

AN EFFICIENT CAMERA HAND-OFF FILTER IN REAL-TIME SURVEILLANCE TRACKING SYSTEM

CHAO-YANG LEE¹, SHOU-JEN LIN¹, CHEN-WEI LEE² AND CHU-SING YANG¹

¹Institute of Computer and Communication Engineering
NCKU Research Center for Energy Technology and Strategy
Department of Electrical Engineering
National Cheng Kung University
No. 1, University Road, Tainan City 701, Taiwan
q3897109@mail.ncku.edu.tw; lsr@tn.edu.tw; csyang@ee.ncku.edu.tw

²Institute of Computer and Communication Engineering
Department of Electronic Engineering
Jinwen University of Science and Technology
Taipei, Taiwan
chenwei@just.edu.tw

Received November 2010; revised March 2011

ABSTRACT. *Recently, an automatic system extensively used for surveillance in wide area environments has been developed to continually track an individual while keep the individual centered in the field of view (FOV). There have long been some knotty problems in the tracking of moving object in computer vision. In a multi-camera surveillance system, both the handoff and assignment among cameras play an important role in generating an automated and persistent object tracking, a condition typical of most surveillance requirements. There has been a lack of studies in camera hand-off issue in PTZ-camera system. This paper investigates the application of automatic methods for tracking individual across cameras via a surveillance network. We propose a camera hand-off filter which can automatically provide an optimal capacity and a solution to perform the camera assignment efficiently. It comprises three fundamental components. Firstly, each camera determines time to trigger camera handoff process. Then, the execution of camera rotation is applied. Finally, the optimal camera should be selected. Moreover, our approach of individual tracking activates surveillance in cameras and achieves seamless tracking of high quality image. We develop an innovative low computational complexity handoff filter that can automatically carry out the camera assignment and handoff task. In the experiment, with a feasible solution for seamless tracking and real-time surveillance, our algorithm can efficiently and automatically perform the hand-off task in a multiple active camera surveillance systems.*

Keywords: Seamless tracking, Handoff task, Camera assignment, Surveillance system, PTZ camera

1. Introduction. In recent years, due to the increasing security concerns, surveillance and monitoring have become even more paramount. Various multi-camera surveillance systems have been developed to strengthen the surveillance in wider areas, track targets of interest or observe one single target from different viewpoints [1]. For a surveillance system with multiple pan-tilt-zoom (PTZ) cameras (or so-called active camera), we may adjust the pan angle, tilt angle and zoom of the cameras where necessary to achieve better monitoring results [2,3]. The camera cannot completely cover the entire space in a single view, but by using pan, tilt, and zoom controls, it can be maneuvered to look at different areas of interest. An automatic system which is able to continually track a person who can be always centered in the field of view (FOV) could be developed. Typically, such methods

are built based on existing image analysis techniques for a single camera, including target segmentation [4] and tracking [5]. Many already existing methods have been proposed to detect the moving motion of object with an active camera [6,7]. Therefore, when vision image is captured by camera, the camera corresponding to the target in the new location should be selected.

The tracking of moving objects has long been a key issue in computer vision. It is important in a wide variety of video surveillance applications and has been applied successfully in people's daily life, including the analysis of human motion, traffic monitoring, market guard, robot tracking and in-house health care [8-10]. The tracking of human targets has become an important category in the field of computer vision which has often been identified as "looking at humans" [11]. This application can extend to several devices, such as face recognition and human motion analysis [12,13]. In previous researches, continuous tracking of moving object requires robust tracking of the object in a video stream until the object goes out of view. In general, upon target detection and positioning, one of the cameras will be commanded to move the pan and tilt motors to track single target [14,15]. One of the approaches for tracking objects in a video sequence is particle filters [16,17]. It has been popular for target tracking because of its non-linear and non-Gaussian structure. P. Guha et al. used mean-shift algorithm for visual tracking and the derivation of the error dynamics for a control action [18].

The camera hand-off among multiple cameras is a difficult task because each camera has a different view for the same target. Thus, the information about the same object may be different. Establishing the correspondence between moving object observed in different views is known as *object handoff*. The camera handoff design allows us to detect various possibilities. Many approaches have been proposed to solve this problem [19]. The color distribution model was proposed in [20] to classify the different targets by matching the color distribution of the object. In [21], a hand-off function was constructed by computing the ratio of co-occurrence between two views without camera calibration. In [22], the authors proposed a continuous object tracking algorithm which performs a probabilistic camera hand-off using the dominant camera probabilities between two frames when multiple cameras were installed. After that, the tracking of individual requires the mechanism to select a camera for certain moving objects and handoff this from one camera to another so as to accomplish seamless tracking. Varcheie et al. [23] proposed an adaptive fuzzy particle filter (PF), i.e., AFPF method, adapted to general object tracking with an active camera. The targets are modeled and tracked based on sampling around predicted positions obtained by apposition predictor and moving regions detected by optical flow. Lu et al. [24] proposed a hybrid visual tracking system for event detection and people tracking. This surveillance system is composed of a stationary camera and a pan/tilt/zoom (PTZ) camera. The purpose of tracking in view of the PTZ camera is to continuously keep the person in the camera view in order to obtain identifying details. In [25], the authors suggested an optimal particle allocation approach to minimizing the total tracking distortion by simultaneously adjusting the proposal variance and the number of particles for each frame.

Pan-tilt-zoom (PTZ) camera networks play an important role in surveillance systems. They have the ability to direct the attention to several interesting events that occur in the scene. Based on the above observations, we find that none of the paper is taking both the camera handoff and camera assignment in a multiple active camera surveillance system into consideration. In practice, we find some issue of the seamless tracking by using camera hand-off method in PTZ camera surveillance system. The object may be loss in the camera view when the size of object in camera view is too large or too small. Moreover, the hand-off process and camera assignment should be low computational complexity to

stratify the real-time application limited. Besides, since traditional approaches greatly depend on the spatial topology of the camera network and calculation of the geometrical relationships among cameras, these approaches of ten become too complicated in the event of a complex topology. In this paper, we proposed a camera handoff filter to solve these problems. Therefore, we propose a newly-developed object seamless tracking algorithm by using the efficient camera hand-off filter. The seamless camera handoff filter comprises three components: (1) time to trigger camera handoff, (2) the execution of camera rotation and (3) the selection of the next optimal camera. This work attempts to resolve the defect in seamless tracking in a real-time multiple active camera environments to help us determine which camera should be selected and when to trigger the camera hand off to achieve seamless tracking with high quality camera view. Moreover, this paper is proposed to decrease the computational complexity and be implemented in the real-time system.

This work is contributed to multiple active camera system in several ways. We develop a simple but effective method for object seamless tracking using efficient camera hand-off filter. The proposed method does not directly analyze the dynamics of motions, but derives a compact trajectory description to reflect the characteristics of object motion. In contrast, a large number of works in the literature only assume single PTZ camera or fix camera surveillance system, but they seldom made informed considers in all active camera to achieve seamless object tracking. Additionally, it is easier to comprehend and implement the proposed method, without the requirements of explicit feature tracking and complex probabilistic modeling of motion patterns. Restated, the filter has a low computational complexity and the selection of the next optimal camera rapidly. Moreover, being based on fast camera hand-off filter, it naturally avoids some problems arising in most previous methods, and it obtains good results in a high speed scenario and exhibits considerable robustness.

The rest of this paper is organized as follows. Section 2 is the preliminary statement on our assumptions. Section 3 presents the real-time seamless tracking system of this study. Next, the proposed handoff filter is developed in Section 4. Experiment results are provided in Section 5. Finally, conclusions are shown in Section 6.

2. Problem Statement and Preliminaries. Combined with camera assignment algorithm and camera hand-off algorithm, areal-time surveillance framework is proposed under a cooperative strategy. The aim of the surveillance framework is to select a camera for a specific individual and hand-off this from one camera to another so as to accomplish seamless tracking with high quality images. The proposed framework is to undertake the task of tracking a current intruder while at the same time monitoring the door to detect any new intruders using multiple cameras. A diagrammatic representation of the surveyed premise in the experiments of our framework is shown in Figure 1. The proposed framework uses PTZ cameras to undertake the task of monitoring and tracking. The AXIS 215 camera was used in this experiment. The camera accepts the HTTP API comments for requesting motion video, still images, setting and inquiry of camera parameters and control commands for panning, tilting, zooming and focusing of the camera. There are total of eight cameras in this example. One of these cameras, i.e., the monitor camera, constantly monitors the entrance to detect any new intruder (camera 7 in Figure 1). This monitor camera is stable and always focuses on the entrance door. Other cameras, namely track cameras, monitor somewhere else in normal state. When an intruder is detected, the system assigns one of the track cameras to track such intruder. In summary, we desire to continuously track as many targets as possible with multiple active cameras under a limited field of view. If the object has been discovered from entrance door at the first

instant, the multi-camera surveillance system will determine which camera should assume the tracking role and rotate in order to focus the target at the next instant.

