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HUMAN SKILL MODELING BASED ON STOCHASTIC SWITCHED DYNAMICS

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Abstract: This paper presents a modeling and analysis strategy of human skill based on stochastic switched dynamics. As a fundamental mathematical model, the Stochastic Switched ARX model (SS-ARX model) is introduced. Then the modeling and analysis strategy of human skill is proposed based on the stochastic switched impedance model which can be regarded as one of the SS-ARX model. Finally, the developed strategy is applied to peg-in-hole task which involves interesting dexterous human skill, and the effectiveness of the proposed strategy is discussed.

Keywords: Human skill, Switched impedance model, Parameter estimation

1. INTRODUCTION

A system, in which an operator and artificial machine play in an interactive manner, is called a man-machine cooperative system. There are so many practical examples of this kind of systems such as, a power extender, automobile and so on. The goals of the man-machine cooperative systems are to enable the operator and artificial machine to work harmoniously. In order to realize this requirement, development of the 'intelligent assist' which does not conflict with the operator's intention must be addressed. Although this problem may include several subproblems, the most important one is the understanding of the operator's behavior by the artificial machine [Nechyba,1997] [Hannaford,1991] [Hirana,2004].

In order to model the operator's behavior, the conventional techniques such as the nonlinear regression models, the neural network and fuzzy systems have been used [Sjoberg,1995][Narendra,1990]. These techniques, however, have some problems as follows: (1) the obtained model often results in too complicated model, (2) this makes it impossible to understand the physical meaning of the operator's behavior. When we look at the human behavior, it is often found that the operator appropriately switches some simple primitive skills. The switching of primitive skills may be caused by operator's decision making. This consideration strongly motivates us to model the human behavior as a Hybrid Dynamical Systems (HDS). By regarding the operator's primitive skill and switching scenario as the continuous and discrete part of HDS, the understanding of the human behavior can be recasted as problem of the parameter estimation in HDS framework. Although many literatures have dealt with the expression, stability analysis, control, verification and identification [Ferrari,2003] [Bemporad,2004] of the HDS in the control and computer science communities, the application of the HDS model to the analysis of the human behavior has not been fully discussed yet.

Roughly speaking, HDS can be classified into two classes. The first one is the HDS where the transition between discrete states (modes) is specified by means of deterministic logics, and the second one is the HDS where the transition is specified by transition probabilities. In [Kim,2005], we have applied the HDS with deterministic mode change to the modeling of the driving behavior. Although this work can capture the motion and decision making aspects in the human behavior, it can not be suitable for the complex behavior analysis due to its high computational cost. This drawback is more emphasized when we consider the real-time application.

In this paper, first of all, a Stochastic Switched AutoRegressive eXogenous (SS-ARX) model is introduced. This model can be regarded as a natural extension of the standard Hidden Markov Model (HMM) [Rabiner,1989][Hannaford,1991] where different ARX model is allocated to each discrete state of the HMM. The significant advantages of using SS-ARX model as the behavior model is described as follows: (1) it can calculate the likelihood of the behavior with reasonable computational burden, (2) it can take into consideration the input and output signals of the human behavior, and (3) it can reflect the stochastic variance in the human behavior. Then, we develop the modeling and analysis strategy of human skill based on the stochastic switched impedance model, and finally, apply it to a peg-in-hole task which involves interesting dexterous human skill.

2. BRIEF REVIEW OF ARX MODEL

As a preliminary for SS-ARX model, the conventional ARX model is briefly reviewed.

The standard ARX model is described by the following difference equation:

$$\begin{aligned} y_t = c_1 y_{t-1} + c_1 y_{t-2} + \cdots + c_n y_{t-n} \\ + d_0 u_t + d_1 u_{t-1} + \cdots + d_m u_{t-m} + e_t \end{aligned} \quad (1)$$

where y_t and u_t are an output and an input of the system at t. They are supposed to be scalar-valued signals. Also, n and m are order of the ARX model, and $c_1, c_2, \cdots, c_n, d_0, d_1, \cdots, d_m$ are parameters. e_t is called an equation error, and is supposed to have a Gaussian distribution with variance σ.

