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ESTIMATION OF NEXT HUMAN ACTION AND ITS TIMING BASED ON THE HUMAN ACTION MODEL CONSIDERING TIME SERIES INFORMATION OF THE SITUATION

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Abstract

In order to realize a system that supports human actions timely, the system must have a certain model of human actions. Therefore, we propose a modeling method of human actions. In this method, it is supposed that a person changes his action according to the situation around him, and the causality between the situation around a person and the change of a human action is modeled. This causality is expressed by an If-then-Rule style where a human action and the situation around a human are expressed by a discrete event and time series data respectively. Moreover, as the necessary function for human support systems, an estimation method of the next human action and its execution timing is consisted based on the proposed modeling method. The usefulness of the proposed modeling and estimation methods is examined through the estimation experiment of next human action and its execution timing with a radio-controlled vehicle.

1 Introduction

In order to realize a system that supports human actions timely, the system must be able to recognize the current action and predict the next one. In general, a human action model is designed for such systems. The modeling methods of human actions are classified in the following two types.

1. Modeling method based on the previous knowledge about human actions.
2. Modeling method based on the past human action data acquired by sensors.

The former method is useful for the application that human action patterns can be modeled in advance such as working processes in a factory or a building site. However, in many cases, it is difficult to design an explicit human action model in advance because human behavior has diversity, environmental dependency, and individuality. Therefore, for the application that human action patterns are not decided in advance, the latter method is mostly used[1]-[4].

In most conventional modeling methods, human action patterns are just modeled with obtained human action data such as walking trajectory, steering signal and so on[5]-[7]. These methods are useful for applications where human actions are not influenced by some sort of situation. On the other hand, it is difficult to apply them for modeling of human actions influenced by situation. Okamoto and Nakauchi[8][9] have proposed modeling methods of human actions considering the situation. However, situations considered in these methods are static one such as scene or location. On the other hand, we focus on the dynamic situation that varies momentarily and continuously.

Sekizawa and Inata[10][11] have proposed modeling methods of the causality between the situation and human actions which are expressed by time series data. In these methods, time series data which express the situation and human actions are modeled by some linear models to be switched timely. However, it is difficult to set such parameters as the length of the time series data or the number of linear models. In addition, the more complicated the human actions or the situation become, the more difficult it is to maintain the quality of the acquired human models. On the other hand, we aim to model this causality using sensing time series data directly in this research.

As the first step, we consider the case that the sensing data for human actions and the situation are obtained as discrete data and time series data respectively. Based on this assumption, we have proposed a modeling method of human actions based on the causality between the situation and human actions[12]. Moreover, in order to realize a system that supports human actions timely, an estimation method of the next human action also have been proposed based on the proposed human action model[13]. In these methods, however, the temporal information of the time series data on the situation was not considered. According to this reason, it was difficult to estimate the execution timing of the next human action based on the change in the temporal information of the situation. In this paper, we propose a modeling method of human actions considering the spatial and temporal information of the time series data which expresses the situation. Moreover, an early estimation method of the next human action and its execution timing is also proposed with the proposed model.

2 Modeling Method of Human Actions

2.1 Outline

We can suppose that a person changes his action according to the change of the situation around a person(which is described as just "situation" below). This causality between the situation and the change of his action is modeled in this research. Here, when it is assumed that the next human action depends on a current one and the situation, this causality can be described by a If-Then-Rule style as following. In this paper, it is called as a human action rule.

$$IF\ \{Current\ action,\ Situation\} THEN \{Next\ action\}$$

It is assumed that human action and the situation are observed with various kinds of sensors. Here, human actions are described as discrete data expressed by $O = \{o_1, o_2, \cdots, o_M\}$, and the situation is described as n dimensional time series data expressed by $X_n = \{x_n(t), x_n(t+1), \cdots, x_n(t+\ell)\}$. M is the number of the action categories, $x_n(t)$ is a sensing signal with n dimension at time t, and ℓ is the length of a time series data. In this method, the reproduced causality with the above expression is extracted from the stored data which consist of human actions and the situation data obtained during the prolonged observation of a person. Therefore, the situation and human actions are subject to the following conditions.

- The situation and human actions are able to be measured with sensors.
- The causality between the situation and a human action has the statistically significant correlation.