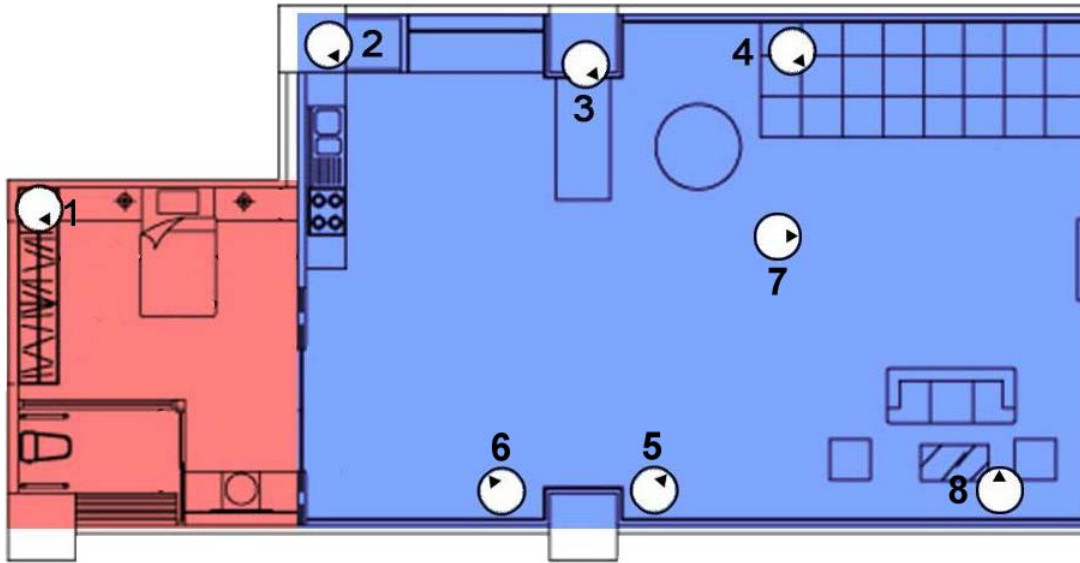


FIGURE 1. The surveyed premise in our framework

The proposed framework is to use PTZ cameras for the purposes of monitoring and tracking. Figure 2 shows the software and hardware architecture of the real-time seamless tracking surveillance system. The infrastructure of our system is composed of several software and hardware which include the indoor PTZ cameras, a network video recorder (NVR), a database server responsible for storage of information about the video, a monitor control server to display the summary, video and location analysis components, and user interface component. The NVR receives video stream from the PTZ camera. The video analysis component retrieves live video stream from the NVR, and analyzes video information and stores results in the database. The location component retrieves the object information and estimates the position of the object. Finally, user interface component displays information.

Figure 3 shows the overall procedure of the proposed continuous object tracking method. When the system begins to track target, it must detect the motion first. This process can effectively cut power consumption and reduce the quantity of transmission. For all tracking systems, segmenting out humans from the background is the very first step prior to human tracking in camera scenes. One commonly used approach to foreground extraction is to subtract the background from the video frames. Following the foreground segmentation, we carry out our seamless tracking algorithm.

We implement webuser interface component display current information and records. The web interface has the characteristic of cross-platform. Users connect the web interface to obtain the information anytime and anywhere. The information includes current parameters and states. Figure 4 shows that the comprehensive information consists of all information. We can observe the camera direction and variation of event, etc. the variation of event can be adjusted through the trajectory. The camera display has shown in Figure 5. This homepage shows all of the current camera view. We can rotate the camera to any angle via pan, title zoom control. Besides, this page supports the manual tracking control. User marks any frames which under the camera view to start/close the tracking task. When the invader has been detected, we start the tracking task up. This

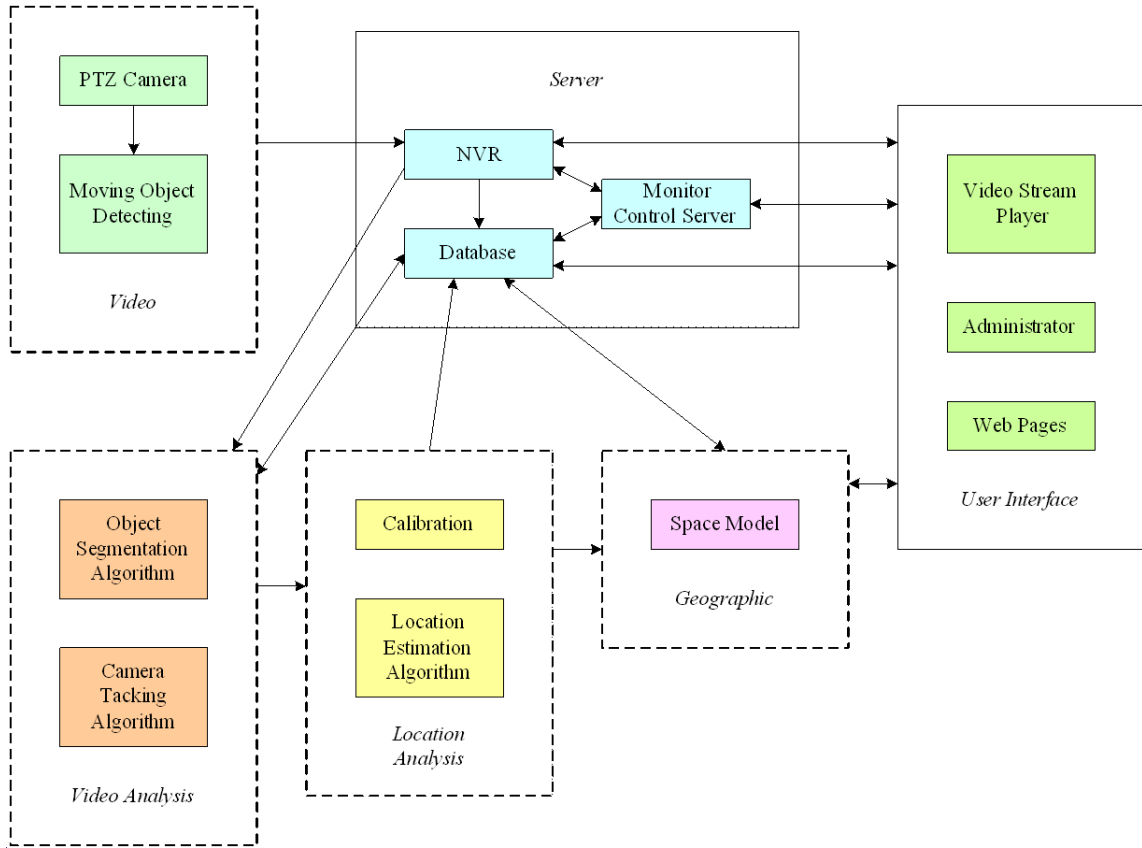


FIGURE 2. The diagram of framework for real-time seamless tracking system

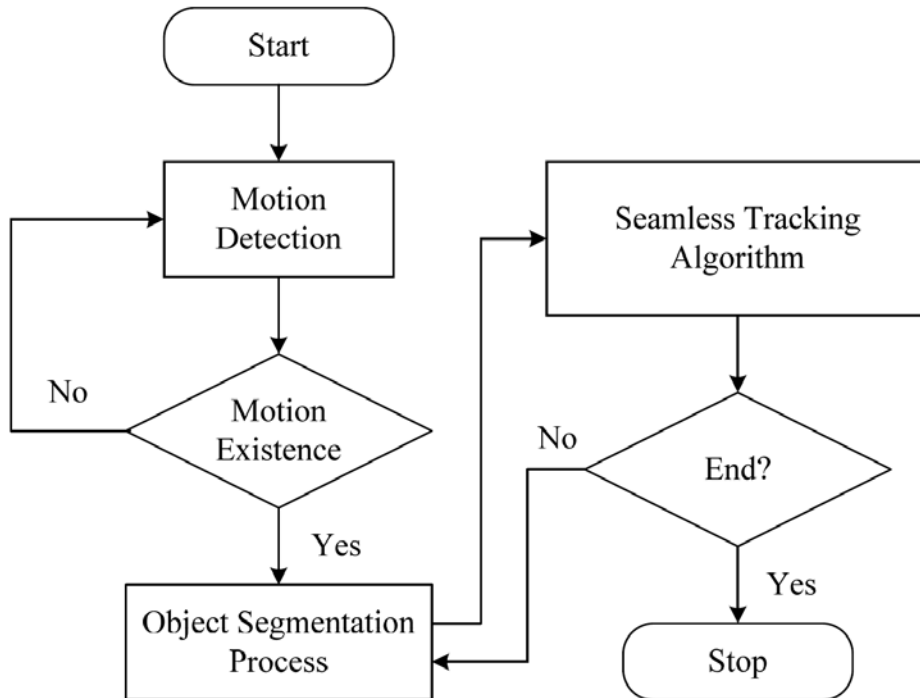


FIGURE 3. The system framework diagram

task can record all of the behavior of invader to MJPEG frames and these frames will be piled up.