By using the following vector form:

$$\boldsymbol{\theta} = (c_1, c_2, \cdots, c_n, d_0, d_1, \cdots, d_m)^T \quad (2)$$

$$\boldsymbol{\psi}_t = (y_{t-1}, y_{t-2}, \cdots, y_{t-n}, u_t, u_{t-1}, \cdots, u_{t-m})^T \quad (3)$$

equation (1) is rewritten as follows:

$$y_t = \boldsymbol{\psi}_t^T \boldsymbol{\theta} + e_t. \quad (4)$$

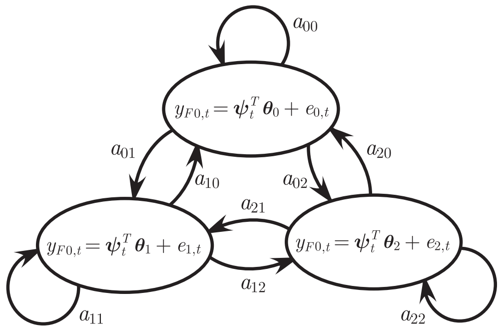

Fig. 1. SS-ARX model (three states)

3. PARAMETER ESTIMATION FOR SS-ARX MODEL

SS-ARX is defined as the system in which an ARX model is switched to other one according to the state transition probability as shown in Fig.1. This model can be regarded as the model in which the ARX model and HMM are combined.

3.1 Parameters in SS-ARX model

The parameters in SS-ARX model are specified as follows:

- Set of discrete states $S[= S_i, (i=0, 1, \cdots, N)]$
- a_{ij}: State transition probability $(i=0, 1, \cdots, N; j=0, 1, \cdots, N)$
- π_i: Initial state probability $(i=0, 1, \cdots, N)$
- $\boldsymbol{\theta}_i$: Parameters in ARX model assigned to S_i $(i=0, 1, 2, \cdots, N)$
- σ_i: Variances of equation error in ARX model assigned to S_i $(i=0, 1, 2, \cdots, N)$

$N + 1$ denotes the number of discrete states. In the following, we denote the set of parameters in the SS-ARX model by $\lambda = (\pi_i, a_{ij}, \boldsymbol{\theta}_i, \sigma_i)$.

3.2 Three fundamental problems

To address several problems listed below, the measured signal and its occurrence probability are defined for SS-ARX model as follows: First of all, a measured signal o_t at time t is defined as the combination of the output y_t and the regressor $\boldsymbol{\psi}_t$, that is, $o_t = (y_t, \boldsymbol{\psi}_t)$. Then, its occurrence probability $b_i(o_t)$ is defined by the assumption of the Gaussian distribution of the equation error, and is given by

$$b_i(o_t) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left\{ -\frac{(\boldsymbol{\psi}_t^T \boldsymbol{\theta}_i - y_t)^2}{2\sigma_i^2} \right\}. \quad (5)$$

Based on these definitions, the following three fundamental problems can be addressed for SS-ARX model.

(1) Evaluation problem
In evaluation problem, the probability that the measured signal sequence $\boldsymbol{O}=(o_0, o_1, \cdots, o_t, \cdots, o_T)$ occurs from the model $\lambda = (\pi_i, a_{ij}, \boldsymbol{\theta}_i, \sigma_i)$ is calculated. This problem can be solved by applying Forward algorithm [Rabiner,1989].

(2) Decoding problem
In decoding problem, the most likely underlying state sequence $\boldsymbol{s}=(s_0, s_1, \cdots, s_t, \cdots, s_T)$, which yields the measured signal sequence $\boldsymbol{O} = (o_0, o_1, \cdots, o_t, \cdots, o_T)$, is found for the model $\lambda = (\pi_i, a_{ij}, \boldsymbol{\theta}_i, \sigma_i)$. This state estimation can be realized by applying Viterbi algorithm [Rabiner,1989].

(3) Estimation problem
In estimation problem, the model parameter $\lambda = (\pi_i, a_{ij}, \boldsymbol{\theta}_i, \sigma_i)$, which gives the highest occurrence probability for the measured signal sequence $\boldsymbol{O} = (o_0, o_1, \cdots, o_t, \cdots, o_T)$, is estimated.