Fig.1 shows the propose human action model. In this research, a human action rule is trying to be described directly using the sensing signal as much as possible. However, the human judgment of the situation has the temporal and spatial ambiguity. In order to consider these redundancy of the time series data which express the situation, these data are modeled by a Left-to-Right Hidden Markov Model(HMM)as Fig.1 shows. Therefore, a human action rule is described as Eq.(1).

$$IF\ \{o_{current}\ ,\ HMM(X_n)\}\ THEN\ \{o_{next}\} \qquad (1)$$

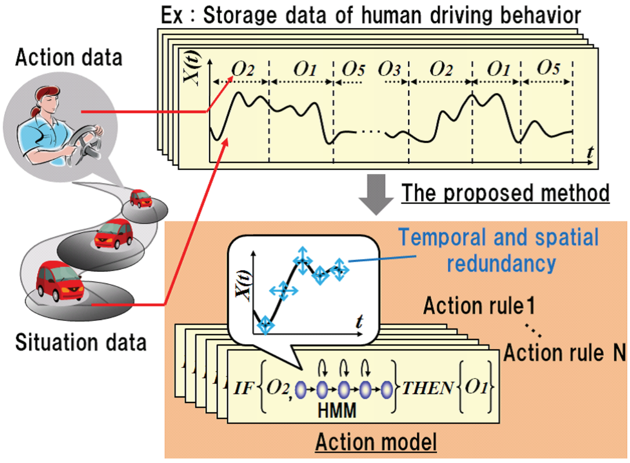

Figure 1. The propose human action model

Various kinds of human action rules are obtained depending on the combination of the situation and the change of human actions. Therefore, a set of obtained human action rules is regarded as a human action model as Fig.1 shows.

2.2 Procedures of human action modeling

A set of human action rules is generated through the following three steps as Fig.2 shows.

Step.1 Segmentation and classification of the stored data based on the human action data.

Step.2 Reclassification of the segmented data based on the situation data.

- **(i)** Classification based on the spatial similarity.
- **(ii)** Extraction of the part which contributes to the next human action induction.
- **(iii)** Classification based on the temporal similarity.

Step.3 Modeling of the situation by HMM and generation of human action rules.

These processes are detailed in the following.

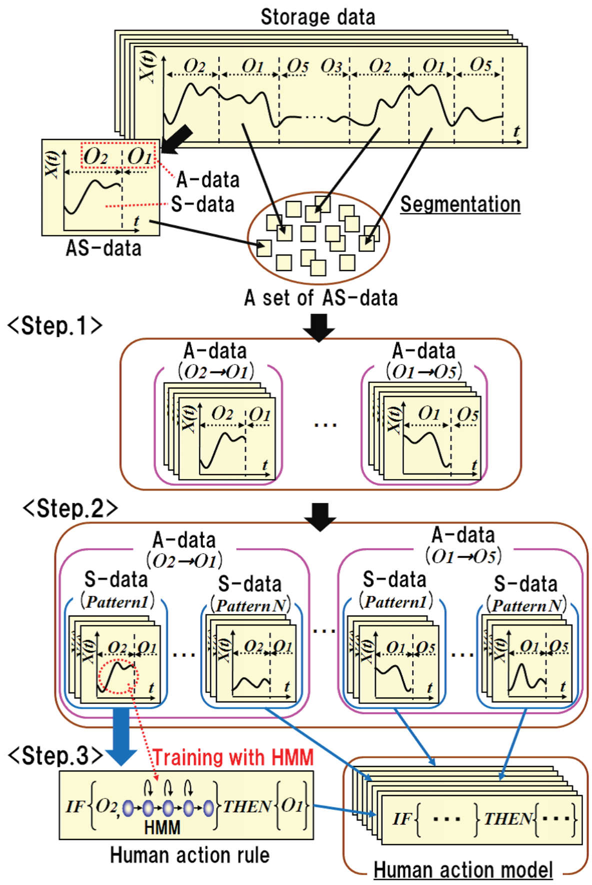

Figure 2. Procedures of human action modeling

(Step.1) Segmentation and classification of the stored data based on the human action data

First of all, the stored data which consists of human actions and the situation data are segmented into parts based on the change of human action as the top figure in Fig.2 shows. Thus, a set of the combination data(AS-data) is obtained, which consists of the discrete data(A-data) and the time series data(S-data) to express the human action change and the situation respectively. Then, the set of AS-data is classified into some groups based on the A-data as Fig.2(Step.1) shows.

