Operator tracking system using particle filter for skill evaluation in nuclear power plant control room

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Abstract: This article proposes an automated operator tracking system by the use of particle filter and image processing technology to help operator skill evaluation in nuclear power plant operator training facilities. In each of the control room of the training facilities, a full-scope plant simulator with mock-up control panels are used for real-time operator training. At this point, the operators' behaviors and plant's events are recorded as video-log and event-log, by a multi-media recording system to evaluate operators' skills at training review meetings in which the instructors and trainees discuss each of their action during the training process. Multiple cameras that are placed on the control room ceiling are used in the recording system. However, the views from these cameras are limited and therefore it is not possible to thoroughly check how each of the operator approaches the target panel within an appropriate timing that corresponds to the plant's event. For example, the instructors have to estimate operators' real-world position from the views; and in some cases other operators might conceal the target operators from the cameras. The purpose of the proposed system is to help checking whether the position and timing of each operator is appropriate during each event or alarm occurrence, by tracking the operators from the recorded video.
To achieve this objective, the real-time image processing technology is newly introduced in this study, where particle filter is one of convenient algorithms for operator tracking. In this algorithm, the main issue is how to recognize multiple operators from the background and to get their positions within the coordinates of the control room. For this purpose, one 3-D particle filter is used for each operator wearing colored vests and the similarity calculation algorithm is based on color histogram. The particles are directly placed inside the control room. By converting the particle coordinates into camera coordinates and taking into account the distance between particles and the camera, the position and size of candidate regions on the video frame for similarity calculation can be easily calculated. The above approach is verified by using actual training environment in the Boiling Water Reactor (BWR) operator training center corporation facility.
Keyword: image processing; operator tracking; particle filter; operator training center

1 Introduction

Nuclear power plant operators are constantly taking skill-development programs at training facilities. The Boiling Water Reactor Operator Training Center (BTC) [1] is one example of such facility. The operators are trained in BTC's plant control rooms of which each room is equipped with a full-scope power plant simulator with mock-up control panels. Real-time trainings are performed based on various kinds of training scenarios.

All of the training processes are recorded by a multi-media recording system. The recorded data includes event-logs that record the changes of power plant status and video-logs at the control room, taken by multiple camera system. The generated data are utilized as part of training materials as well as the base of discussions at the review meetings for the instructors and the trainees for the evaluation of trainee's operation skills.

The operation-skill evaluation is based on trainees' actions and behaviors in each of the training scenario. Figure 1 depicts about an example of training scenario. As shown in Fig.1, whenever an alarm goes off, each trainee should take specified actions, such as to reach specified points and to complete specified operations with specified postures such as pointing and calling [2].