FIGURE 4. Comprehensive information

A lot of researchers discuss the tracking issue in the static camera environment, and deployment a lot of camera to obtain the full coverage. It causes the heavy deployment cost and difficult to implement in the real world. Recently, the active camera has applied in the surveillance to reduce the cost. For a surveillance system with multiple active cameras, we may adjust the pan angle, tilt angle and zoom of the cameras where necessary to achieve better monitoring results. During the implement, we find some object tracking and camera assignment issue of tracking process. When the invader has been detected in the monitor area, a camera would be assigned to track the invader. The invader may walk or run randomly, and try to avoid the camera view. The traditional tracking algorithm may cause the tracking loss. It is due to the unpredictable invader walking direction, variability walking speed, property of active camera and camera rotation delay, and so on. Figure 6 shows the samples of the pointless image for tracking process, we cannot identify the invader. Besides, it may cause the tracking loss. Therefore, we try to solve the tracking problems by a camera filter to assign an optima camera and time to trigger the camera hand-off automatically.



FIGURE 5. Camera display

3. Real-Time Seamless Tracking System. Segmenting out humans from the background is the first priority prior to human tracking in camera scenes for all tracking systems. The detection of moving objects in video sequences remains an important but tough research issue in tracking applications. One commonly used approach to foreground extraction is to subtract out the background from the video frames. This approach consists of maintaining a reference background image for the scene observed and extracting new foreground objects by comparing the current image against the reference background. Background/Foreground Detection, Object Segmentation and Object Tracking are thus three components in tracking system.

3.1. Object extraction. The difference between the current frame and the previous-frame is calculated and segmented as follows:

$$F_n(x, y) = |f_n(x, y) - f_{n-1}(x, y)| \quad (1)$$

$$FM_n(x, y) = \begin{cases} 1, & \text{if } F_n(x, y) \geq TH_F \\ 0, & \text{if } F_n(x, y) < TH_F \end{cases} \quad (2)$$

where $f_n(x, y)$ represents the gray-scale value of a pixel with position (x, y) in the n th frame. If the frame different $F_n(x, y)$ is smaller than a threshold TH_F , then the corresponding pixel is classified as a stationary pixel. Besides, a pixel with position (x, y) belongs to an object candidate, if the frame different $F_n(x, y)$ is bigger than a threshold TH_F and is masked using $FM_n(x, y)$.

A pixel fixing still for a long time is considered to be reliable background pixels and registered in the background buffer. The background registration process uses the following two equations:

$$S_n(x, y) = \begin{cases} S_{n-1}(x, y) + 1, & \text{if } FM_n(x, y) = 0 \\ 0, & \text{if } FM_n(x, y) = 1 \end{cases} \quad (3)$$

$$B_n(x, y) = \begin{cases} f_n(x, y), & \text{if } S_n(x, y) \geq N_F \\ 0, & \text{if } S_n(x, y) < N_F \end{cases} \quad (4)$$



(a)



(b)

FIGURE 6. Pointless image for tracking

where $S_n(x, y)$ is a stationary index which is according to the $FM_n(x, y)$ values, and $B_n(x, y)$ is the background buffer value of a pixel with position (x, y) in the n th frame. When a pixel stays fixed for a long time (which is bigger than a threshold N_F), the corresponding pixel is stored in the background buffer.

Finally, the object extraction distinguishes moving objects from the background, and its operations are shown as follow:

$$O_n(x, y) = |f_n(x, y) - B_n(x, y)| \quad (5)$$

$$OM_n(x, y) = \begin{cases} 1, & \text{if } O_n(x, y) \geq TH_O \\ 0, & \text{if } O_n(x, y) < TH_O \end{cases} \quad (6)$$

where $O_n(x, y)$ is the object segment from background difference and $OM_n(x, y)$ is the object extraction mask of a pixel with position (x, y) in the n th frame. If the object segment $O_n(x, y)$ is bigger than a threshold TH_F , then the corresponding pixel is classified as an object pixel and masked using $OM_n(x, y)$.

In summary, this setup determines whether a pixel in frame n belongs to a moving object or a background by using $OM_n(x, y)$ and $B_n(x, y)$. A pixel is classified to be within a moving object when $OM_n(x, y)$ equals 1.

3.2. Object tracking. Adaptive foreground detection is used to recognize the moving object from background. After that, the detection cuts the foreground object and tracks it via PTZ cameras. The algorithm of adaptive Background/ForegroundDetection is described as above. The block diagram of this approach is displayed in Figure 7. In the field of object tracking which enjoys high popularity, many algorithms had been proposed. In this paper, the step of object tracking is implemented using mean shift algorithm. The Open CV library [27] provides the mean shift source program. Mean shift algorithm is suitable for real-time tracking system since it is a nonparametric statistical method which can realize rapid optimal matching during object tracking. Therefore, we use the algorithm in our tracking system.

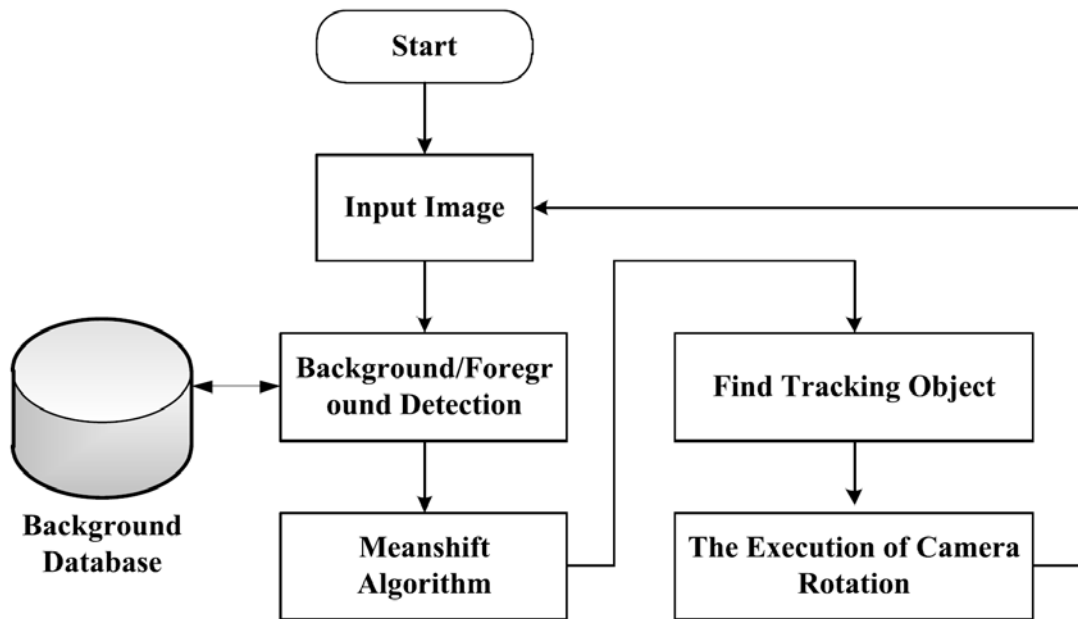


FIGURE 7. The diagram of tracking procedure

4. Efficient Camera Assignment and Hand-off Algorithm. In this section, we describe an innovative effect seamless tracking which includes both camera assignment and hand-off algorithm to achieve continuous object tracking for surveillance. Figure 8 shows the overall procedure of our three stages. In camera decision process, our proposed is used to assign the camera to focus the interest target. The camera tracking stage is the same as the [5]. We can obtain the position of individual by using the positioning estimation.