(Step.2) Reclassification of the segmented data based on the situation data

In this step, a set of AS-data which has the same A-data is reclassified based on the S-data as

Fig.2(Step.2) shows. S-data has the spatial and temporal patterns. The spatial pattern means the difference in the waveform of the time series data. On the other hand, the temporal pattern means the difference in the changing velocity of one. In conventional researches about human action modeling, there are some examples that consider the spatial pattern. However, there are few examples that explicitly consider both patterns. This is because these action models are mainly used to recognize the only type of human actions, which means the system recognized all actions as the same even if each action has a different temporal pattern. However, when a system offers the supports to be synchronized with human actions like cooperative works, the human action model must be able to recognize not only the spatial information but also the temporal one like the timing on human actions. For this reason, the classification of spatial and temporal patterns is executed. Although most classification methods of time series data are based on the Continuous Dynamical Programming Method or HMM, these methods cannot evaluate the temporal and spatial patterns separately because of the comprehensive evaluations. Therefore, this study provides the classification method which can separate the temporal patterns based on the each similarity.

Moreover, the time series data which expresses the S-data may contain the part which does not contribute to the next human action induction. For example, when a person drives a car on the straight road, the situation on the straight road does not contribute to his next action around a curve after the straight road. This means that the situation on the straight road does not have the causality relationship to the change of human action around the curve after the straight road. According to this reason, it is executed to extract the part to contribute to the next human action from S-data. The followings detail these processes.

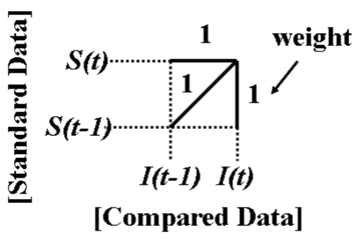

Figure 3. Slope constraint of CDP

-(i) Classification based on the spatial similarity

First of all, a set of AS-data which has the same A-data is classified based on the spatial similarity of the S-data. Here, CDP(Continuous Dynamic Programming[14][15]) with the slope constraint shown in Fig.3 is applied to evaluate the only spatial similarity between two time series data respectively the S-data express. One S-data is arbitrarily chosen as a standard data in CDP, and the others are treated as compared data as Fig.4(Step.2-i) shows. Then, the spatial similarity between the standard data and the compared data is evaluated continuously from the end to the start. This is because it is assumed that the sensing data just before the action change mainly contributes to the next action induction. If the situation expressed by the compared data is spatially different from the one expressed by the standard data, the similarity between the two data will be calculated low immediately. Therefore, the period for the spatial similarity evaluation is set from the end of the data, and the spatial similarity in this period is calculated. When the calculated value is lower than the threshold, the compared data is regarded to be a spatially different pattern from the standard one.

-(ii) Extraction of the part to contribute to the next human action

Next, the part to contribute to the next action induction is extracted from the compared data which is regarded to be spatially similar to the standard data. It is assumed that the end of the S-data mainly contributes to the next action induction. In addition, it is supposed that the reproducible part in the S-data contributes to the next action induction. Therefore, the similarity evaluation in the previous process is continued for the spatially similar pattern. When the value of the spatial similarity falls below the previous threshold, the similarity calculation is terminated, and the partial data in the period is cut out as Fig.4(Step.2-ii) shows.

-(iii) Classification based on the temporal similarity

Finally, the compared data to be cut out in the Step.2-(ii) is classified based on the temporal similarity. The temporal pattern of S-data means the difference of the change velocity of time series data.

Therefore, it is assumed that the difference of the length of the time series data is calculated as the temporal similarity. When this similarity is lower than the threshold, the compared data is regarded as a temporally similar pattern to the standard data as Fig.4(Step.2-iii) shows.