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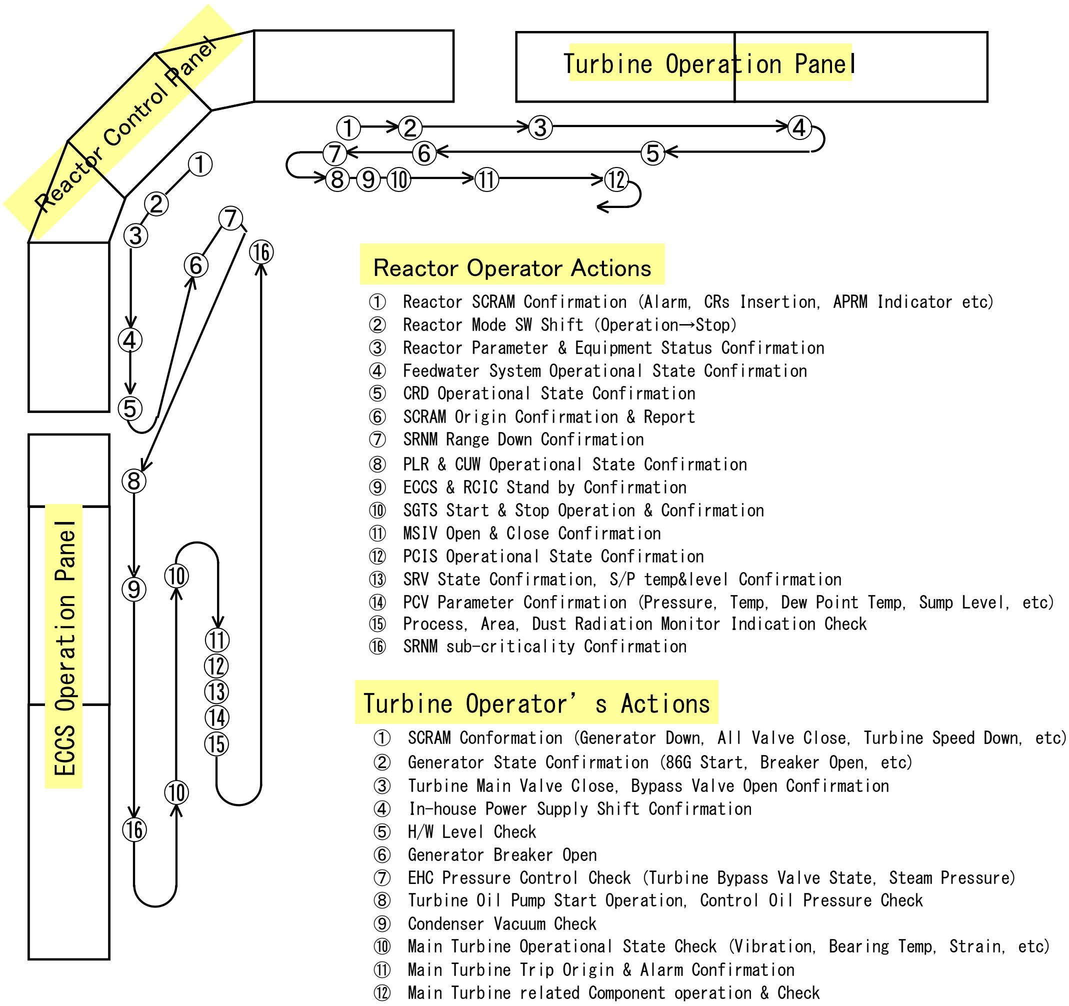

Fig.1 Example of training scenario:
the needs for trainees' movement directions on the ground plan of the control room and operations.

At present, the main way to obtain information for trainees' skill evaluation that identifies the relationship between the events on the power plant and the actions of the trainees is to manually read the event logs and the video logs. These measures are very time-consuming and labor-intensive, while also poses difficulties in the evaluation of skill in quantitative manner.

There are two issues that shall be addressed for the improvement of the skill evaluation system, namely: (i) automatically acquire all necessary information including trainees' positions, operations as well as behaviors and mental status, in order to reduce evaluation cost; and (ii) no change in the hardware of the training environment as the changes are irrelevant and unnecessary for trainees and will affect their concentration. Having said this, one of the best ways is to use image-processing technology to get all necessary information from the video log taken by the existing multimedia recording system [3].

Many image-processing techniques have been proposed from the computer vision field for object detection, tracking classification and pattern recognition based on image sequence. Background subtraction is a useful technique for object detection [4-6]. However, it is difficult to use background subtraction to detect and distinguish multiple objects especially in case of objects occlusion.

Particle filtering algorithm [7-8] offers a simple and convenient approach to realize tough and steady object-tracking and is widely introduced in various object-tracking systems [9-11]. However, an assumption in those studies is that the size of the objects to be tracked in the video is almost constant and that there is no need to differentiate each object from another. The video log in the BTC was taken inside the control room and the cameras are located very close to the trainees, so that whenever the trainees move into the control room, the subject distance, which refers to the distance between the trainees and the cameras, will drastically change. This condition leads to the size of the trainees on the video frame change drastically as well. Moreover, there are several difficulties in the application of only one of above-mentioned techniques to the video logs, as follows:

(1) There are four trainees in one training team and each of them should be tracked and distinguished from one another,
(2) The trainees will overlap on the video frame, which will cause occlusions, and
(3) Background subtraction will be difficult by unclear image.

In this article, we propose a way to track multiple trainees from multiple synchronized videos by using combination of 3-D particle filter and background subtraction. In this regard, the particles are scattered inside the space of the control room and the likelihood or similarity of each particle is calculated based on histogram distance. A tracking system based on this idea has been developed which may provide the position on the room floor for each trainee. Our experiments suggested that this system is very efficient and steady.