The solution for problems (1) and (2) are same as ones for the standard HMM. However, the parameter estimation algorithm for the SS-ARX model requires some extension to the one for the standard HMM. In the following subsection, the concrete parameter estimation algorithm for the SS-ARX model is derived.

3.3 Parameter estimation

Here, we assume that L measured signal sequences are collected for the parameter estimation of SS-ARX model.

3.3.1. EM algorithm First of all, we consider an unmeasurable state sequence

$$\boldsymbol{s} = (s_0, s_1, \cdots, s_t, \cdots, s_T) \quad (6)$$

and measurable signal sequences

$$\boldsymbol{O_l} = (o_{l,0}, o_{l,1}, \cdots, o_{l,t}, \cdots, o_{l,T}) \quad (7)$$

(where l represents the index of the measured signal sequence). The maximization of the likelihood value of the $\boldsymbol{s}$ and $\boldsymbol{O_l}$, $\sum_{l=1}^{L} L(\boldsymbol{s}, \boldsymbol{O_l}; \lambda) = \sum_{l=1}^{L} P(\boldsymbol{s}, \boldsymbol{O_l}|\lambda)$ is achieved by introducing the EM (Expectation and Maximization) algorithm.

Generally, the EM algorithm tries to find the parameter λ' which maximizes the following Q function:

$$Q(\lambda, \lambda') = \sum_{l=1}^{L} E[\log\{P(\boldsymbol{s}, \boldsymbol{O_l}|\lambda')\}\,|\boldsymbol{O_l}, \lambda] \quad (8)$$
$$= \sum_{l=1}^{L} \sum_{\boldsymbol{s}} P(\boldsymbol{s}|\boldsymbol{O_l}, \lambda) \log\{P(\boldsymbol{s}, \boldsymbol{O_l}|\lambda')\} \quad (9)$$

by executing following procedures iteratively.

(1) Specify an initial parameter λ.
(2) Find the λ' which maximizes the $Q(\lambda, \lambda')$.
(3) Substitute λ' for λ, and iterate (2) until $\lambda' = \lambda$ holds.

3.3.2. Parameter estimation algorithm The parameters of SS-ARX model before and after the update are supposed to be given by $\lambda = (\pi_i, a_{ij}, \boldsymbol{\theta}_i, \sigma_i)$, and $\lambda' = (\pi'_i, a'_{ij}, \boldsymbol{\theta'}_i, \sigma'_i)$. From (9),

$$Q(\lambda, \lambda') = \sum_{l=1}^{L} \left\{ \sum_{\boldsymbol{s}} \frac{1}{P(\boldsymbol{O_l}|\lambda)} P(\boldsymbol{s}, \boldsymbol{O_l}|\lambda) \times \log\{P(\boldsymbol{s}, \boldsymbol{O_l}|\lambda')\} \right\}. \quad (10)$$

Now, we replace $\frac{1}{P(\boldsymbol{O_0}|\lambda)}, \frac{1}{P(\boldsymbol{O_1}|\lambda)}, \cdots, \frac{1}{P(\boldsymbol{O_L}|\lambda)}$ in (10) by $k_0, k_1, \cdots, k_L$.

Since $k_0, k_1, \cdots, k_L$ are constant, the maximization of $Q(\lambda, \lambda')$ implies the maximization of $\tilde{Q}(\lambda, \lambda')$ given by

$$\tilde{Q}(\lambda, \lambda') = \sum_{\boldsymbol{s}} P(\boldsymbol{s}, \boldsymbol{O_l}|\lambda) \log\{P(\boldsymbol{s}, \boldsymbol{O_l}|\lambda')\}. \quad (11)$$

