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Modeling of Human Behavior in Man-Machine Cooperative System Based on Hybrid System Framework

Hiroyuki Okuda, Soichiro Hayakawa, Tatsuya Suzuki and Nuio Tsuchida

Abstract— **Recently, the demand for a man-machine cooperative system, where the machine assists the human operator, is rapidly growing in the industrial fields. To meet this demand, the human model is required to design the suitable assist controller in the man-machine cooperative system. This paper presents a new human behavior model based on a piece-wise affine model which is a class of hybrid dynamical system, and apply it to a sliding task. Since the human behavior is considered to consist of several primitive motions expressed by continuous dynamics and a decision-making expressed by the discrete switch, it seems to be natural to introduce the hybrid system modeling. Particularly, the decision strategy for the number of discrete modes is addressed by using a hierarchical clustering technique, and the measured data are classified into several modes. Then, each primitive motion in each mode is identified based on the affine model. Finally, the switching conditions among modes are identified by applying support vector machine to the classified data. The obtained piece-wise affine model can quantitatively represent both primitive motions and decision-making in the human behavior.**

I. INTRODUCTION

Recently, industrial production systems are shifting from the small-variety mass production to the high-variety variable-lot production or the cell manufacturing. Because of the requiement for cost reduction of labors and the lack of labors, the man-machine cooperative system is attracting great attention in the industrial fields. As far as the authors know, “Extender” developed by Kazerooni in [1] was the origin of this type of robot system. Although various types of man-machine cooperative system may exist, one of the typical class is a so called ‘Power Assist System’. There are many studies about power assist systems as listed in [2], [3]. In the factory, the operator assist system is developed to assist moving heavy works and/or positioning in assembling works. The power assist system is generally designed based on the impedance control framework. Some works were devoted to clarify the ‘good’ impedance parameters to reduce the inconsistency between the worker and machine, and to improve the efficiency of the task [2], [4]. Although these researches focused on the design of the parameters used for the assist controller, the characteristics of the human skill or behavior was not explicitly included in the design process.

When we look at the human behavior, it is often found that the operator appropriately switches some simple motions instead of adopting the complex nonlinear motion. The switching mechanism can be regarded as a kind of operator’s decision-making in the behavior. Therefore, it is highly recommended that the model of the human behavior involve both physical motions and the decision-making aspect (switching condition). This kind of expression can be categorized into a class of Hybrid Dynamical System (HDS). HDSs are systems, which consist of both continuous dynamics and logical conditions. The former are typically associated with the differential (or difference) equations, the latter with combinatorial logics, automata and so on. Although many literatures have dealt with the expression, stability analysis, control, verification and identification of the HDS in the control and computer science communities [5][6] , the application of the HDS model to the analysis of the human behavior has not been fully discussed yet [7].

Based on these considerations, this paper presents a new human behavior model based on the piece-wise affine model, which is a class of hybrid dynamical system, together with the application to a sliding motion. One of the theoretical contributions of this paper is to develop the identification strategy for the HDS where the number of discrete modes is unknown. This is particularly important when we apply the HDS model to the modeling of human behavior because the number of modes in the human behavior can not be designed in advance. Also, the switching conditions among modes are identified by introducing a Support Vector Machine (SVM). Based on the developed strategy, the sliding task is analyzed and modeled under the framework of the HDS. The obtained piece-wise affine model can quantitatively represent both physical skills and decision-making in the human behavior.

II. EXPERIMENTAL SYSTEM

A. Configuration of experimental system

The configuration of our power assist system is shown in Fig. 1. The handling machine is a one d.o.f. linear slider. The force sensor and the grip is attached on the slider head. The operator moves the slider head by manipulating the grip. The motion of the slider head is also assisted by a force generated by servo driver which executes the velocity control of the slider head. This slider has the linear encoder. The observed signal of the encoder and the force sensor are fed back to the control PC. Then the velocity reference is calculated based on the impedance parameters implemented on the PC and is supplied to the servo driver. The block diagram of this experimental system is shown in Fig. 2.