Tracking of individual requires the mechanism to select a camera for a specific individual and hand-off this from one camera to another so as to accomplish seamless tracking. The camera hand-off among multiple cameras is a difficult task because each camera has a different view for the same target. Most existing algorithms require unlimited

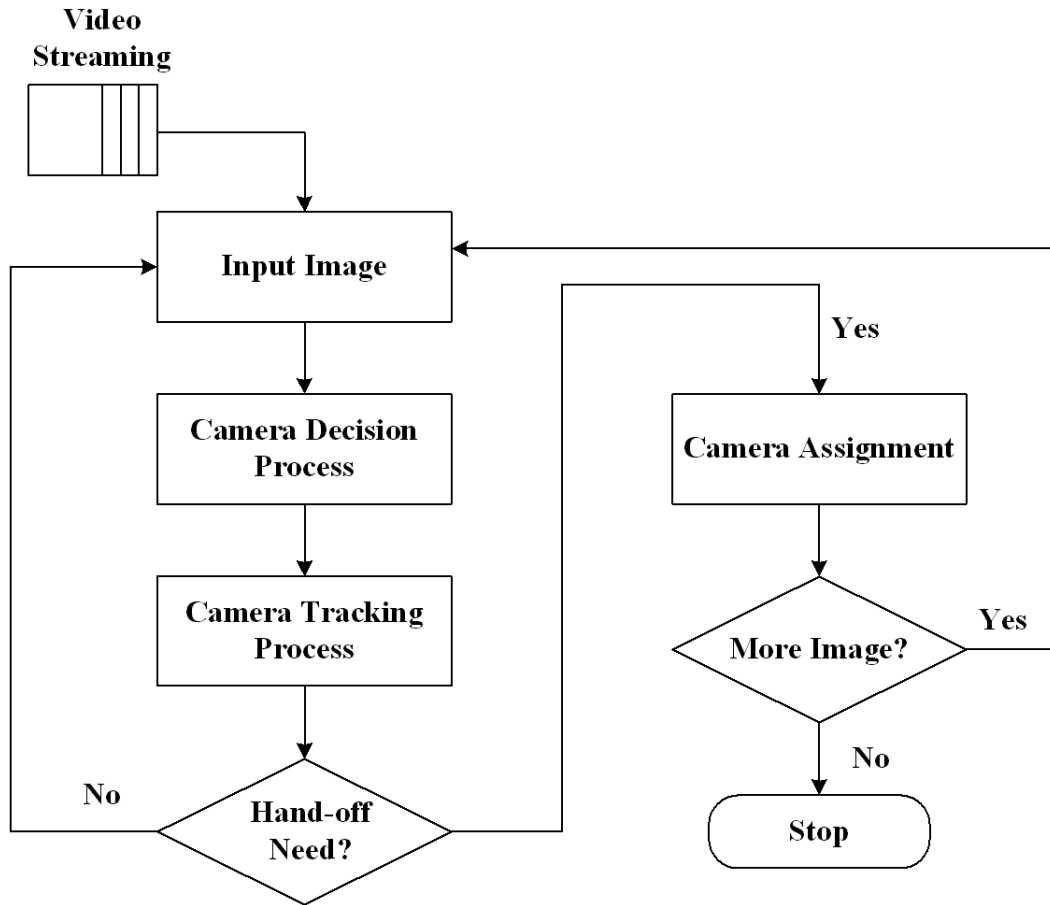


FIGURE 8. The process of the seamless tracking algorithm

computational resources from observing cameras. Since traditional approaches greatly depend on the spatial topology of the camera network and calculation of the geometrical relationships among cameras, they often become too complicated in the event of a complex topology. The location of intruder would affect the tracking performance of cameras which will continuously rotate during its tracking. Therefore, a real-time surveillance system should be equipped with both low computational complexity and high quality image for a seamless tracking system.

Due to the confined capability of the camera, we hereby define the camera state first. In this paper, we use the Sight Quality Indication (SQI) to indicate the vision level of camera. In general, if the distance between object O and active camera $CAMERA_i$ is too short or too long, we may gain the image with lower quality from active camera $CAMERA_i$. Besides, these active cameras may have their respective fields of view (FOV) due to different properties including pan, tilt, zoom, focus, etc. As the scene content is subject to change over time, this one belongs to a dynamic property. This parameter determines whether the object in the field of view (FOV) is clear or not. Therefore, the distance between object and camera as well as the capability of camera are consequently important parameters in this system. To summarize, different active cameras have different capacities. In other words, each active camera has different viewing and the best distance. The SQI value of i th camera SQI_i is obtained by following Gaussian distribution:

$$SQI_i(i) = \frac{1}{2\pi\sigma_i} e^{-\frac{d_i^2}{2\sigma_i^2}} \quad (7)$$

where σ_i is the standard deviation for i th device, d_i is the distance between object O and active camera $CAMERA_i$. Based on Maximum Likelihood criteria, the L2 metric is proven to be the optimal distance measure for the Gaussian distribution models [20]. where

$$d_i = \sqrt{(x_p - x_i)^2 + (y_p - y_i)^2} \tag{8}$$

During the hand-off decision process, two factors should be taken into consideration. On one hand, the surveillance system should try to maximize the utilization of a high Sight Quality Indication (SQI) and high suitability. On the other hand, the number of unnecessary task migration should be minimized to avoid degrading the Sight Quality Indication (SQI) and suitability of current view.

Assume that a space comprises Q camera. The distance from object O to the active cameras $CAMERA_i$ ($1 \leq i \leq Q$) is d_i , and the φ_i is the mean of suitable position for $CAMERA_i$. The φ_i means the camera can play the video with best quality. We define $\varepsilon_i = |SQI_i - \varphi_i|$. Thus, when $d_i = \varphi_i$, $\varepsilon_i = 0$.

Let samples of ε_i^t be taken at equally spaced time intervals of T seconds. Let $S(N)$ denote all the information available for decision making at the N th sampling instant as

$$S(N) = \{[\varepsilon_i(N), \varepsilon_i(N - 1), \dots, \varepsilon_i(N - P + 1)]_{i=1, \dots, Q}, H, \Phi(N - 1)\} \tag{9}$$

In (9), $\varepsilon_i(N), \varepsilon_i(N - 1), \dots, \varepsilon_i(N - P + 1)$ is the sequence of the latest P samples of ε_i , $\varepsilon_i(N)$ is the latest of ε_i . Also, in (3), H is the sampling instant of last hand-off, and $\Phi(N)$ is the device selection at sampling instant N , which is a function of $S(N)$:

$$\Phi(N) = \xi(S(N)) = \begin{cases} i, & 1 \leq i \leq Q, \text{ choose } Camera_i \\ 0, & \text{queue} \end{cases} \tag{10}$$

Thus, $\Phi(N - 1)$ in (9) is the device selection at sampling instant $N - 1$. Based on the above definitions, we can reach the summary that if $\Phi(X) \neq \Phi(Y)$, camera selections at sampling instants X and Y are different, which means that there is at least one hand-off between X and Y . Specifically, when $\Phi(X) \neq \Phi(Y)$, and $Y = X + 1$, it means that there is an hand-off at sampling instant Y .

Based on $\Phi(N)$, we can get the following expression for H :

$$(\forall j \in H \dots N - 2)((\Phi(j) = \Phi(N - 1)) \cap (\Phi(H - 1) \neq \Phi(N - 1))) \tag{11}$$

In addition, when we assume that at sampling instant N , $CAMERA_i(N)$ is the most-suitable one, we can get the following result.

$$\varepsilon_i(N) = MIN(\varepsilon_1(N), \varepsilon_2(N), \dots, \varepsilon_Q(N)) \tag{12}$$

Based on the handoff policy, we make the following assumptions for the hand-off conditions:

1. Assume that an object O initially is not in any camera ($SQI_i = 0$). When the object O is in the FOV of a $CAMERA_j$ with $\varepsilon_j > \theta_j$, the object O will switch to $CAMERA_j$.
2. Assume that an object O is in $CAMERA_i$. When $\varepsilon_i < \theta_i$, the O will switch from $CAMERA_i$ to $CAMERA_j$ (if the object O can sense another $CAMERA_j$ with $\varepsilon_j > \theta_j$).

The θ means the threshold can be adjusted according to the different capability in cameras. It indicates the threshold of position in which objects can be monitored clearly through the camera. Thus, we can get the following results for the migration policy:

$$\begin{aligned} \Phi(N - 1) \neq \Phi(N) &\leftrightarrow \{\Phi(N - 1) = 0 \cap [\exists j(\varepsilon_j(N) > \theta_j)]\} \\ \cup \{\Phi(N - 1) > 0 \cap \varepsilon_i(N) < \theta_i \cap [\exists j(\varepsilon_j(N) > \theta_j)]\} \end{aligned} \tag{13}$$

where

$$\exists j[\varepsilon_j(N) > \theta_j] = D_{\Phi(N-1)}(N) < \theta_i \leftrightarrow \text{MIN}[\varepsilon_j(N)]_{j=1,\dots,Q} > \theta_j \quad (14)$$

In the real word conditions, situation 1 can be ignored in a perfect tracking surveillance system. Thus we can get the hand-off policy and modify the (12) as the following equation:

$$\Phi(N-1) \neq \Phi(N) \leftrightarrow \{\Phi(N-1) > 0 \cap \varepsilon_i(N) < \theta_i \cap [\exists j(\varepsilon_j(N) > \theta_j)]\} \quad (15)$$

Thus, we can get the definition of $\Phi(N)$ as:

$$\Phi(N) = \begin{cases} \Phi(N-1), & \varepsilon_{\Phi(N-1)}(N) \geq \theta_i, \\ \text{MIN} \varepsilon(N), & [\varepsilon_{\Phi(N-1)}(N) < \theta_i] \cap [\exists j(\varepsilon_j(N) > \theta_j)] \\ 0, & \text{in queue} \end{cases} \quad (16)$$

Finally, we use Equation (16) to accomplish the seamless tracking in a real-time multiple active camera surveillance system. Each camera decides the situation that what times the tracking process should be handoff to others, and which camera is the best selection.