By using the definition, $\tilde{Q}(\lambda, \lambda')$ can be decomposed as follows:

$$\tilde{Q}(\lambda, \lambda') = \tilde{Q}_1(\lambda, \pi'_i) + \tilde{Q}_2(\lambda, a'_{ij}) + \tilde{Q}_3(\lambda, \boldsymbol{\theta'}_i, \sigma'_i) \quad (12)$$

where

$$\tilde{Q}_1 = \sum_{l=1}^{L} \sum_{i=0}^{N} k_l \pi_i b_i(o_{l,0}) \log\{\pi'_i\}\, \beta(l, i, 0) \quad (13)$$
$$\tilde{Q}_2 = \sum_{l=1}^{L} \sum_{t=1}^{T} \sum_{i=0}^{N} \sum_{j=0}^{N} k_l \log\{a'_{ij}\} \times \alpha(l, i, t-1) a_{ij} b_j(o_{l,t}) \beta(l, j, t) \quad (14)$$
$$\tilde{Q}_3 = \sum_{l=1}^{L} \sum_{t=0}^{T} \sum_{i=0}^{N} k_l \log\{b'_i(o_{l,t})\} \alpha(l, i, t) \beta(l, i, t). \quad (15)$$

The forward probability $\alpha(l, i, t)$ and backward probability $\beta(l, i, t)$ in (13), (14) and (15) are defined as follows:

$$\alpha(l, i, t) = \sum_{s_0=0}^{N} \sum_{s_1=0}^{N} \cdots \sum_{s_{t-1}=0}^{N} \pi_{s_0} b_{s_0}(o_{l,0}) \times a_{s_0 s_1} b_{s_1}(o_{l,1}) \times \cdots \times a_{s_{t-1} s_t} b_{s_t}(o_{l,t}) \quad (16)$$

$$\beta(l, i, t) = \sum_{s_{t+1}=0}^{N} \sum_{s_{t+2}=0}^{N} \cdots \sum_{s_T=0}^{N} a_{s_t s_{t+1}} b_{t+1}(o_{l,t+1})$$

$$\times a_{s_{t+1}s_{t+2}} b_{s_{t+2}}(o_{l,t+2}) \times \cdots \times a_{s_{T-1}s_T} b_{s_T}(o_{l,T}). \quad (17)$$

The meaning of $\alpha(l,i,t)$ is the probability for SS-ARX model λ to generate the lth measured signal subsequence $\boldsymbol{O_l} = (o_{l,0}, o_{l,1}, \cdots, o_{l,t})$ until t and reach the state S_i at t (i.e. $s_t = S_i$). Also, the meaning of $\beta(l,i,t)$ is the probability for SS-ARX model λ to generate the lth measured signal subsequence $\boldsymbol{O_l} = (o_{l,t+1}, o_{l,t+2}, \cdots, o_{l,T})$ starting from S_i at t (i.e. $s_t = S_i$) and reach the final state at T.

Then, by maximizing $\tilde{Q}_1(\lambda, \pi'_i)$, $\tilde{Q}_2(\lambda, a'_{ij})$ and $\tilde{Q}_3(\lambda, \boldsymbol{\theta'}_i, \sigma'_i)$, $\tilde{Q}(\lambda, \lambda')$ can be maximized. λ' which maximizes the $\tilde{Q}(\lambda, \lambda')$ can be obtained as follows:

$$\pi'_i = \frac{\sum_{l=1}^{L} k_l \pi_i b_i(o_{l,0}) \beta(l,i,0)}{\sum_{i=0}^{N} \sum_{l=1}^{L} k_l \pi_i b_i(o_{l,0}) \beta(l,i,0)} \quad (18)$$

$$a'_{ij} = \frac{\sum_{t=1}^{T} \sum_{l=1}^{L} k_l \alpha(l,i,t-1) a_{ij} b_j(o_{l,t}) \beta(l,j,t)}{\sum_{j=0}^{N} \sum_{t=1}^{T} \sum_{l=1}^{L} k_l \alpha(l,i,t-1) a_{ij} b_j(o_{l,t}) \beta(l,j,t)} \quad (19)$$

$$\boldsymbol{\theta}'_i = \left\{ \sum_{t=0}^{T} \sum_{l=1}^{L} k_l \boldsymbol{\psi}_{l,t} \boldsymbol{\psi}_{l,t}^T \alpha(l,i,t) \beta(l,i,t) \right\}^{-1} \times \left\{ \sum_{t=0}^{T} \sum_{l=1}^{L} k_l \boldsymbol{\psi}_{l,t} y_{l,t} \alpha(l,i,t) \beta(l,i,t) \right\} \quad (20)$$

$$\sigma_i'^2 = \frac{\sum_{t=0}^{T} \sum_{l=1}^{L} k_l |\boldsymbol{\theta}_i'^T \boldsymbol{\psi}_{l,t} - y_{l,t}|^2 \alpha(l,i,t) \beta(l,i,t)}{\sum_{t=0}^{T} \sum_{l=1}^{L} k_l \alpha(l,i,t) \beta(l,i,t)}. \quad (21)$$

By iterating three steps in the EM algorithm together with (18), (19), (20) and (21), the parameter λ is locally maximized.