The sampling period was 200[μs]. In this experiment, the impedance parameters were set as follows. The mass M was

Hiroyuki Okuda, Soichiro Hayakawa and Nuio Tsuchida are with Toyota Technological Institute, 2-12-1, Hisakata, Tenpaku-ku, Nagoya, Japan s_hayakawa@toyota-ti.ac.jp

Tatsuya Suzuki is with the Department of Mechanical Science and Engineering, Graduate School of Engineering, Nagoya University, Furo-cho, Chikusa-ku, Nagoya, Japan t_suzuki@nuem.nagoya-u.ac.jp

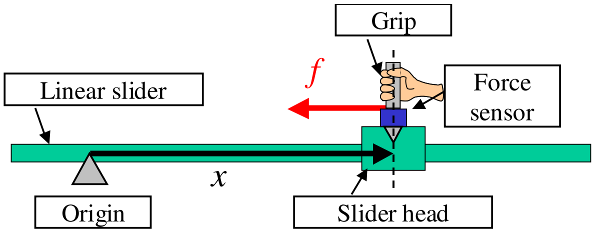

Fig. 1. Overview of experimental system

set to be 10[kg]. The stiffness K was set to be 0[N/m]. The dampling D was set to be 50[Ns/m] or 80[Ns/m].

B. Procedure of experiment

The experiments on the sliding task using the developed system was carried out. Cursors are attached on the slider head and the origin of the slider as the reference of positioning target. At the beginning, the slider head is located at 300[mm] from the origin. The examinee is supposed to manipulate the grip toward the origin until the position of two cursors coincide. Four examinees have demonstrated the task. Ten trials have been made by each examinee. During the experiment, the slider head position x and the operating force f were measured. For practice of the examinees, ten trials have been made before the experiments. The information on the velocity and the acceleration of the slider head was calculated by taking differentiation of the position x. We also assumed that there exist time delay between the recognition and the operation in the human behavior, and it was set to be 200[ms] (See eq.(5)). The experiment was carried out under two different virtual damping parameters D=50[Ns/m] and D=80[Ns/m]. As an example, three profiles of the examinee A are shown in Fig. 3. The horizontal axis represents the time and the vertical axes represent the force, position, velocity and acceleration, respectively.

III. MODELING OF HUMAN BEHAVIOR AS HYBRID SYSTEM

There have been so many strategies to represent the human behavior, such as Artificial Neural Network [8] , Hidden Markov Model, Fuzzy logic, and so on. The obtained nonlinear model, however, often results in very complex model, and is not suitable to understand the underlying principle of the human behavior. This drawback is particularly evident when we consider the design problem of the human assist system based on the human behavior model.