5. Experiment Results. In this section, we present some experiment results to demonstrate the effectiveness of the proposed algorithm. The AXIS 215 camera was used in this experiment. The camera offers remote monitoring with pan, tilt and zoom over IP networks. The total magnification capacity of $48\times$ ($12\times$ optical zoom and $4\times$ digital zoom) increases monitoring options with the ability to show a detailed and precise view of the zoomed-in area. The AXIS 215 PTZ can pan $\pm 180^\circ$ from position 0° and tilt $\pm 90^\circ$ from position 0° . The limited of active camera may cause the tracking **loss**. The image size is conventional 640×480 . First, we show the experiment result in a simple environment in Figure 9. The proposed method has been tested and evaluated along with the traditional tracking method. The proposed algorithm is compared with PTZ camera tracking method [23] by using particle filter which minimizes the total tracking distortion, and camera allocation depends on the minimum distance between PTZ camera and object.

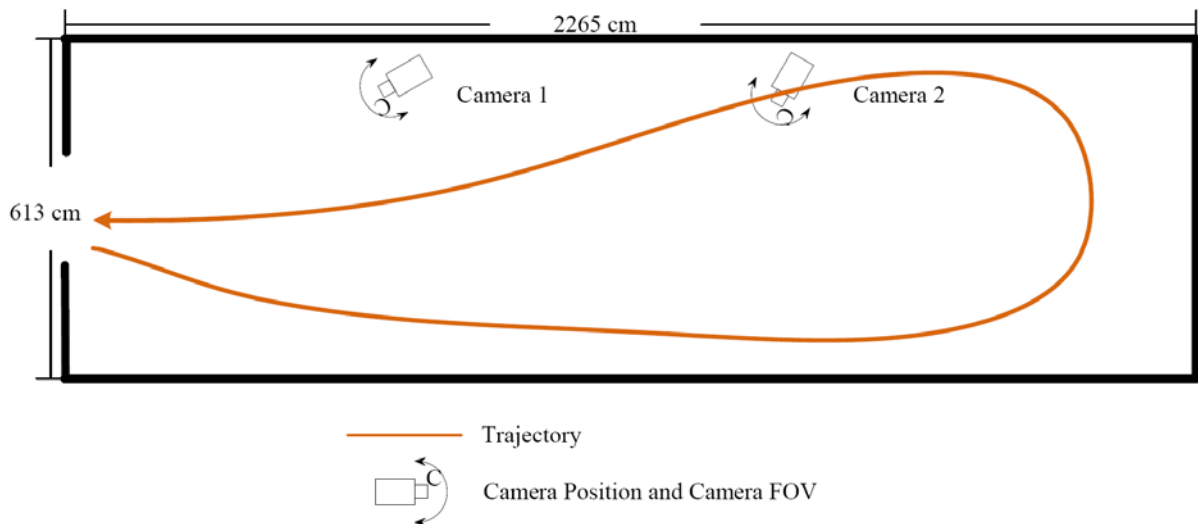
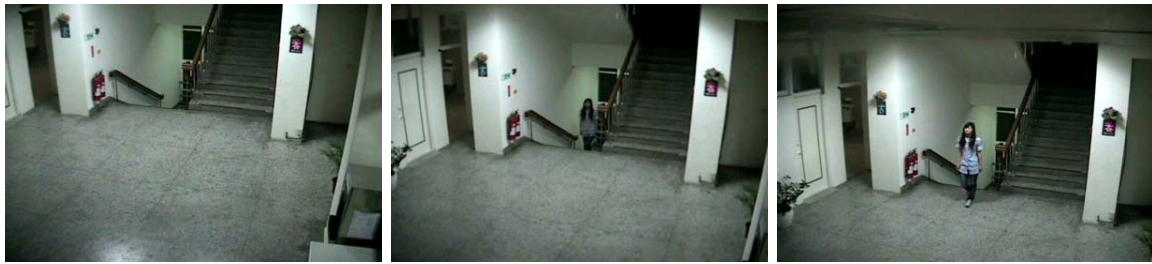


FIGURE 9. An illustration of floor plan

The Figures 10 and 11 show the FOV of cameras 1 and 2 for the continuous object tracking based on our proposed algorithm, receptivity. The intruder walks into the monitor area from the stair in camera 1's view, as show in Figure 10(b). Because the intruder has detected, we carry out the continuous tracking algorithm by using camera hand-off filter. The intruder should be in whichever of the camera view in order to achieve the



(a)

(b)

(c)



(d)

(e)

(f)



(g)

(h)

(i)



(j)

(k)

(l)



(m)

(n)

(o)

FIGURE 10. Experiment results for the object continues tracking in camera 1's FOV based on our proposed algorithm

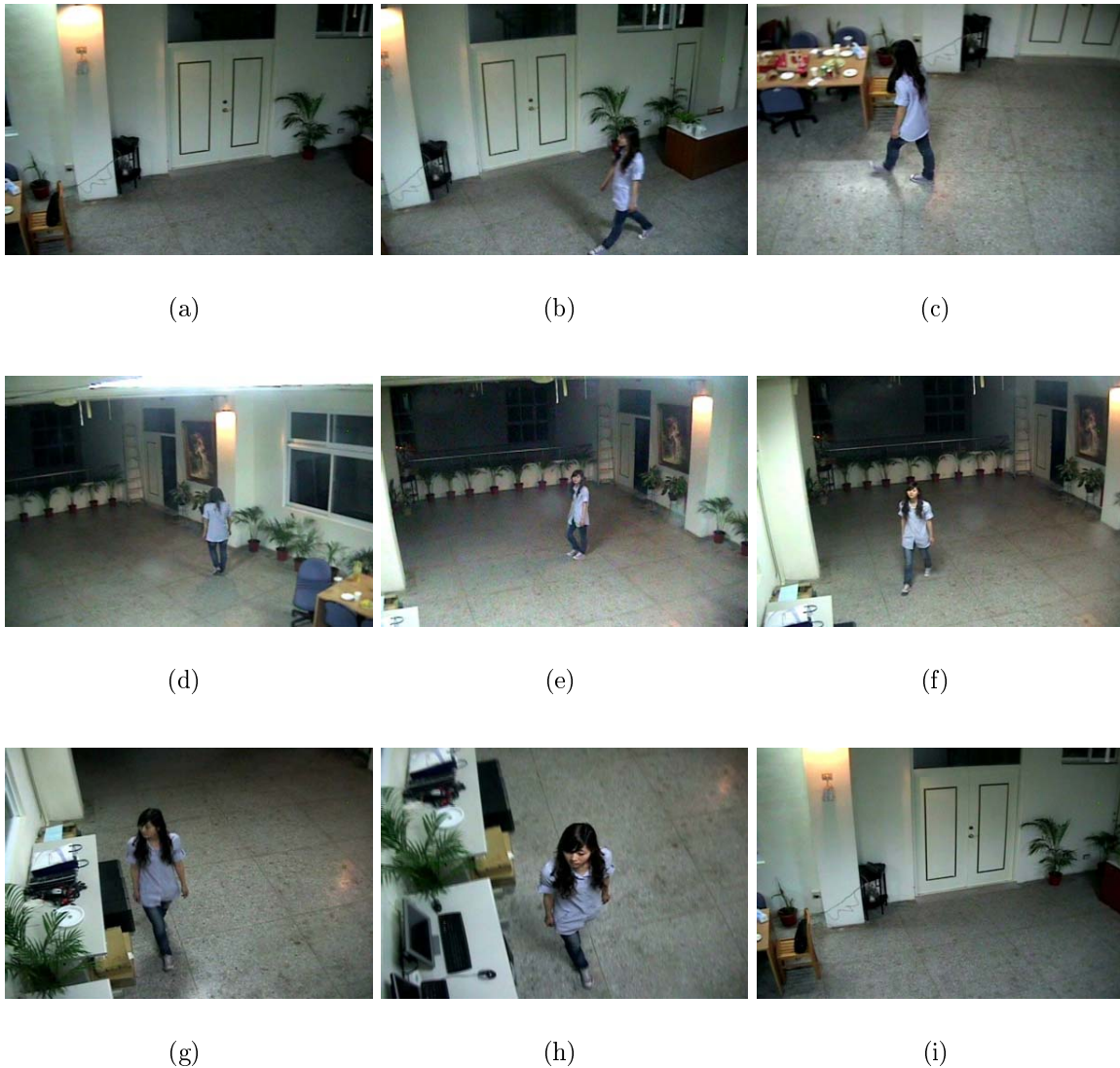


FIGURE 11. Experiment results for the object continues tracking in camera 2's FOV based on our proposed algorithm

continuous tracking. In Figure 10(h), the camera 1 should be hand-off to the camera 2, and then back to the home point, as show in Figure 10(i). The camera 2 tracks the intruder in Figures 11(b)-11(h). In Figure 11(h), the intruder is too close the camera 2 and should hand-off to camera 1. Then, camera continues track the intruder until she walks out of the monitor area, as show in Figures 10(j)-10(o). Figures 12 and 13 show the FOV of cameras 1 and 2 for the object continuous tracking based on PTZ camera tracking method, receptivity. Figures 12(b)-12(g) show the FOV of camera 1. The Figure (g) shows camera hand-off. The camera 2 tracks the intruder in Figures 13(b)-13(l). Note that, the intruder is too close to the camera 2 and causes the loss of the tracking, as shown in Figure 13(l). In summary, our camera filter can achieve the continuous tracking, the intruder always in the camera view of camera 1 or camera 2. The traditional tracking method, PTZ camera tracking method, may cause the tracking loss in some scenarios. Besides, the results show that our proposed algorithm can hand-off to the best camera to obtain the higher quality image automatically.