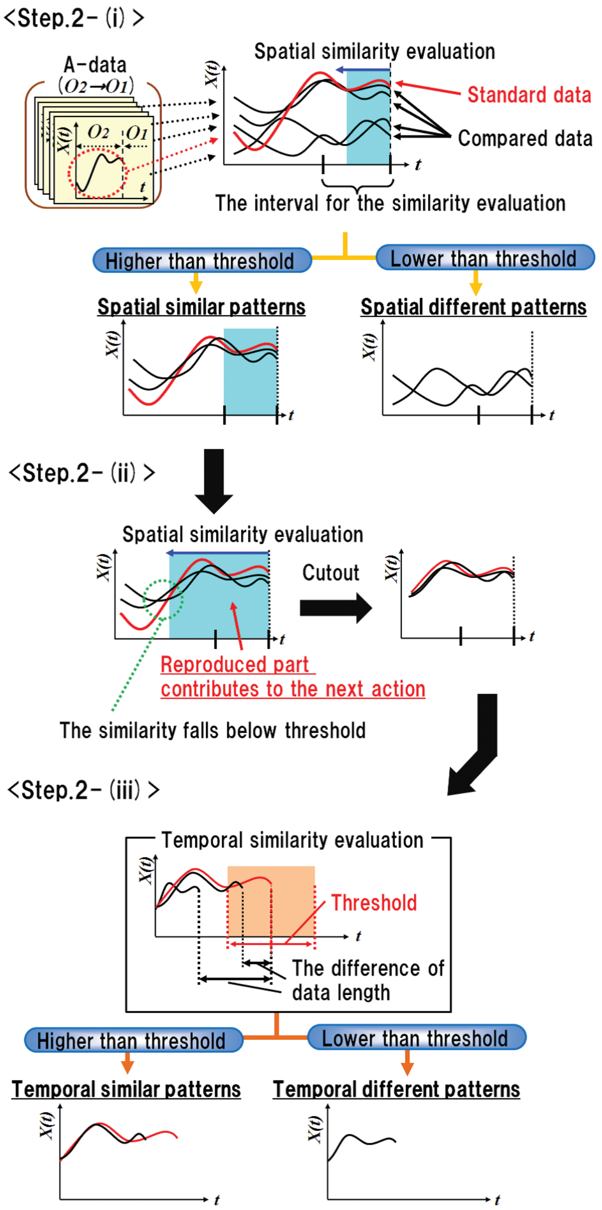

Figure 4. Reclassification and extraction of the AS-data

A new standard data is chosen from the S-data which have been spatially and temporally different from the old one, and the processes from Step.2-(i) to -(iii) are repeated until all AS data obtained in Step.1 are reclassified into each pattern of the AS-data.

(Step.3) Modeling the situation by HMM and generating human action rules

The AS-data classified in the previous two steps are used as training data for HMMs. After training HMMs, they are incorporated into the If-Then-Rules, and human action rules are obtained as Fig.2(Step.3) shows. A set of obtained human action rules is regarded as a human action model in this method.

3 Estimation of Next Human Action and Its Execution Timing

In order to realize a system to support human actions timely, the system must be able not only to recognize the current action and predict the next one. In this section, it is described how to estimate the next human action and its timing early based on the previous human action model.

3.1 Estimation method of next human action

It is assumed that a system is obtaining a discrete data and time series data which express the current human action and the situation respectively as Fig.5 shows. Now the system chooses action rules with the same current human action from all human action rules in the human action model as Fig.5(Step.1) shows. Then, the system evaluates the similarity between the time series data which expresses the current situation and the HMMs in the chosen action rules, and the HMM with the highest similarity to the current situation(Optimal HMM) is chosen as Fig.5(Step.2) shows. Note that the Optimal HMM is chosen early before the actual execution of the next human action. The method to choose Optimal HMM is described in Section 3.2 in detail. The next human action and its execution timing are estimated based on the action rule with Optimal HMM(Optimal rule).