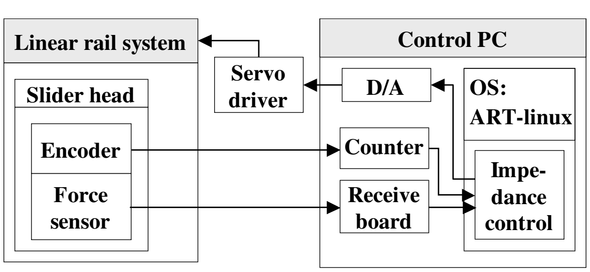

Fig. 2. Block diagram of experimental system

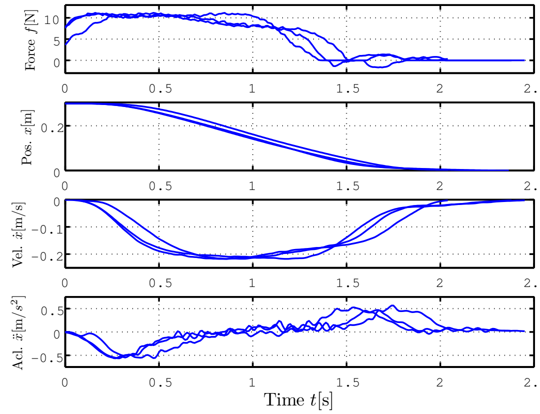

Fig. 3. Measured data profiles of examinee A

When we look at the human behavior, it is often found that the operator appropriately switches some simple motions instead of adopting the complex nonlinear motion. The switching mechanism can be regarded as a kind of operator's decision-making in the behavior. Based on this consideration, this paper presents a human behavior model shown in Fig. 4. Our proposed model involves both decision-making and primitive motions explicitly. Here, we consider that the human operator selects the most suitable mode based on the recognized environmental information, and outputs the operation signal according to the primitive dynamics in each mode. This kind of architecture can be regarded as a kind of HDS [5], where the discrete switch and continuous dynamics are involved simultaneously.

In the following, we discuss the identification problem of the behavior model. First of all, the number of modes (primitive motions) must be identified. Most of the previous identification strategies developed for HDS requires the information on the number of modes in advance[6]. This problem becomes particularly significant when we consider the application to the human behavior modeling. For this problem, the hierarchical clustering technique is introduced in the following section and applied to the measured data.

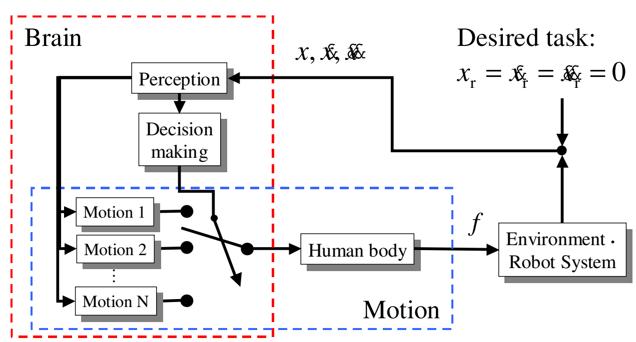

Fig. 4. Proposed human behavior model

Once the measured data are suitably classified, then the parameters in each primitive motion can be estimated by applying standard LMS technique. Also, the switching conditions among modes are estimated by introducing SVM.

IV. ESTIMATION OF NUMBER OF MODES IN BEHAVIOR

A. Hierarchal clustering technique

As the first step to develop the HDS model of the human behavior, the measured data must be classified. For this purpose, a so called clustering technique is introduced. The clustering technique is one of the statistical analysis to classify the measured data. There are two types of the clustering technique, the hierarchal clustering and the non hierarchal clustering. The former does not require information on the number of clusters, the later, however, needs that information. In the human behavior, since it is not straightforward to decide the number of clusters (i.e. modes), the hierarchical one seems promising. The hierarchal clustering is also divided into two types according to how to construct the hierarchal structure. They are the aggregative clustering and the divisive clustering. In this work we adopt the aggregative hierarchal clustering since it is easier to decide the number of clusters. The aggregative hierarchal clustering construct the 'dendrogram' which shows the evolution of the clusters (See Figs.5 and 6 as examples).

The procedure of the aggregative hierarchal clustering is described as follows:

As the first step, each data point is regarded as each cluster, then calculate the distances between all two clusters (data points in the first iteration). The distance ${d_{rs}}^2$ between the clusters s and r is computed by

$$ {d_{rs}}^2 = \| \mathbf{x}_r - \mathbf{x}_s \|_2{}^2 \tag{1} $$

where $\| \mathbf{x}_r - \mathbf{x}_s \|_2$ shows the Euclidean distance between $\mathbf{x}_r$ and $\mathbf{x}_s$.