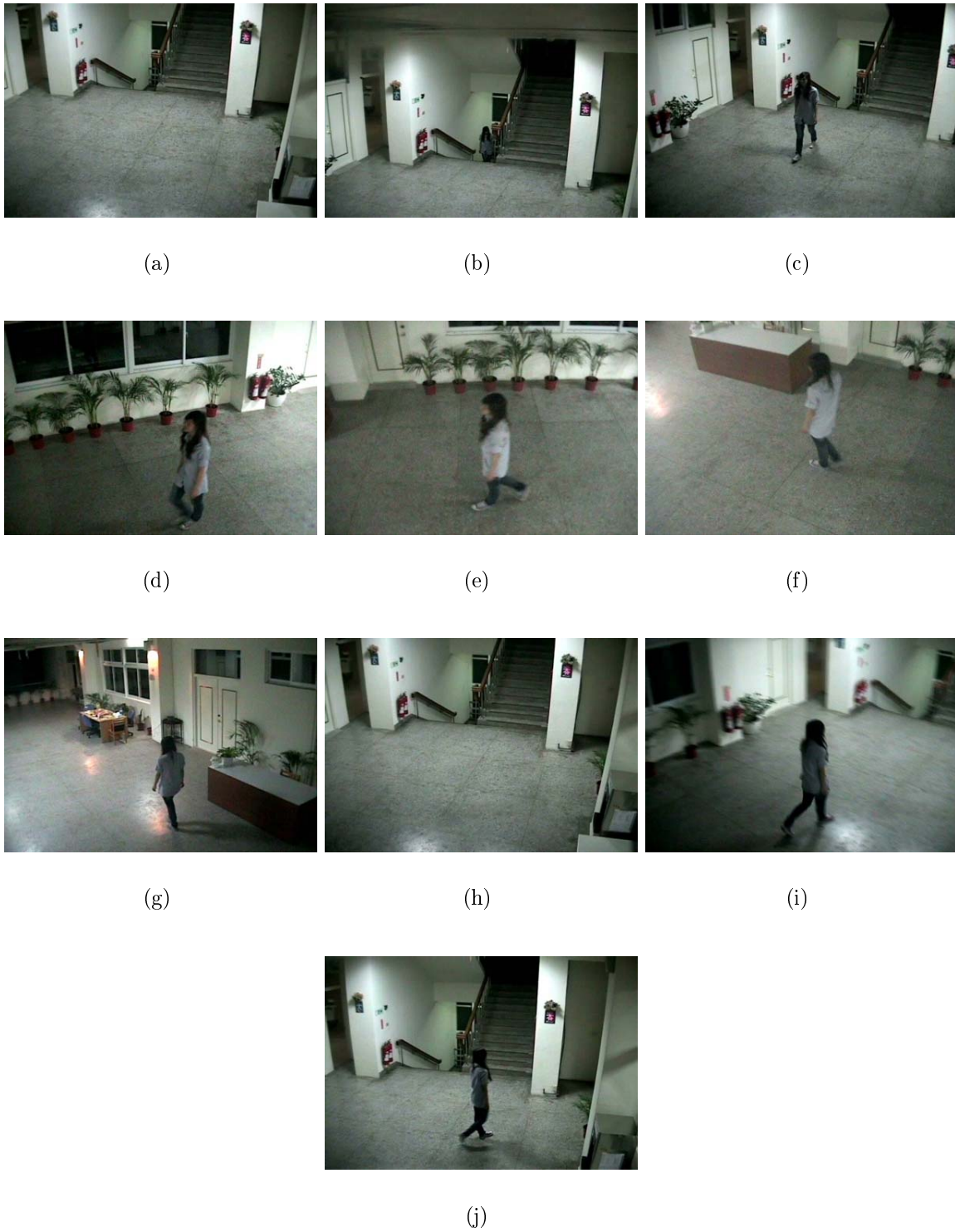


FIGURE 12. Experimental results for the continuous object tracking in camera 1's FOV based on PTZ camera tracking method

Next, we implement the tracking methods in more complex environment, as show in Figure 1. The monitored area is a $1000m \times 800m$ field. The AXIX 215 camera was also used in this experiment. Points are uniformly sampled in the ground plane. The deployment of each camera is displayed in the blue area of Figure 1. The proposed method has been tested and evaluated along with other two traditional surveillance methods.



(a)

(b)

(c)



(d)

(e)

(f)



(g)

(h)

(i)



(j)

(k)

(l)



(m)

(n)

FIGURE 13. Experimental results for the continuous object tracking in camera 2's FOV based on PTZ camera tracking method

Object is modeled as rectangular bounding box. For a pedestrian object, the bounding box has variable width and height, and the orientation is not modeled. Its distance field value is taken at the center of the bounding box, which is assumed to be on the ground plane. The proposed algorithm is compared with PTZ camera tracking method [23] and video camera tracking scheme [25] for different walking speed of object. The proposed and PTZ camera tracking system is composed of a stationary camera and six pan-tilt-zoom (PTZ) camera. The PTZ camera tracking method tracks object by using particle filter which minimizes the total tracking distortion, and camera allocation depends on the minimum distance between PTZ camera and object. The particle filter has been widely applied in people detection and tracking in many applications. Another method, video camera tracking scheme, also uses particle filter for object tracking. All of the camera in this surveillance system is stationary camera and cannot rotate. Static cameras generally cannot be used to capture wide areas owing to their limited view angles.

This work attempts to resolve the defect in seamless tracking to help us determine which camera should be selected and when to perform the handoff to achieve high quality camera view. First, we discuss the continuous tracking rate in Figure 14. The continuous tracking rate is defined as the chance of successful detection of the object in a FOV. Our algorithm provides a higher continuous tracking success rate than both PTZ camera tracking method and video camera tracking scheme. Our method delivers high continuous tracking success rate for object at both normal and brisk speed. Incomplete tracking record often occurs with a static camera due to its limited view. In PTZ camera tracking method, when object moves close to the camera it may fall out of the FOV, causing a discontinued tracking. When the object walks slowly, success rate of PTZ camera tracking method is same with our method; however, the success rates of both methods are close to the 100 percent. Another scene, the number of handoff in our method outnumbering that of other methods is a possible phenomenon, as shown in Figure 15. This work attempts to achieve continuous tracking with high quality FOV in selected camera. The pixel of object which is in the camera view is too heavy or too less may cause the target loss. Therefore, our method decides to handoff the tracking to another camera of higher quality view, especially when the object gets too close or too far to the camera. Our proposed can keep the object in camera view to avoid the tracking loss. The high numbers of handoff is the trade-off and it can enhance the efficiency of system.

Next, the quality of camera view is assessed in Figures 16, 17 and 18. This work attempts to obtain high quality image in selected camera view and decide the time to trigger the handoff. It can also be extended to areas such as face recognition or human motion recognition applications. Our method provides highest quality image in tracking system among all three, as show in Figure 16. As the walking speed of object increases, the FOV suitable rates in both PTZ camera tracking and video camera tracking methods decrease accordingly. Such a result is attributable to great variation of object size in camera view, as shown in Figures 17 and 18. The bounding box size of our method has the least variation, meaning that the distance between object and selected camera has the least variation. As the walking speed of object increases, the variation of bounding box size increases, and the image quality of camera view reduces as well. The employment of our method not only improves seamless tracking success rate but also ensures better flexibility in the selection of optimal views for object of interest.