Note that eq. (20) can be regarded as the weighted least mean square solution in which the weight parameters are specified by $\alpha(l,i,t)\beta(l,i,t)$, i.e. the probability that the $o_{l,t}$ is generated from the state S_i.

Also, the parameter estimation algorithm described in this section can be easily extended to the multiple output case.

4. APPLICATION TO ANALYSIS OF HUMAN SKILL

4.1 Task environment

The task environment addressed in this paper is depicted in Fig.2. The peg is supposed to move only in $x - z$ plane.

Peg and hole are made of Aluminum and rubber, respectively. The clearance of the hole is 0.1[mm]. The operator executes the task based on the scenario depicted in Fig.3.

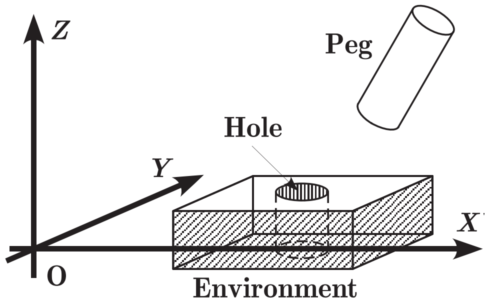

Fig. 2. Peg-in-hole task

In this scenario, since the switchings from (1) to (2) and (4) to (5) are considered to be deterministic, the transition from (2) to (4) were analyzed based on stochastic switched dynamics.

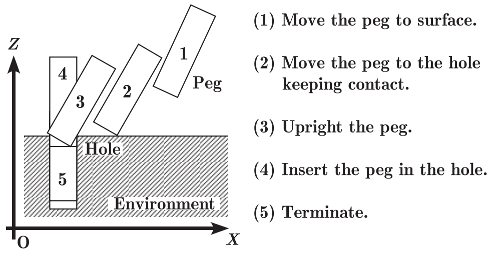

Fig. 3. Motion of peg

4.2 Impedance model representing human skill

4.2.1. Impedance model In the field of robotics, the impedance model has been considered as typical dynamical model to represent the human skill. In this work, therefore, we define the ARX model at each discrete state by impedance model to represent the dexterous human skill. The impedance model considered for the peg-in-hole task is shown in Fig.4, and can be described by (22), (23) and (24).

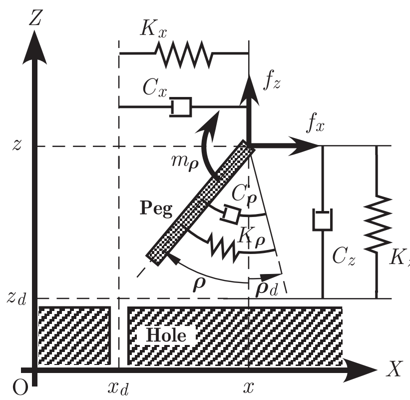

Fig. 4. Impedance model

$$M_{xi}\ddot{x} + C_{xi}\dot{x} + K_{xi}x + D_{xi} = f_x \quad (22)$$

$$M_{zi}\ddot{z} + C_{zi}\dot{z} + K_{zi}z + D_{zi} = f_z \quad (23)$$

$$M_{\rho i}\ddot{\rho} + C_{\rho i}\dot{\rho} + K_{\rho i}\rho + D_{\rho i} = m_\rho. \quad (24)$$

In Fig. 4, eqs. (22), (23) and (24), x, z, ρ denote position of peg, f_x, f_z, m_ρ denote interactive force, and M_{xi}, M_{zi}, $M_{\rho i}$, C_{xi}, C_{zi}, $C_{\rho i}$, K_{xi}, K_{zi}, $K_{\rho i}$ denote impedance parameters at ith discrete state. Also, $D_{xi} = -K_{xi}x_d + f_{xdi}$, $D_{zi} = -K_{zi}z_d + f_{zdi}$, $D_{\rho i} = -K_\rho \rho_d + m_{\rho di}$. x_d, z_d, ρ_d denote reference position, and f_{xdi}, f_{zdi}, $m_{\rho di}$ denote virtual reference force.