As the second step, find the combination of clusters which shows the minimum distance over all calculated distances, and combine the corresponding clusters. For example, if ${d_{rs}}^2$ shows the minimum value, then create new cluster c by combining the clusters s and r. Also,

$$ n_c = n_s + n_r \tag{2} $$

n_i is the number of the data samples in the cluster i.

As the third step, compute the distance between the aggregated new cluster c and all other clusters by using following definition.

$$ {d_{ci}}^2 = n_c n_i \frac{\| \overline{\mathbf{x}_c} - \overline{\mathbf{x}_i} \|_2{}^2}{n_c + n_i} \tag{3} $$

$\overline{\mathbf{x}_i}$ is the centroid of the cluster i defined as follows:

$$ \overline{\mathbf{x}_i} = \frac{1}{n_i} \sum_{l=1}^{n} \mathbf{x}_{il} \tag{4} $$

where $\mathbf{x}_{il}$ is lth data sample in the cluster i.

Finally, repeat the second and third step until all clusters are aggregated. Dendrogram shows the distance d^2 whenever an aggregation occurred in the second step. By looking at the dendrogram, we can estimate the appropriate number of clusters. This leads to the estimation of the modes in the human behavior.

B. Decision of number of modes by using dendrogram

The experimental data x, $\dot{x}$, $\ddot{x}$ and f measured in section I I.B are now analyzed by using the hierarchical clustering. All data were normalized in advance to neglect the effect of the difference in the unit. Then, the sample data set is clustered in 4-dimensional space (x, $\dot{x}$, $\ddot{x}$, f). Ten trials data of one examinee under one virtual damping condition were used for the cluster analysis. The data were originally collected with sampling interval of 200[μs] in the experiment, however, the sampling rate for the cluster analysis was reduced to 10[ms] to decrease the computational burden. The dendrograms obtained by applying the clustering procedure to the examinees A and B are shown in Figs. 5 and 6. For the simplicity, the index of sample data are not shown in the horizontal axis. The vertical axis represents the square distance between clusters which are aggregated.

Generally speaking, the accuracy of the model (measured by output error) will be improved as the number of modes goes up. Our objective, however, is to understand the task scenario which the human operator used. In this sense, too many mode model is unlikely to meet our objective. Therefore, the dendrogram is used for decision of the number of modes in this work. The dendrograms shown in Figs. 5 and 6 represent the structure of subclusters generated by clustering procedure. Also, the dotted horizontal lines represents the square distance when the number of clusters is changed from 3 to 2 and 4 to 3, respectively. When we look at this dendrogram, we can say that the four mode clustering is too high resolution (too small square distance among clusters), and the three mode clustering seems reasonable. Therefore, we decided the number of modes is three. Note that for other examinees, we obtained similar results.

In [2], it is also reported that the control scenario based on three mode decomposition is natural. Based on this clustering results, the original position profile can be decomposed into three modes as shown in Fig.7. The human operator is regarded to switch the primitive motion according to this decomposition. Hereafter, we denote each mode by Mode 1, Mode 2 and Mode 3. Note also that the number of modes strongly depend on the task and environment.

V. HUMAN BEHAVIOR MODEL FOR SLIDING TASK

A. Piece-wise affine behavior model

The number of modes in the task was decided in the previous section. In this section, we consider the mathematical model of each mode, i.e. each primitive motion. As the basic mathematical model of the behavior, the Piece-Wise Affine (PWA) model is introduced as follows:

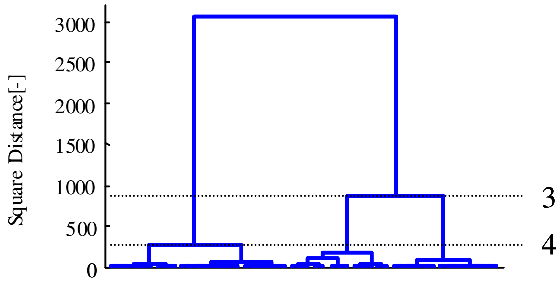

Fig. 5. Dendrogram of examinee A

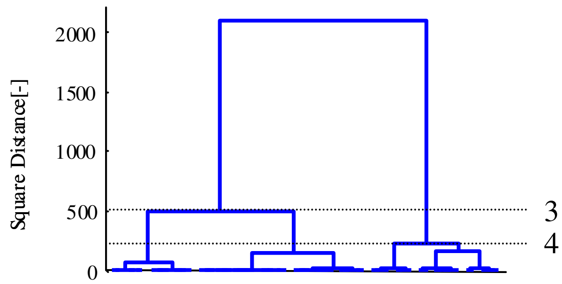

Fig. 6. Dendrogram of examinee B

$$\begin{cases} f_{k+\tau} = \alpha_1 x_k + \beta_1 \dot{x}_k + \gamma_1 \ddot{x}_k + \zeta_1 & (\mathbf{x}_k \in C_1) \\ f_{k+\tau} = \alpha_2 x_k + \beta_2 \dot{x}_k + \gamma_2 \ddot{x}_k + \zeta_2 & (\mathbf{x}_k \in C_2) \\ f_{k+\tau} = \alpha_3 x_k + \beta_3 \dot{x}_k + \gamma_3 \ddot{x}_k + \zeta_3 & (\mathbf{x}_k \in C_3) \end{cases} \quad (5)$$

Here, the number of modes is three. C_i represents subspace of the input space where the corresponding mode exists. The subscript k is the sampling index, τ is the time delay between input and output in the human behavior. The state vector $\mathbf{x}_k$ is defined as $\mathbf{x}_k = [x_k, \dot{x}_k, \ddot{x}_k]$. α_i, β_i, γ_i are the coefficients in each affine model. ζ_i is the constant term.

The PWA model is simple but can represent the input-output relationship of the human behavior from viewpoint of both motion and switching aspects. Moreover, the PWA model is useful for the design of the assist system because of its simplicity

B. Identification of PWA model

Since the measured data are already clustered, the identification of parameters in the PWA model (5) can be executed at each mode independently. The least mean square method was used for identification of these parameters. The data sets of ten trials of each examinee were used for the identification. The parameter identification results are shown in TABLE I. The comparison between the measured force profile and calculated force profile by using the identified model of examinee A in the case of $D = 50$[Ns/m] is shown in Fig.8. In this figure, the solid line is the measured force profile and the broken line is the output of the identified PWA model. These two profiles agree well with each other. This

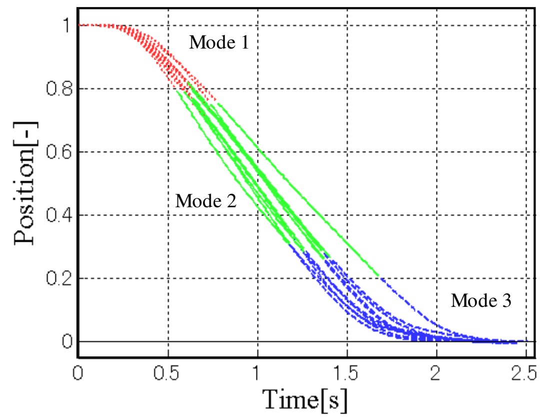

Fig. 7. Decomposition of position profile

implies that the identification (including the mode number estimation) works well. In the Mode 1 in TABLE I, the value of constant term ζ tends to be larger than the value of other coefficients in all cases. This implies that the 'feed-forward' control is the principal strategy in the Mode 1 because the constant term does not depend on any feedback information. In the Mode 2, the magnitude of ζ becomes smaller compared with the Mode 1, and the coefficient value for the feedback information does not show any clear tendency. This is probably because the primitive motion in Mode 2 varies from examinee to examinee. Also, in the Mode 3, the coefficient value of the position feedback α tends to be large, and the value of the constant term ζ become almost zero. This implies that the control strategy was switched from the 'feed-forward' to the 'feedback'

