POSTURE RECOGNITION OF NUCLEAR POWER PLANT OPERATORS BY SUPERVISED LEARNING

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ABSTRACT

This paper proposes a postures recognition method of nuclear power plant operators by a supervised learning approach. Operator's silhouettes in the images are detected by combinations of several image processing techniques such as a background subtraction, noise reductions and others. Their postures are recognized by a machine learning technique. Their operations are summarized and visualized with human body computer graphics. The posture recognition is a challenging task because an operator usually takes various postures during power plant operations. To recognize the detected silhouettes, the method uses the four postures that have been classified by the cognitive scientists engaged in human factors research of nuclear power plant operations. In evaluation experiments with over twenty thousand images, the silhouettes are classified to the four postures successfully and the operations are summarized by the classified postures.

1. INTRODUCTION

An operations training of nuclear power plants is performed by full-size power plant simulators. The training is always recorded on videotapes. Many examples such as optimal and not optimal operations are included in the video images. The images are very useful teaching materials for other operators. We need to protect operator's privacies so that an individual cannot be specified from the video images, when we use the images as the teaching materials.

A simple approach is a mosaic method that covers an operator's face with a mosaic mask. However, operators are identified by their gestures and walks [1]. From the reason, the operator's privacies cannot be protected by the mosaic method. Popular approaches are model-based methods that use kinematic 2D or 3D models of a human body [2][3]. They require the accurate 2D or 3D models and initialization processes of correspondence between the model and the human body in the beginning. Other approaches are learning-based methods that use a lot of sample images [4][5]. They don't require the accurate 2D or 3D models and the initialization processes between the model and the human body.

This paper proposes a postures recognition method of nuclear power plant operators by a supervised learning. Operator's silhouettes in the images are detected by several image processing techniques such as a background subtraction, noise reductions and others. Their postures are recognized by a machine learning technique. Their operations are summarized and visualized with human body Computer Graphics (CG).

The method uses Support Vector Machines (SVM) [6] as one of machine learning tools. The SVM has been successfully used in many computer vision applications and well founded in statistical learning theory. However, the posture recognition is still a challenging task because a plant operator takes various postures in the video images. To recognize the detected silhouettes, the method uses the four postures that have been classified by the cognitive scientists engaged in human factors research of nuclear power plant operations [7]. In evaluation experiments with over twenty thousand images, the silhouettes are classified to the four postures successfully and the operations are summarized by the classified postures.

We describe the operations training and the four postures in section 2. Section 3 presents the method overview and section 4 presents the experimental results. We conclude in Section 5.

Figure 1. An image of the operations training

Table 1. Conditions and postures of an operator.

Condition	Postures
Standing	1) Observation 2) Operation 3) Pointing 4) Answering Phone
Moving	1) Observation 3) Pointing

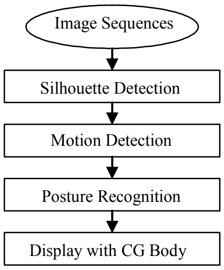


Figure 2. The outline of the method.

2. THE FOUR POSTURES

The training centers of the nuclear power plant operations have a lot of videotapes that recorded the operations training. The images in the existing videotapes were recorded under the constant light condition by a single stationary camera. The white balance and the focus of the camera were also fixed. Figure 1 shows an image example and the Vanishing Point (VP) of the image.

Operator's actions in the front of an operation panel have been classified into the following postures: 1)observation, 2)switch operation, 3)pointing, and 4)phone [7]. These postures are also classified into the two conditions: standing and moving (see Table 1).

3. OVERVIEW OF THE METHOD

Operator's silhouettes in the images are detected by combinations of several image processing techniques such as a background subtraction, noise reductions and etc. The detected silhouettes are classified into the four postures by the SVM. The operations training are summarized and visualized by the human body CG. Figure 2 shows the outline of the method.

3.1. Silhouette Detection

The first part in the silhouette detection is a background subtraction that calculates the absolute difference between a new image and the background image. The subtracted images include a lot of noises in general. To remove the noises, it uses threshold T and the standard deviation that is calculated when making the background image from n images. The lower pixels than the standard deviation or the threshold T are set to zero in the subtracted image.