The next human action in the consequent part of Optimal rule is regarded as its estimation result. The execution timing of the next human action is calculated using Optimal HMM and the acquired time series data. Here, in the proposed modeling method, a HMM models the time series data that expresses the situation until execution of the next human action. Moreover, in a Left-to-Right HMM, each state models a partial time series data, and the whole time series data is described by connecting all states in order as Fig.6 shows. Therefore, when the Optimal rule is chosen, the time expressed by the length of time series data from the current state to the final one can be regarded as the time until the execution of the next human action as Fig.6 shows. This time is called as Estimated idle time in this research, and it can be assumed that the next action will be executed after Estimated idle time passes from the current time. Estimated idle time is calculated by the following equations(2)-(4).

$$K_{s_i} = \frac{1}{1 - a_{s_i,s_i}} \tag{2}$$

$$L_{s_i s_j} = \sum_{n=i}^{j} K_{s_i} \tag{3}$$

$$\hat{A}_{s_x} = L_{s_x s_M} - F_{s_x} \tag{4}$$

K_{s_i} : length of the time series data on the i-th state s_i

$a_{s_i s_i}$: transition probability from s_i to s_i

$L_{s_i s_j}$: length of the time series data from s_i to s_j

$\hat{A}_{s_x}$: Estimated idle time

x : current state

M : final state

F_{s_x} : the elapsed time since current state transited s_x

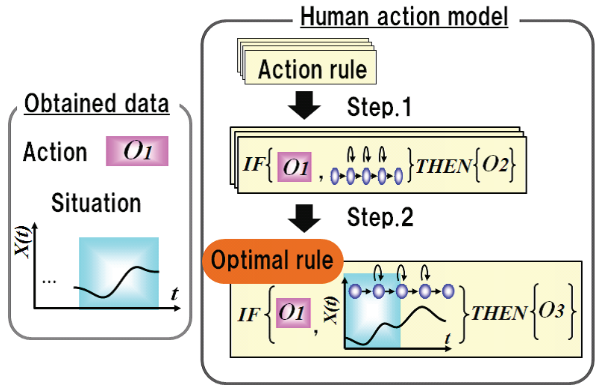

Figure 5. Choice of Optimal rule

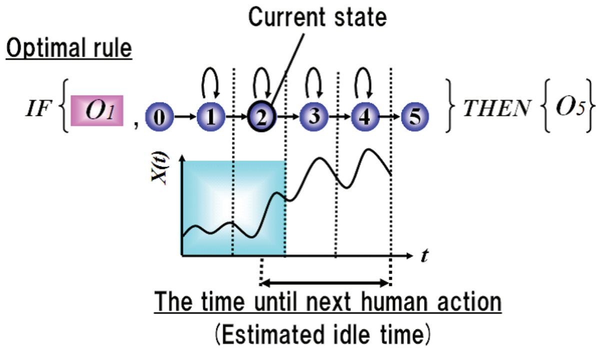

Figure 6. Estimation method of execution timing of next action

3.2 The method to choose the optimal HMM

In the previous estimation method, the similarity is evaluated between the time series data expressed by a current situation and a HMM in order to choose the optimal rule. Described in 2.2 Section, the time series data expressed by a current situation have spatial and temporal patterns. Therefore, it is necessary to evaluate both similarities.

The spatial similarity is evaluated based on End State Free Continuous Viterbi Algorithm(CVA). This method has been proposed as a real-time recognition method of time series data with a HMM. The optimal state transition sequences in a HMM is estimated when a sensing data is input to the HMM continuously. Then, the similarity is evaluated between the input time series data and the partial time series data expressed by the state transition sequences from the initial state to an arbitrary one in the HMM. Therefore, the Optimal HMM is chosen early.

When the time series data which expresses the current situation is input to the HMMs, the HMMs with higher likelihoods calculated by CVA than a preset threshold are chosen. These HMMs are regarded to be spatially similar to the input current situation. The threshold is set based on the calculated likelihood with training data of a HMM by the following equation.

$$T(i) = L_{ave}(i) - \rho * L_{dev}(i) \tag{5}$$

The parameter $T(i)$ is the threshold for the HMM in the i-th action rule. $L_{ave}(i)$ is the average of likelihoods for the data used for the HMM training. $L_{dev}(i)$ is the deviation of likelihoods. ρ is the weight for $L_{dev}(i)$, which is decided by a system designer.