TABLE I

COEFFICIENTS IN PWA MODEL IN EACH MODE

Examinee	D	Mode	α	β	γ	ζ
A	50	1	-0.82	0.06	-0.23	1.55
		2	0.68	-0.59	-0.23	-0.15
		3	3.38	0.72	0.12	0.02
	80	1	-2.55	0.23	-0.40	3.12
		2	0.36	-0.37	-0.13	0.28
		3	2.19	0.15	0.04	0.01
B	50	1	0.38	-0.03	-0.29	0.34
		2	1.34	0.36	-0.22	0.18
		3	2.86	1.00	0.19	0.01
	80	1	-6.10	1.05	-0.58	6.75
		2	0.81	-0.09	-0.09	0.11
		3	2.81	0.67	0.13	0.02
C	50	1	-1.29	0.35	-0.51	1.89
		2	1.12	0.30	0.02	0.24
		3	2.68	0.80	0.12	0.03
	80	1	1.03	-0.44	-0.34	-0.50
		2	0.60	-0.46	-0.04	0.01
		3	2.63	0.49	0.12	0.01
D	50	1	-2.18	0.77	-0.55	2.83
		2	1.11	0.12	-0.04	-0.03
		3	1.99	0.62	0.15	0.00
	80	1	-1.11	0.32	-0.49	1.74
		2	0.53	-0.60	-0.13	-0.15
		3	1.96	0.27	0.05	0.00

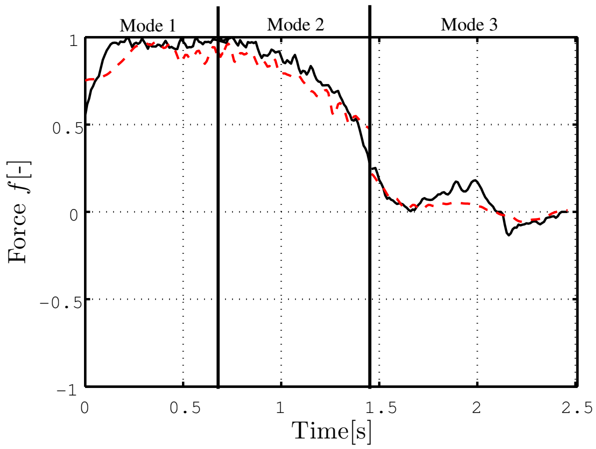

Fig. 8. Model output of examinee A

mainly based on the position information.

Thus, we can understand the control scenario of the human operator by applying simple PWA model.

C. Estimation of mode switching condition

Each primitive motion was identified in the previous subsection. In this part, the separation plane between modes are identified and investigated. While the ARX model in each mode represents the motion aspect, the separation planes between modes represent the mathematical model of the decision making (switching) in human behavior. In this work, the Support Vector Machine (SVM) is used to identify the separation plane [7][9]. Here, we assume that the primitive motions are executed sequentially. This assumption enables us to derive the mode switching condition by only identifying the neighboring two modes. The separation plane is supposed to be described by

$$ax + b\dot{x} + c\ddot{x} + h = 0 \tag{6}$$

Example of the identified separation planes are shown in Fig.9 together with the input data. In this figure, the plane between the Mode 1 and 2 is labeled by Plane 1, and the plane between the Mode 2 and 3 is labeled by Plane 2. The identified switching condition from the Mode 1 to 2 and the condition from the Mode 2 to 3 are expressed by

$$\begin{cases} C_1 \rightarrow C_2 : 6.87x + 1.02\dot{x} - 10.26\ddot{x} - 3.51 < 0 \\ C_2 \rightarrow C_3 : 9.43x - 7.87\dot{x} - 0.47\ddot{x} - 6.77 < 0. \end{cases} \tag{7}$$

As the result, it has been found that the mode change occurs when the condition $C_i \rightarrow C_{i+1}$ is satisfied in the mode i. The coefficient values of all separation plane among modes are listed in TABLE II.