Figure 3. An example of a detected silhouette

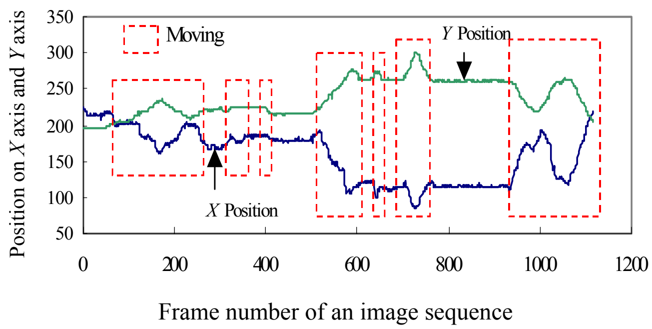


Figure 4. Separation of conditions: moving and standing

The next part is also another noise reduction with morphological filters that remove isolated pixels. The final part is the grouping of the remaining pixels. Connected or near pixels are labeled as one group. The near pixels are defined within the threshold L:

$$L = \frac{80}{2} \times \frac{|\mathbf{P}_2|\cos\theta_2}{|\mathbf{P}_1|\cos\theta_1}$$

where $\mathbf{P}_1$ is a vector from the VP (see Figure 1) to the entrance of the left panel and θ_1 is the angle between the horizontal line and the vector. $\mathbf{P}_2$ is a vector from the VP to a labeled group and θ_2 is an angle between the horizontal line and the vector. The constant value 80 is height (pixels) of an operator at the entrance of the left panel. Figure 3 shows an example of a detected silhouette.

3.2. Motion Detection

The detected silhouettes are classified into the two conditions at the movement speed of them. We use a sigma band to classify the silhouettes into the conditions. Figure 4 shows positions of the silhouettes on X and Y axis in the images. An average over m frames and a standard deviation d are calculated at each line in Figure 4. We use the standard deviation d as the separation threshold of the two conditions. We set m=20 and d=1.5 in the experiments. In Figure 4, the threshold divided the 1,118 images into the two conditions: 520 images as the standing condition and 598 images as the moving condition.

3.3. Posture Recognition

The height sizes of the phone postures are clearly different from other three postures (see Figure 5). The graph in Figure 5 shows the height sizes of the detected silhouettes that are normalized with the distances from the VP. The valley portions of the graph are obviously phone postures. The reason is that all phones have been installed at the lower part of the operation board. The operators have to bend their body to catch the phones.

The other three postures are not classified by the height sizes. To classify the other three postures, the method uses the form features that are 512 dimensions of the upper half of the normalized silhouettes (32 × 32 pixels).

The posture recognition is a two-classification problem when the silhouette is classified into the moving condition (see Table 1). On the other hand, it is a three-classification problem when the silhouette is classified into the standing condition. The SVM is a two-classification algorithm. We use a one–against-one strategy [8] for the three-classification problem in the method.

4. EXPERIMENTS

We mainly describe the SVM classification results of the three postures: the observation, the operation, and the pointing.

4.1. SVM Classification

We prepared 935 training silhouettes for the SVM from the image sequences in Figure 4. Examples of the training silhouettes are shown in Table 2. The details of the manually classified 935 silhouettes are as follows: 562 silhouettes for the observation posture, 265 for the operation posture, and 108 for the pointing posture. We used the classified silhouettes to investigate the recognition accuracy of the method.

We changed training ratios of the SVM from ten percent to fifty percent in the 935 silhouettes. The correct recognition rates for the remaining silhouettes are shown in Figure 6.

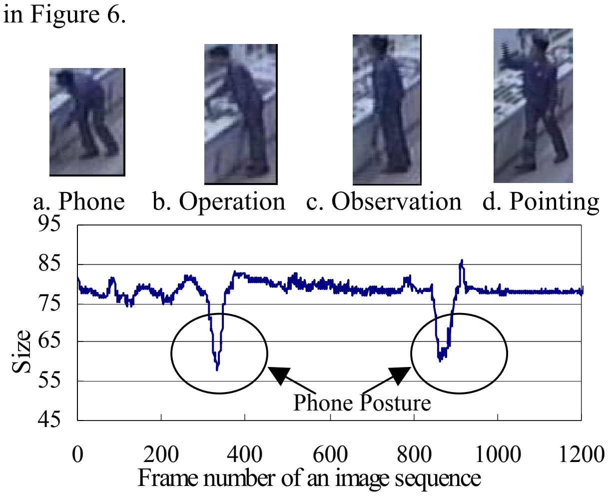
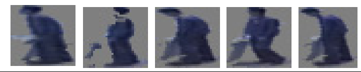


Figure 5. Separation of the phone postures and the others.

Table 2. Examples of the normalized silhouettes

Posture	Sample silhouettes
Observation	
Operation	
Pointing	

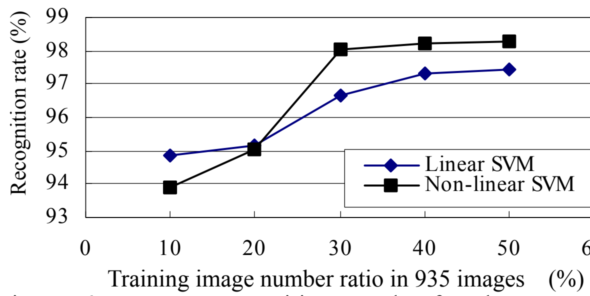


Figure 6. Posture recognition results for the manually classified silhouettes

Table 3. Learning ratios for the 935 silhouettes

Features	Observation	Operation	Pointing
Size	83%	87%	37%
Color	91%	88%	63%
Form	100%	100%	99%

Figure 6 also shows not only gaussian-kernel results of the SVM but also linear-kernel results. The SVM classification achieved about ninety eight percent recognition rates at the fifty percent training. Even in the ten percent training, the recognition rate was ninety four percent. The gaussian-kernel showed better results than the linear-kernel when the training rates were more than twenty percent.