In order to choose the Optimal HMM early, the similarity between the time series data of the current situation and a HMM is evaluated by matching the time series data of the current situation to the partial time series data from the initial state to a decided one in the HMM. This decided state is called Decision state in this paper. In the Step.2, the HMMs where the current state passes Decision state are chosen from among the HMMs chosen by the previous step. Decision state is decided through the learning based on the estimation result of the next human actions with training data. The learning method is described below. At first, the initial value of Decision state is given to a HMM in each action rule. Then, the estimation of the next human action is performed for training data based on the proposed method described in Section 3.1. When a wrong action is output as the estimation result, Decision state shifts to the next one. The learning is terminated when Decision states for all HMMs are not updated. The initial number of Decision state is 2 in this paper.

After the spatial similarity is evaluated, the temporal similarity is evaluated. In this method, we assume that the difference of the data length between the time series data from the initial and current state in a HMM and input time series data is regarded as temporal similarity. A HMM is chosen ,whose difference is the most smallest in the chosen HMMs in the spatial similarity evaluation. This HMM is regarded as the Optimal HMM. Note that the length of time series data from the initial and current state in a HMM is calculated Eq.(4) in Section 3.1.

4 Experiment

4.1 Experimental setup

In this paper, human operations of a radio controlled vehicle are modeled as an example of the application of the proposed modeling method. Fig.7 shows the experimental setup. S-data and A-data are obtained while an examinee operates a radio controlled vehicle in the course as Fig.7(a) shows. In this experiment, S-data is expressed by the time series data of the distances of three directions from the vehicle to the edge of the course as shown in Fig.7(b). On the other hand, A-data is expressed by one signal data in three types of the controller operations, Forward(F), Right turn(R), and Left turn(L) as Fig.7(c) shows. There are three types of velocities of the radio controlled vehicle, high(45[cm/s]), medium(30[cm/s]), and low speed(20[cm/s]). Therefore, S-data which have several temporal patterns are obtained.

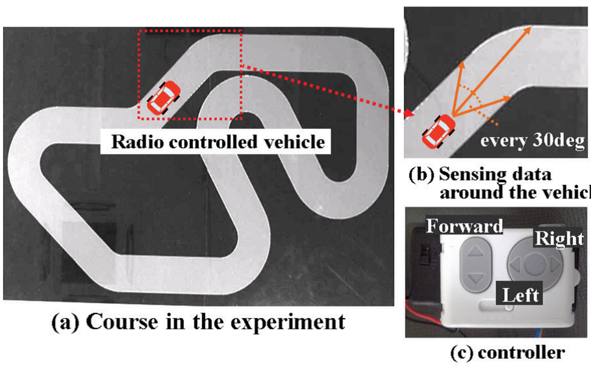

Figure 7. Experiment setup

4.2 Generation of human action model

The examinee operated the vehicle total 300 times at all speed conditions in total. The human action model is acquired with the obtained data in the experiment based on the proposed modeling method. The temporal and spatial thresholds of similarity of CDP are 5 and 20 respectively. The number of the state in each HMMs is 10. The parameter ρ in Eq.(5) is 3. Note that these parameters are determined based on the accuracy of estimation experiment of next action discussed as section 4.3. Moreover, the gauss distribution is used for the output probability of HMM. The acquired human action model has 34 action rules(21 F→R-rules, 2 R→F-rules, 9 F→L-rules, and 2 L→F-rules). The many action rules with the same human action change are obtained. This is because a person performs his own action adjusting the vehicle position and the timing of the next action according to the shape of curve and the vehicle velocity. This result suggests that human behaviors are very complicated even if a task seems simple such as the operation of the radio controlled vehicle in this experiment.

Fig.8 shows the difference between the actual three direction distance at an action change F→R and modeled one by a HMM in a F→R-rule. As this figure shows, it is confirmed that the causality between an action change F→R and the situation around a person is appropriately modeled based on the proposed modeling method. Moreover, comparing Fig.8 (a) with Fig.8 (b), the time series data modeled by F-R rule 2 has the same waveform as the one modeled by F-R rule 1, but the change velocity is different. Therefore, it is confirmed that the action rules with several temporal patterns are acquired based on the proposed modeling method.