This article consists of five sections, of which the following Section 2 describes about the detailed design of the proposed tracking system and Section 3 elaborates about the details of particle likelihood calculation. Section 4 explains about the implementation and experiments of the proposed system as well as the discussion of the experimental results whereas Section 5 concludes the article with suggestions for future works.

2 3-D particle filter based tracking

2.1 System architecture

The architecture of the proposed tracking system is shown in Fig.2. The input of the system has four synchronized videos. Figure 3 shows one frame of the input video. The video of Camera C-4 was not used. Each trainee wore colored vests, namely red, blue, yellow and green.

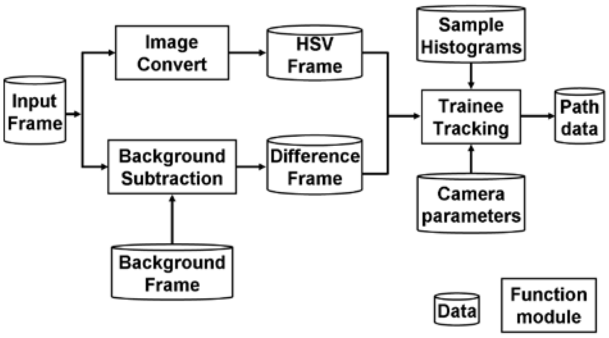

Fig.2 Architecture of the tracking system.

The Image Convert module converts the input frame from Red-Green-Blue (RGB) color space to Hue-Saturation-Brightness (HSV) color space. The Background-Subtraction module calculates the abstract difference frame of the input frame and the background frame. The Trainee-Tracking module implements the tracking algorithm to extract the path data, which is the data sequence of target trainees' floor location, from each HSV frame and absolute difference frame. The camera parameters include camera position and a homography determinant used for the transformation between the coordinates of the control room space and the frame image from each camera.

Fig.3 One frame of the input video.

The sample histograms are the histograms of trainees' image samples that were taken from the input video. More than one sample was used for each trainee in each video stream. Figure 4 shows examples of the image.

Fig.4 Examples of image sample.

The output of this system is path data, which refers to the location of each trainee in the control room.

2.2 Particle filter

Particle filter offers a framework to give approximate probability distribution of the trainees in the entire control room space by using a set of particles. In our proposed design, each particle has its state, which is the world coordinate of the control room. The particles are restricted on a plane parallel to the floor of the control room. The distance between the plane and the floor is 1.25**m**, with the average height of between the floors up to the center of the trainees' vests. The weight of each particle is a value of 0.0 to 1.0 for indicating how much the particle's location matches the location of the trainee that is to be tracked. Particle filter based tracking algorithm is simple and sensitive to noise and change of environment.

The tracking algorithm used in our proposed system is as follows:

(i) Initialization: one set of particles is created for each trainee.

(ii) Prediction and re-sampling: each particle moves to its adjacent location. The direction and distance of the movement is based on the normal distribution model.

(iii) Observation: to calculate the likelihood value of each particle. The likelihood values are normalized such as:

$$\sum_{i=1}^{N} w_i = 1 \qquad (1)$$

where N is the number of particles and $\boldsymbol{w_i}$ is the likelihood value of particle $\boldsymbol{i}$.
The detail of the calculation is provided in the next section.

(iv) Measurement: to obtain the location of the trainee $\vec{P}$ from positions of the particles weighted by their likelihood values with the following equation:

$$\vec{P} = \sum_{i=1}^{N} \vec{p}_i \cdot w_i \qquad (2)$$

where $\vec{p}_i$ is the position of particle $\boldsymbol{i}$.

The above steps (ii), (iii) and (iv) are conducted for each frame in the input video.

3 Calculation of likelihood

The likelihood of each particle is calculated based on two kinds of normalized histogram distance:

- ***ds***: histogram distance between the trainees' image sample and the candidate region on the input frame according to the location of the particle. The value of ***ds*** is from 0.0 to 1.0 and small ***ds*** means that the particle is close to the position of the target trainee.
- ***dd***: histogram distance between the candidate region according to the location of the particle and the **background sample** (a region that obviously does not include any trainee) on the absolute difference frame. The value of ***dd*** is from 0.0 to 1.0 and small ***dd*** means the particle is not close to any trainee. The reason of using background sample is to avoid the influence of noise on the absolute difference frame. The noise is caused by the illumination changing inside the training room. As shown in Figure 6, the value is not 0 even in the background area on the absolute difference frame.