6. Conclusions. The tracking of individual requires the mechanism to assign a camera for a specific individual and hand-off this from one camera to another to achieve seamless tracking. In this paper, we design a measure to quantitatively formulate the effectiveness of object tracking in order to trigger camera handoff on a timely basis and appropriately

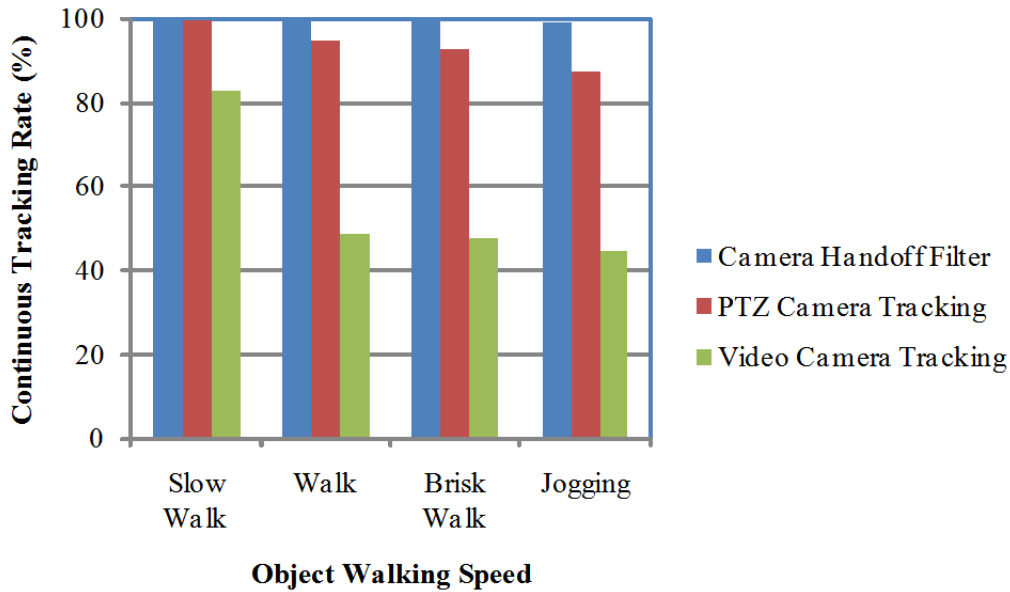


FIGURE 14. Comparison of the continuous tracking rate in terms of different object walking speed

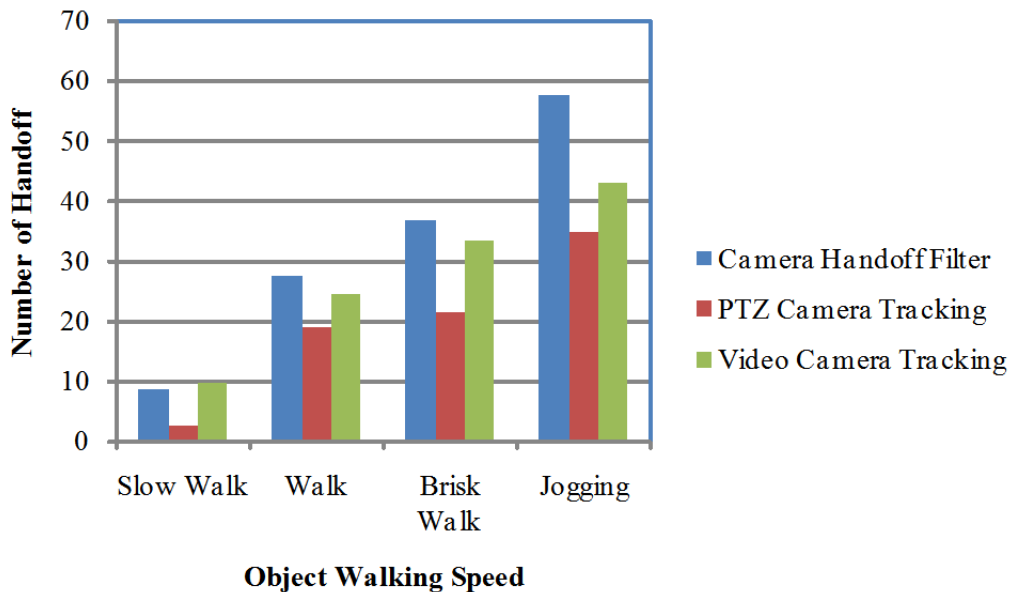


FIGURE 15. Comparison of the number of handoff in terms of different object walking speeds

select next camera for tracking before the object falls out of the field of view (FOV) of the currently monitoring camera. In addition, the proposed also provides low computational complexity camera filter for seamless tracking in selecting the optimal views covering the object of interest. Since several elements including long substantial distances and different capabilities of multiple cameras may be involved in the successful capture of high quality image, we have to deal with the camera hand-off task skillfully. Our approach has two adaptive environment considerations which include the positioning of individual and activation of camera capability. Besides, when the image quality is getting lower or the

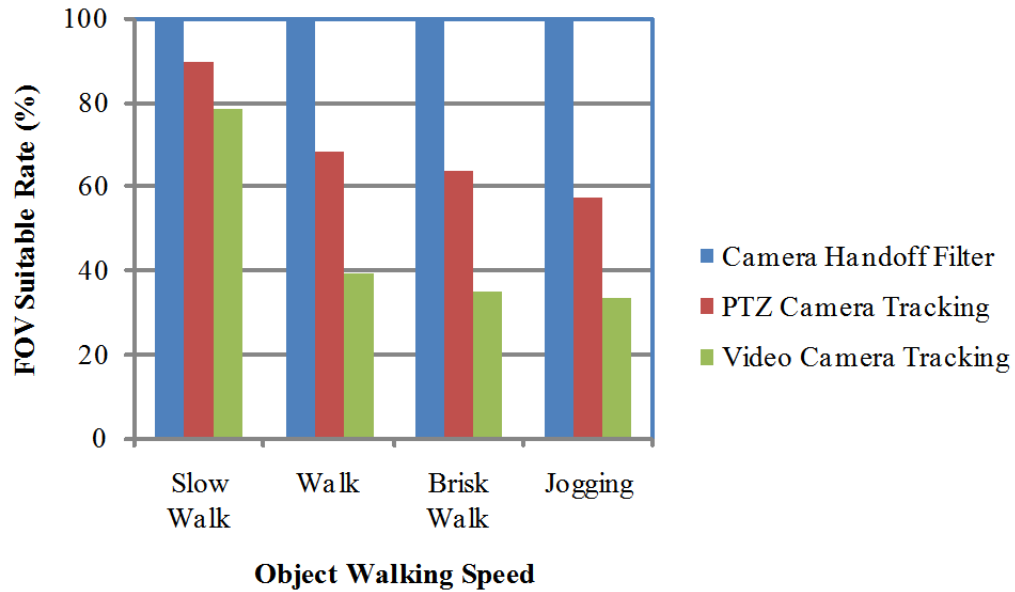


FIGURE 16. Comparison of FOV suitable rate in terms of walking speeds of different objects

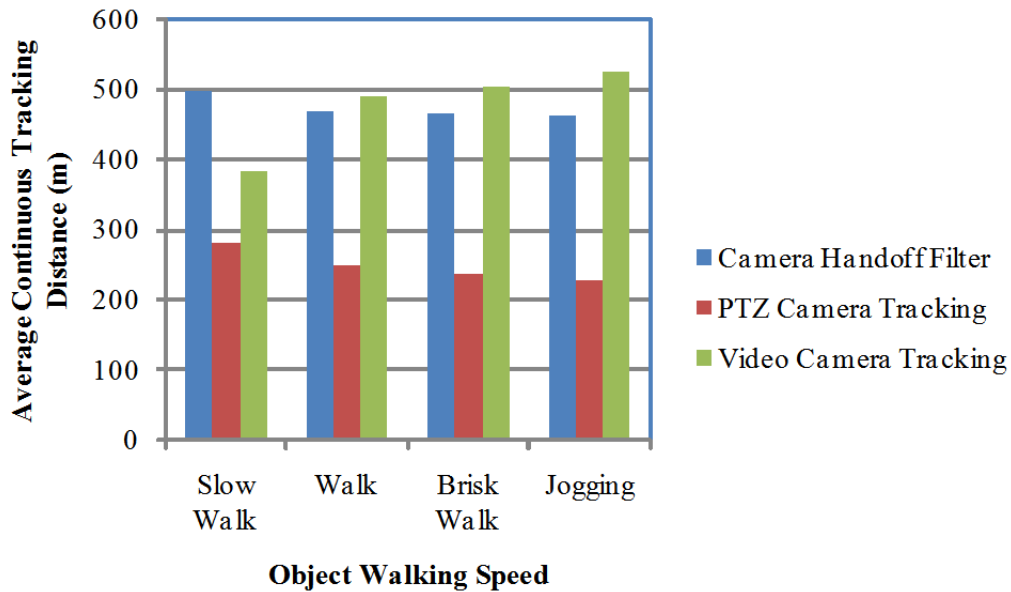


FIGURE 17. Comparison of average continuous tracking distance in terms of walking speeds of different objects

object is leaving the FOV of the current monitoring camera, the above approach can swiftly choose the next suitable camera to recapture the targeted object. The handoff filter of our constructed can be designed to switch among cameras automatically. Experimental results have demonstrated that our proposed paper would constitute a feasible solution to realize accurate and efficient seamless tracking task. Its excellent performance and convenient implementation are the main merits of this algorithm. With the increase in the scale and complexity of a surveillance system, our method can accomplish demanding