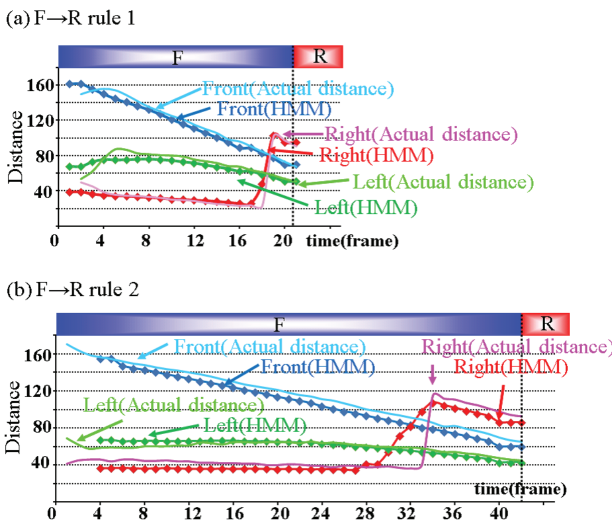

Figure 8. Comparison between the actual situation and the modeled one by a HMM at F→R

4.3 Discussion of the estimation result of next human action

The estimation experiments of the next action and its timing were performed with the acquired human action model in the previous section. In this experiment, 300 data of the vehicle operarions were used as test data. Test data were input to the acquired action model every each frame off-line, and the next human action and its timing were estimated based on the estimation method described in section 3.1. The estimation of the next human action was regarded to succeed when the next action in the input data was the same as estimation result. In this experiment, Idel time is the time until the actual next action execution after its estimation result was obtained. Therefore, the difference between Estimated idle time and Idle time was evaluated for the execution timing estimation.

In this experiment, estimation accuracy of the proposed method was compared with the one of the conventional modeling method proposed in our previous research referred to [13]. In the conventional method, unlike the proposed method, the temporal pattern of the time series data to express the situation is not considered. The usefulness of considering the temporal pattern of the situation was examined by comparing both results.

The estimation result of the next action is shown in Table 1. Table 1 shows the estimation accuracy with the conventional and proposed action models. From the result, the estimation accuracy keeps high in both cases. Therefore, in the proposed modeling method, the causality between the situation and human action is modeled without deterioration.

Table 1. Estimation result of the next human action

	The number estimation success	
Change of action	Conventional action model	proposed action model
$F \to R$	719/719	719/719
$R \to F$	242/242	242/242
$F \to L$	738/738	738/738
$L \to F$	247/247	247/247

Fig.8 shows the change of likelihood calculated with a HMM in each action rule until the action in the input data changes from F to R. The vertical axis is the likelihood, and the horizontal axis is the frame number of the input data. The action rules shown in Fig.8 are top 2 rules in F→R-rules and F→L-rules. The human action actually changes at 57th frame in this case. The likelihoods of F→R-rules keep high until the human action actually changes, while the likelihoods of F→L-rules fall rapidly at 38th frame.

This is because that the situation data which contribute to the next action R are input to the action model from 38th frame. The estimation result of the next action is acquired at 40th frame. These results show that the system can estimate right actions successfully before the human actions actually change by selecting the Optimal rules.

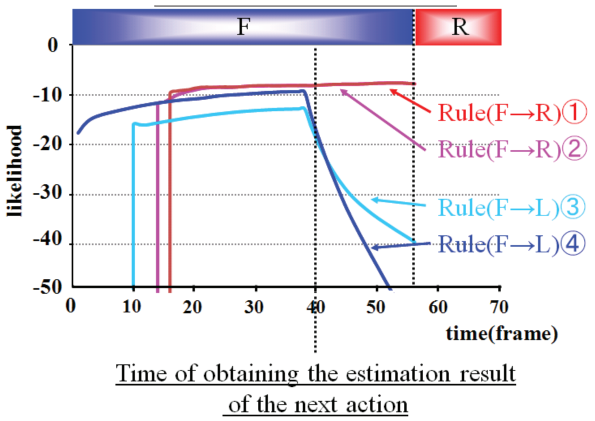

Figure 9. The change of likelihood (Forward to Right)

Fig.10 shows the average and deviation of error of the Estimated idle time. It is verified that estimation accuracy is improved as Fig.10 shows. This reason is considered as below. Fig.11 shows the chosen action rules with HMMs higher likelihoods than threshold calculated by CVA and the Optimal rule when a test data input to the proposed action model. The action rules with several temporal patterns of time series data which express the situation are chosen by evaluating their likelihoods as Fig.11 shows. Moreover, the Optimal rule is appropriately chosen by evaluating the similarity of temporal pattern of the time series data. On the other hand, in the conventional modeling method, the action rule with the right temporal pattern is confused with ones which have the same spatial pattern with different temporal patterns. Then, in order not to consider the temporal patterns of input data, the estimation error increases.