The procedure of the likelihood calculation for particle $\boldsymbol{P_{3d}}$ in the 3D space of the training room is as follows:

(i) Get the projection point $\boldsymbol{P_{2d}}(v)$ on each video image $\boldsymbol{I}(v)$ for v = 1, 2 and 3 as referred to in Fig.5.

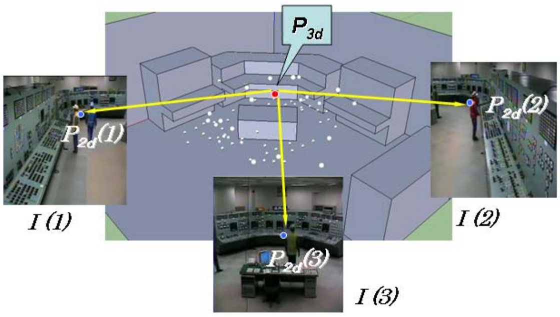

Fig.5 Projection points of a 3-D particle.

(ii) For each $\boldsymbol{I}(v)$($\boldsymbol{v}$=1,2,3), get the histogram $\boldsymbol{Hc}(v)$ of the candidate region around $\boldsymbol{P_{2d}}(v)$ on the input frame and the histogram $\boldsymbol{Hd}(v)$ of the candidate area on the absolute difference frame. The center of the region is $\boldsymbol{P_{2d}}(v)$ and the size $\boldsymbol{L}(v)$ of the region is given by the equation below:

$$L(v) = -k(v) \cdot D(v) + c(v) \tag{3}$$

Here $\boldsymbol{D}(v)$ is the distance between the position of $\boldsymbol{P_{3d}}$ and the position of camera v; $\boldsymbol{k}(v)$ and $\boldsymbol{c}(v)$ are positive constants for $\boldsymbol{I}(v)$.

(iii) For each $\boldsymbol{Hc}(v)$, get the minimum value $\boldsymbol{ds}(v)$ of

$$ds(v,i) = HD(Hc(v), Hs(v,i)) \tag{4}$$

where $\boldsymbol{Hs}(v,i)$ $(i = 1, M)$ is the sample histograms for $\boldsymbol{I}(v)$ and $\boldsymbol{M}$ is the number of sample histograms; $\boldsymbol{HD}(\boldsymbol{H1},\boldsymbol{H2})$ is the Bhattacharyya Distance of normalized histograms $\boldsymbol{H1}$ and $\boldsymbol{H2}$ given by the equation below:

$$HD(H1, H2) = \sqrt{1 - \sum \sqrt{H1_i \cdot H2_i}} \tag{5}$$

(iv) Get the histogram distance $\boldsymbol{dd}(v)$ by $\boldsymbol{HD}(\boldsymbol{Hd}(v),\boldsymbol{Hb})$; where $\boldsymbol{Hb}$ is the histogram of the background sample taken from the left-top corner of the absolute difference frame that obviously does not include any trainee (Fig.6).

(v) The likelihood value $\boldsymbol{w}(v)$ for $\boldsymbol{I}(v)$ is given as follows:

$$\boldsymbol{w}(v) = (1.0 - \boldsymbol{ds}(v)) * \boldsymbol{dd}(v) \tag{6}$$

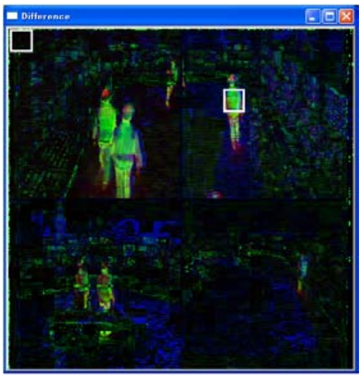

Fig.6 The absolute difference frame (in HSV space), the background sample (on the left-top corner) and the candidate region on the target trainee.