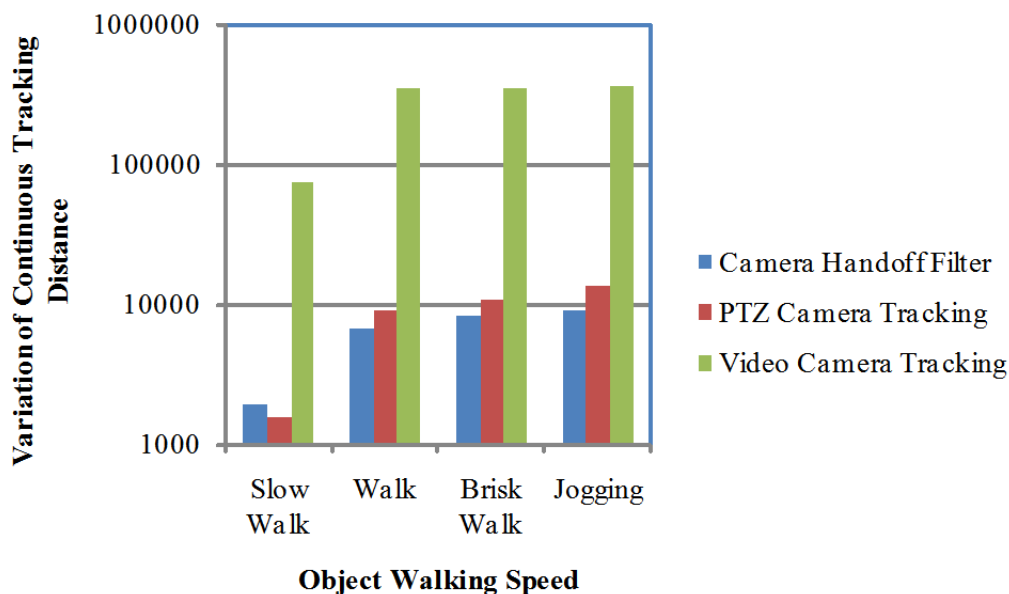


FIGURE 18. Comparison of variation of continuous tracking distance in terms of walking speeds of different objects

object tracking and monitoring with the required resolution and continuity. By means of its application, the scalability in the IP-surveillance system is hereby provided.

Acknowledgment. The authors would like to acknowledge the valuable comments and suggestions of the reviewers, which have improved the quality of this paper. Funding from the Research Center for energy Technology and Strategy, National Cheng Kung University, under projects from the Ministry of Education and the National Science Council (D100-23003 and NSC 99-2221-E-228-003) of Taiwan is gratefully acknowledged.

REFERENCES

- [1] Q. Cai and J. K. Aggarwal, Tracking human motion in structured environments using a distributed-camera system, *IEEE Trans. Pattern Anal. Mach. Intell.*, vol.21, pp.1241-1247, 1999.
- [2] J.-S. Hu and T.-M. Su, Robust environmental change detection using PTZ camera via spatial-temporal probabilistic modeling, *IEEE/ASME Transactions on Mechatronics*, vol.12, no.3, pp.339-344, 2007.
- [3] K.-T. Song and J.-C. Tai, Dynamic calibration of pan-tilt-zoom cameras for traffic monitoring, *IEEE Transactions on Systems, Man, and Cybernetics, Part B*, vol.36, no.5, pp.1091-1103, 2006.
- [4] L. Maddalena and A. Petrosino, A self-organizing approach to background subtraction for visual surveillance applications, *IEEE Transactions on Image Processing*, vol.17, no.7, 2008.
- [5] C.-S. Yang, R.-H. Chen, C.-Y. Lee and S.-J. Lin, PTZ camera based position tracking in IPSurveillance system, *Proc. of the IEEE International Conference on Sensing Technology*, Tainan, Taiwan, pp.142-146, 2008.
- [6] S. Araki, T. Matsuoka, N. Yokoya and H. Takemura, Realtime tracking of multiple moving object contours in a moving camera image sequences, *IEICE Transaction on Information and System*, vol.E83-D, no.7, pp.1581-1591, 2000.
- [7] M. Shibata, T. Makino and M. Ito, Target distance measurement based on camera moving direction estimated with optical flow, *Proc. of the 10th IEEE International Workshop on Advanced Motion Control*, pp.62-67, 2008.
- [8] M. Valera and S. A. Velastin, Intelligent distributed surveillance systems: A review, *IEE Proc. of Vision, Image and Signal Processing*, vol.152, no.2, pp.192-204, 2005.

- [9] L. C. Shiu, The robot deployment scheme for wireless sensor networks in the concave region, *International Journal of Innovative Computing, Information and Control*, vol.6, no.7, pp.2941-2953, 2010.
- [10] J. Ren, M. Xu, J. Orwell and G. A. Jones, Real-time modeling of 3-D soccer ball trajectories from multiple fixed cameras, *IEEE Transactions on Circuits and Systems for Video Technology*, vol.18, pp.350-362, 2008.
- [11] M. Wan and J.-Y. Herve, 3D target tracking using multiple calibrated cameras, *Proc. of the 2006 IEEE International Conference on World Automation Congress*, pp.1-6, 2006.
- [12] X. Wei, C. Zhou and Q. Zhang, ICA-based features fusion for face recognition, *International Journal of Innovative Computing, Information and Control*, vol.6, no.10, pp.4651-4661, 2010.
- [13] J.-B. Li, H. Gao and J.-S. Pa, Common vector analysis of gabor features with kernel space isomorphic mapping for face recognition, *Journal of Innovative Computing, Information and Control*, vol.6, no.9, pp.4055-4064, 2010.
- [14] D. Murray and A. Basu, Motion tracking with an active camera, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol.16, pp.449-459, 1994.
- [15] A. Yilmaz, X. Li and M. Shah, Contour-based object tracking with occlusion handling in video acquired using mobile cameras, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol.26, no.11, pp.1531-1536, 2004.
- [16] S. Arulampalam, S. R. Makell, N. J. Gordon and T. Clapp, A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking, *IEEE Transactions on Signal Processing*, vol.50, no.2, pp.174-188, 2002.
- [17] J. H. Kotecha and P. M. Djuric, Gaussian particle filter, *IEEE Transactions on Signal Processing*, vol.51, no.10, 2003.
- [18] P. Guha, D. Palai, D. Goswami and A. Mukerjee, DynaTracker: Target tracking in active video surveillance systems, *Proc. of the 12th International Conference on Advanced Robotics*, pp.621-627, 2005.
- [19] Y. Li and B. Bhanu, A comparison of techniques for camera selection and handoff in a video network, *Proc. of the 3rd ACM/IEEE International Conference on Distributed Smart Cameras*, pp.1-8, 2009.
- [20] J. Orwell, P. Romano and G. Stein, Multiple camera color tracking, *Proc. of the IEEE International Workshop on Visual Surveillance*, pp.4-24, 1999.
- [21] Y. Jo and J. Han, A new approach to camera hand-off without camera calibration for the general scene with non-planar ground, *Proc. of the ACM International Workshop on Video Surveillance and Sensor Networks*, pp.195-202, 2006.
- [22] J. Kim and D. Kim, Probabilistic camera hand-off for visual surveillance, *Proc. of the 2nd ACM/IEEE International Conference on Distributed Smart Cameras*, pp.1-8, 2008.
- [23] P. D. Z. Varcheie and G.-A. Bilodeau, Adaptive fuzzy particle filter tracker for a PTZ camera in an IP surveillance system, *IEEE Transactions on Instrumentation and Measurement*, vol.60, no.2, pp.354-371, 2011.
- [24] Y. Lu and S. Payandeh, Cooperative hybrid multi-camera tracking for people surveillance, *Canadian Journal of Electrical and Computer Engineering*, vol.33, no.3, pp.145-152, 2008.
- [25] P. Pan and D. Schonfeld, Dynamic proposal variance and optimal particle allocation in particle filtering for video tracking, *IEEE Transactions on Circuits and Systems for Video Technology*, vol.18, no.9, pp.1268-1279, 2008.
- [26] N. Sebe, M. S. Lew and D. P. Huijsmans, Toward improved ranking metrics, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, pp.1132-1143, 2000.
- [27] Intel, *Open Computer Vision Library*, www.intel.com/technology/computing/opencv/, 2008.