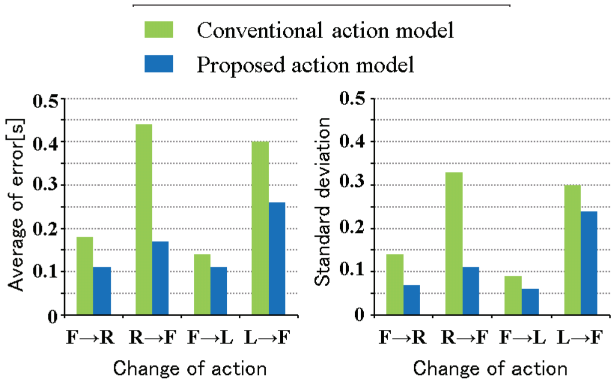

Figure 10. The error of Estimated idle time

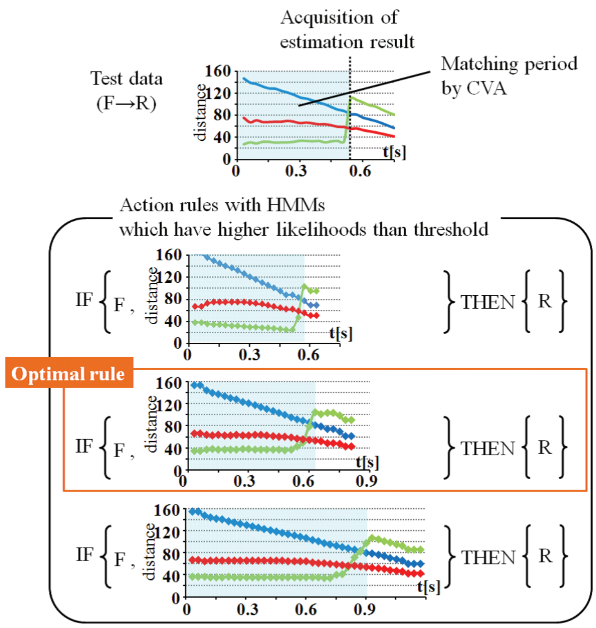

Figure 11. Comparison of action rules with different temporal patterns

Here, the estimation accuracy of the execution timing is discussed. The result of the preparatory experiment showed that ± 0.06[s] error happened when the examinee pushed a controller button at a decided timing. Therefore, the error of the estimated idle time includes the redundancy of timing of the action execution or human judgment. Considering the results of the preparatory experiment and the Fig.10, it is verified that the estimation accuracy of the execution timing is adequate in the proposed method.

Conclusion

We proposed a modeling method of human actions based on the causality between the situation expressed by a time series data and the human action expressed by a discrete data. Moreover, an estimation method of the next human action and its execution timing was proposed, which considered the similarities of spatial and temporal patterns of the time series data based on the proposed modeling method. In this modeling method, human action rules were generated which expressed causalities between the human actions and the situation around a person by If-Then rule styles. In this estimation method, the similarity between an input data and an action rule was evaluated considering the spatial and temporal patterns of the time series data to express the situation. Therefore, the accurate estimation of the next human action and its execution timing could be realized. In this paper, actual human operations of a radio controlled vehicle were modeled based on the proposed method. According to the experimental results with the generated human action model, it was verified that the next human action and its execution timing could be estimated successfully at high accuracy. In addition, it was also verified that the next human action could be obtained before the actual human action change occurred.

For the future work, we will try to apply this modeling and estimation method to more practical problems like a driving support system, a machine operation support system and so on. The proposed model can estimate the next human action and its execution timing. Therefore, it is considered that the proposed method is useful for prevention of human error and navigation of operation for the driver and operator by presenting the estimated next human action and its execution timing. Moreover, a new modeling method will be tackled, which can deal with multiple choices of human actions under the same situation and continuous human actions in order to expand the range of the application of the proposed method.

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