(vi) Due to the dead angle of the camera, the projection point of some particles will be out of the view range of the camera and cannot be retrieved, whereas $\boldsymbol{w}(1)$, $\boldsymbol{w}(2)$ and $\boldsymbol{w}(3)$ cannot always be available together. Therefore, the likelihood $\boldsymbol{w}$ of $\boldsymbol{P_{3d}}$ is given as follows:

- If only one of $\boldsymbol{w}(1)$, $\boldsymbol{w}(2)$ or $\boldsymbol{w}(3)$ is available, $\boldsymbol{w}$ is given as the available value.
- If two of them were availabl**e**, $\boldsymbol{w}$ is given as the average of the two values.
- If three of them were available**,** $\boldsymbol{w}$ i**s** given as the average of the larger two values among them.

4 Implementation and experiments

To validate the proposed idea, an experimental system was developed. As an image processing toolkit OpenCV [12] was used. Camera parameters used to coordinate conversion are identified by the use of mesh type markers set on the floor.

4.1 Experiment of likelihood calculation

This experiment tested the calculation algorithm of likelihood. Figure 7 shows the result of which the left part is the input frame and the right part indicates the likelihood value that is the function of the 3-D particle position. At this point the target trainee wears a red-colored vest. In this frame, only the image from camera C-2 may provide higher likelihood value. The brightness of green color on the right part, which is the ground plan of the control room, is according to the value of likelihood obtained from the image of camera 2, whereas the red point is the estimated position of the target trainee.

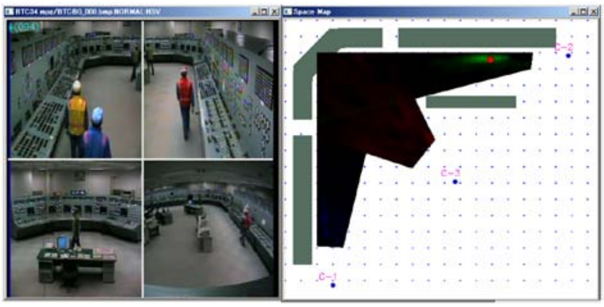

Fig.7 The likelihood distribution and the estimated position of the red-colored vest trainee (Note: image from one camera is available).

Figure 8 is another result of likelihood calculation test. Here the same target trainee can be viewed from cameras C-2 and C-3, as seen on the left part of Fig.8 and the images from C-2 and C-3 provide higher values of likelihood. The brightness of green and red color on the right part of Fig.8 is according to the likelihood values on the images from C-2 and C-3.

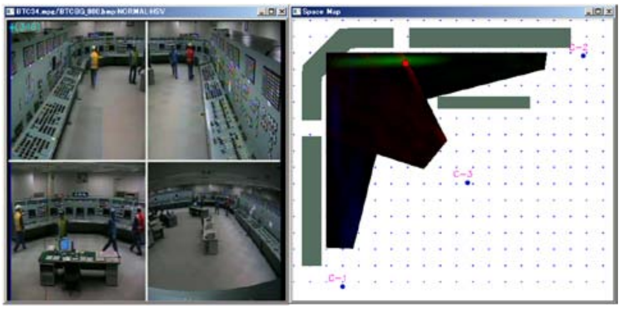

Fig.8 The likelihood distribution and estimated position of the red-colored vest trainee (Note: images from two cameras are available).

Figure 9 is the result of which the target trainee can be viewed from all of the three cameras as seen on the left part of Fig.9. The brightness of blue, green and red color on the right part of Fig.9 is according to the likelihood values obtained from the images from cameras C-1, C-2 and C-3.

4.2 Experiment of trainee tracking

Figure 10 shows an example of trainee-tracking result from a 786 frame (26.2 seconds) video clip. The left part shows the coordinates of the estimated moving path and the real-time moving path, whereas the right part shows the estimated moving path on the ground plane of the training room.

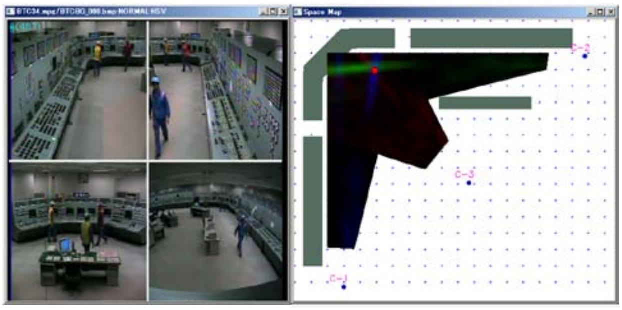

Fig.9 The likelihood distribution and the estimated position of the red-colored vest trainee (Note: images from three cameras are available).