We made comparison experiments using the size features and the color features to investigate the validity of the form features. The size features are 3 dimensions: a height/width ratio of the detected silhouette, a ratio of the silhouette area in a surrounded rectangle, and a diagonal line length of the rectangle. The color features are 1024 dimensions that are color histograms (32×32) on the rg-space (r=(R+G+B)/R, g=(R+G+B)/G) of the upper-half of the silhouette. The learning rates of the SVM with the 935 silhouettes are shown in Table 3. The form features showed the best learning rates.

4.2. Postures Recognition

The postures recognition results of new three hundred forty images are illustrated in Figure 7 and Figure 8. The images didn't include phone postures. The recognition results of all the detected silhouettes are drawn as a graph in Figure 7. The operator's positions and his postures are displayed with the CG in Figure 8. All postures were recognized perfectly by the method.

We evaluated the method with ten thousand images for the operator O_1 and with ten thousand images for another operator O_2. Phone postures were included in the twenty thousand images. Each recognition rate was ninety nine percent and ninety five percent. The details are in Table 4. The classification results of the operator O_1 are better than the other operator O_2. The main reason is that the SVM was trained with the 935 silhouettes of the operator O_1 in advance.

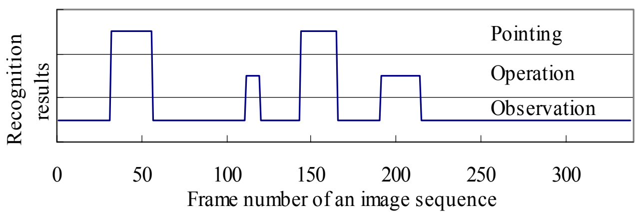


Figure 7. Recognition results of the three postures for 340 images.

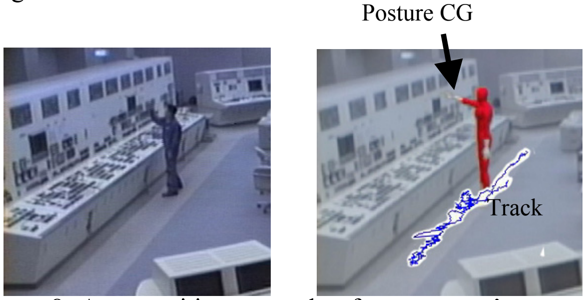


Figure 8. A recognition example of an operator's posture and his motion track.

Table 4. Correct classification rates for twenty thousand images.

Postures	Observation	Operation	Pointing
Operator: O_1	99%	100%	90%
Operator: O_2	97%	85%	93%

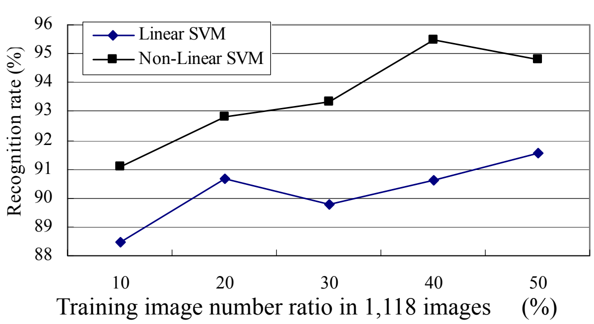


Figure 9. Condition classification results with the lower half of the body.

4.3. Condition Classification

In the above experiments, we used the sigma band of the movement speed to classify the silhouettes into the two conditions: the standing and the moving. To investigate applicability of the SVM classification for the condition classification, we did another experiment using the labeled 1,118 silhouettes that described in the subsection 3.2. In the experiment we used the form features that were 512 dimensions of the lower half of the normalized silhouettes (32×32 pixels). The SVM training ratios were changed from ten to fifty percent in the 1,118 silhouettes.

Figure 9 shows the condition classification results. The maximum classification rate was about ninety five percent. The condition classification by a single image was more difficult than the posture classification (see Figure 6 and Figure 9).

5. CONCLUSION

This paper presented a postures recognition method of the nuclear power plant operators by the supervised learning technique. To simplify the challenging task, we proposed to use the four postures that have been classified by the cognitive scientists.

In the evaluation experiments with over twenty thousand images, the actions of the operators were classified to the four postures successfully by the method. The method can be applied to the existing video image libraries to make the teaching materials.

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