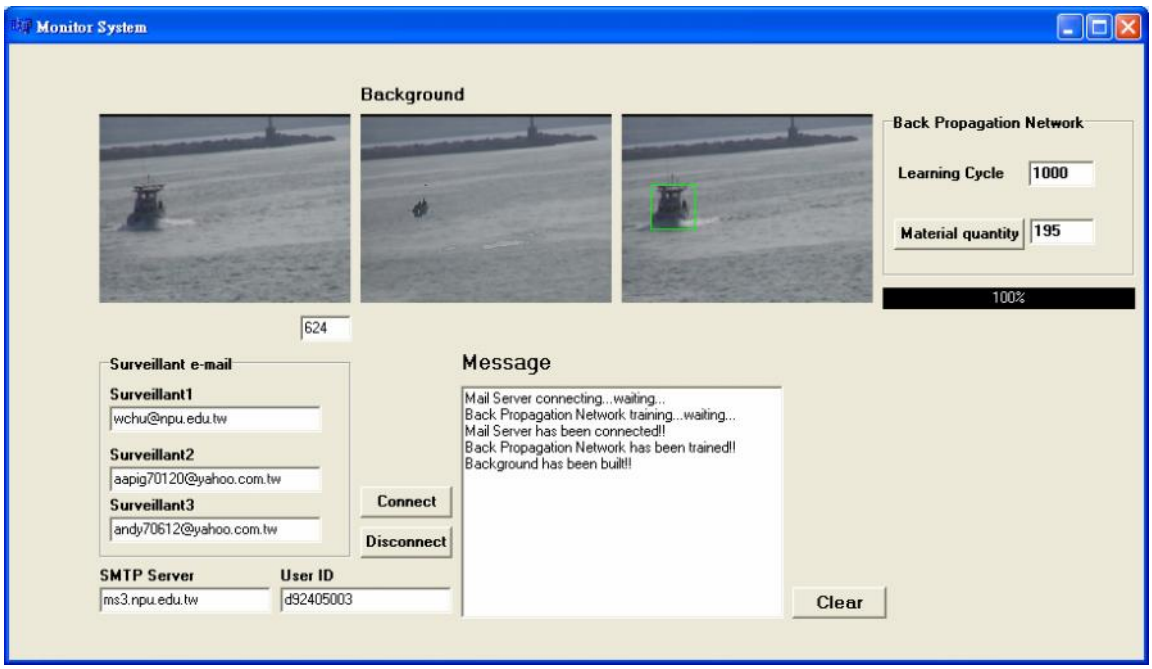
(a)


Monitor System
Background
Back Propagation Network
Learning Cycle
1000
Material quantity
195
100%
6
Surveillant e-mail
Surveillant1
wchu@npu.edu.tw
Surveillant2
aapig70120@yahoo.com.tw
Surveillant3
andy70612@yahoo.com.tw
Message
Mail Server connecting...waiting...
Back Propagation Network training...waiting...
Mail Server has been connected!!
Back Propagation Network has been trained!!
Background has been built!!
Connect
Disconnect
SMTP Server
ms3.npu.edu.tw
User ID
d92405003
Clear

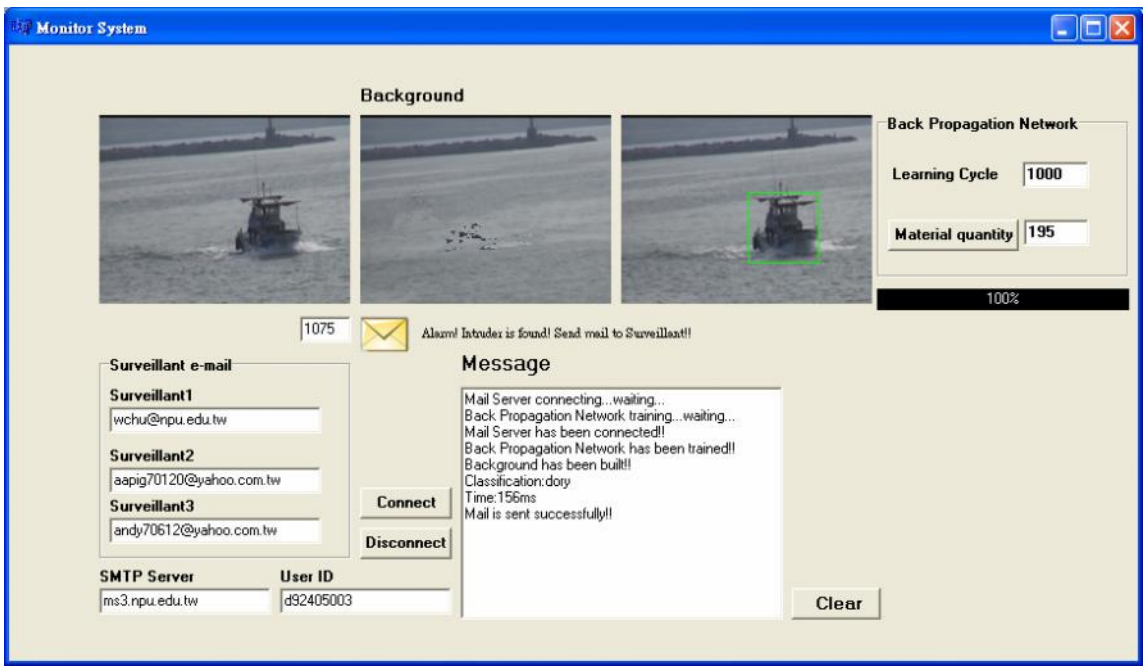
(b)


Monitor System
Background
Back Propagation Network
Learning Cycle
1000
Material quantity
195
100%
146
Surveillant e-mail
Surveillant1
wchu@npu.edu.tw
Surveillant2
aapig70120@yahoo.com.tw
Surveillant3
andy70612@yahoo.com.tw
Message
Mail Server connecting...waiting...
Back Propagation Network training...waiting...
Mail Server has been connected!!
Back Propagation Network has been trained!!
Background has been built!!
Connect
Disconnect
SMTP Server
ms3.npu.edu.tw
User ID
d92405003
Clear

(c)



(d)



(e)

Fig. 12. The results of using proposed visual surveillance system.