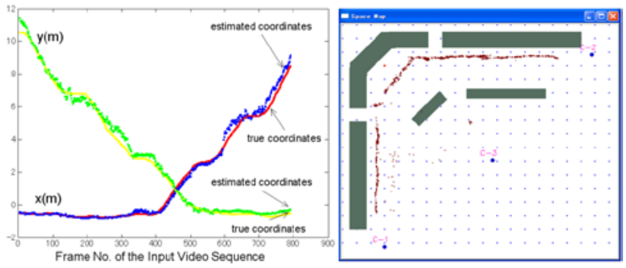

Fig.10 Example of trainee-tracking result.

Figure 11 shows the error of estimated position on each frame. Figure 12 shows the error distribution of Fig.11.

The following results were achieved during the experiments:

(i) A normal standard computer has enough power to realize real-time tracking from the input video.

(ii) The average of tracking error can be less than 0.5**m**.

(iii) The tracking accuracy can be improved by the use of multiple synchronized video streams to avoid occlusion.

(iv) HSV color mode is more effective than RGB color model.

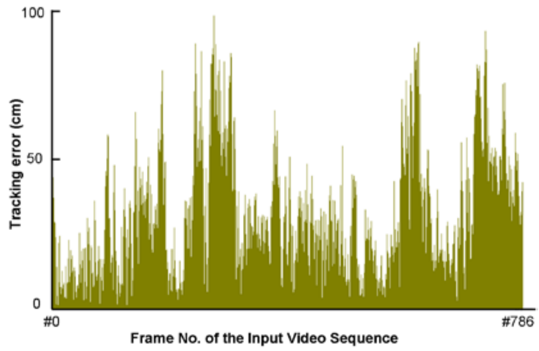

Fig.11 Tracking error: The distance between the real position and the estimated position in each frame.

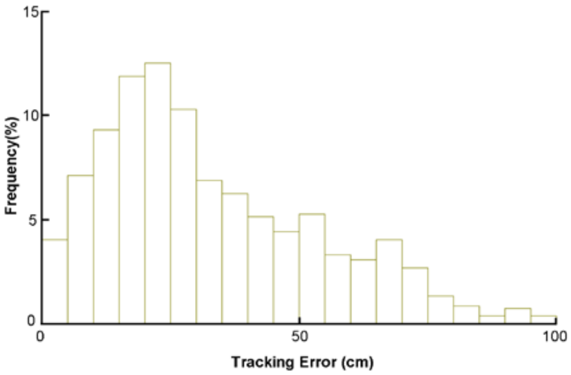

Fig.12 Tracking error distribution of Fig.11.

5 Conclusions

This article proposes an image-processing method to determine output of the trainees' moving paths in the training room of BTC from the image sequence of the video log. This is the first step to automatically getting trainees' action history for improving the skill evaluation in the training facility. This method serves to estimate the trainees' location on the room floor by using 3-D particle filter algorithm. The trainees were identified by the different color of vests that they wore.

An experimental image processing system was developed and experiments were conducted with the video data recorded by the existing recording system. Although the quality of the video data was not very good, it has been proven that the proposed method works well.

The future works of this research will be:

(i) Improvement of the accuracy and performance by reviewing each step of the likelihood calculation, including the use of noise filters or other pattern recognition techniques, instead of histogram distance.

(ii) Improvement of the video recording system by introducing high-resolution cameras and Omni directional cameras, which may cover the whole area of the control room.

(iii) Improvement of trainee identification. It is necessary to identify methods other than colored-vests. For example, putting small colored markers on trainee's uniform will result in the minimum change on the training environment of the control room and will no longer disrupt the trainees.

(iv) An important issue for operation-skill evaluation in the training facility, especially for fully digital control rooms, is to identify the direction of trainee's faces and eyes. Trainees' faces and eye direction-tracking will be the main task in future research for which a new multimedia record system using multiple network cameras located on the control panels will be further studied.

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