Although the separation planes seem to depend on the examinee and the damping coefficient, the Plane 1 tends to show the larger magnitude of b and c than that of a. This implies that the switching from the Mode 1 to 2 is caused mainly by the velocity and acceleration information. On the other hand, the Plane 2 clearly shows the larger magnitude

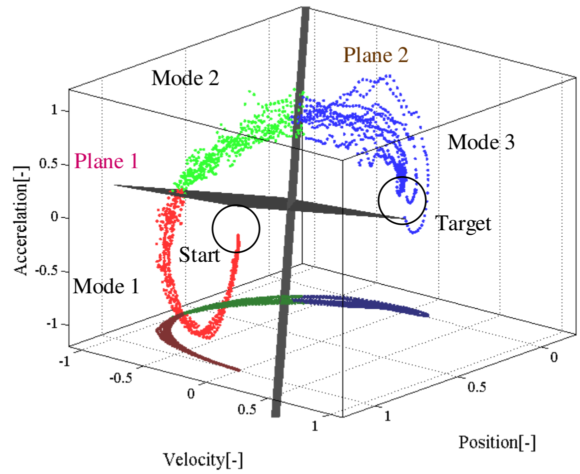

Fig. 9. Identified seperation planes

TABLE II
COEFFICIENTS OF SEPARATION PLANES

Examinee	D	Plane	a	b	c	h
A	50	1	12.30	8.01	-7.06	-2.72
		2	15.34	-1.06	-5.26	-3.33
	80	1	2.89	7.93	-8.01	-1.91
		2	15.45	-2.29	-1.44	-6.85
B	50	1	6.87	1.02	-10.26	-3.51
		2	9.43	-7.87	0.47	-6.77
	80	1	2.61	8.69	-6.21	-1.21
		2	9.25	-7.43	0.05	-8.17
C	50	1	3.69	2.85	-10.73	-2.28
		2	11.37	-3.32	-6.19	-3.45
	80	1	3.94	5.01	-9.98	-2.53
		2	18.84	-1.55	-3.20	-4.77
D	50	1	4.64	3.20	-10.88	-1.66
		2	7.66	-11.82	1.88	-5.30
	80	1	3.56	5.50	-8.52	-2.54
		2	12.18	-5.85	-1.94	-7.48

of a than that of b and c. This implies that the switching from the Mode 2 to 3 is caused by the position information.

This kind of switching condition can be regarded as a kind of decision making in the human operator. One of the typical application of this model is to design the assist ssystem based on a switched impedence controller. The switching scenario of the impedance parameter is designed so as to syncronize the switching of the human behavior.

VI. CONCLUSIONS

This paper has presented a new human behavior model based on a piece-wise affine model which is a class of hybrid dynamical system, and applied it to a sliding task. Since the human behavior is considered to consist of several physical motions expressed by continuous dynamics and a decision-making expressed by the discrete switch, it seems to be natural to introduce the hybrid system modeling. Particularly, the decision strategy for the number of discrete modes was addressed by using a hierarchical clustering technique, and the measured data were classified into several modes. Then, each primitive motion in each mode was identified based on the affine model. Finally, the switching conditions among modes were identified by applying support vector machine to the classified data.

The obtained piece-wise affine model gave us the following interpretations for sliding task: First of all, the task can be divided into three modes. In the Mode 1, the operator manipulates the slider head by feed-forward control. In the Mode 2, the operator pays loose attention on the environmental informations. In the Mode 3, the operator controls the slider head mainly by the position feedback information. Second, while the switching from Mode 1 to 2 is caused mainly by the velocity and acceleration information, the switching from the Mode 2 to 3 is caused by the position information. Thus, the obtained piece-wise affine model can quantitatively represent both primitive motions and decision-making in the human behavior

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