Note that virtual reference force varies from discrete state to state, and D_{xi}, D_{zi} and $D_{\rho i}$ are also unknown.

4.2.2. Transformation to discrete-time model Since equations (22), (23) and (24) are model in continuous time domain, their discrete-time model are derived with preserving parameters in continuous time model (See [Wada,1993] for detail). The transformation from continuous-time model to its discrete-time model is derived as follows: In the following, p represents one of the coordinate, i.e. p is a substitute for one of x, z and ρ. Note that D_{pi} is replaced by $D_{pi}d$ by introducing a parameter $d = 1$ in the following.

$$F_{pF}(z) = M_{pi}P_{F0}(z) + C_{pi}P_{F1}(z) + K_{pi}P_{F2}(z) + D_{pi}D_F(z) \quad (25)$$

where

$$F_{xF}(z) = \frac{(\frac{\Delta}{2})^2(1+z^{-1})^2}{\left\{(1+\nu\frac{\Delta}{2}) - (1-\nu\frac{\Delta}{2})z^{-1}\right\}^2} F_x(z) \quad (26)$$

$$D_F(z) = \frac{(\frac{\Delta}{2})^2(1+z^{-1})^2}{\left\{(1+\nu\frac{\Delta}{2}) - (1-\nu\frac{\Delta}{2})z^{-1}\right\}^2} D(z) \quad (27)$$

$$P_{Fk}(z) = \frac{(\frac{\Delta}{2})^k(1+z^{-1})^k(1-z^{-1})^{2-k}}{\left\{(1+\nu\frac{\Delta}{2}) - (1-\nu\frac{\Delta}{2})z^{-1}\right\}^2} P(z) \quad (28)$$

$(k=0,1,2)$. $F_p(z)$, $D(z)$ and $P(z)$ are z-transform of f_p, d and p. ν is a time constant of the filter, and was set to be $\nu = 20$ in this work. Finally, by applying inverse z-transform to (25), and adding equation error $e_{pi,t}$, we obtain

$$\begin{aligned} f_{pF,t} &= M_{pi}p_{F0,t} + C_{pi}p_{F1,t} \\ &\quad + K_{pi}p_{F2,t} + D_{pi}d_{F,t} + e_{pi,t} \quad (29) \\ &= \boldsymbol{\psi}_{p,t}^T \boldsymbol{\theta}_{pi} + e_{pi,t}. \quad (30) \end{aligned}$$

Thus, the discrete-time impedance model can be obtained with preserving the parameters in continuous time domain.

Now , the parameter vectors $\boldsymbol{\theta}_{xi}$, $\boldsymbol{\theta}_{zi}$ and $\boldsymbol{\theta}_{\rho i}$ and regressor vectors $\boldsymbol{\psi}_{x,t}$, $\boldsymbol{\psi}_{z,t}$ and $\boldsymbol{\psi}_{\rho,t}$ are defined for each coordinate as follows:

$$\boldsymbol{\theta}_{xi} = (M_{xi}, C_{xi}, K_{xi}, D_{xi})^T \quad (31)$$

$$\boldsymbol{\theta}_{zi} = (M_{zi}, C_{zi}, K_{zi}, D_{zi})^T \quad (32)$$

$$\boldsymbol{\theta}_{\rho i} = (M_{\rho i}, C_{\rho i}, K_{\rho i}, D_{\rho i})^T \quad (33)$$

$$\boldsymbol{\psi}_{x,t} = (x_{F0,t}, x_{F1,t}, x_{F2,t}, d_{F,t})^T \quad (34)$$

$$\boldsymbol{\psi}_{z,t} = (z_{F0,t}, z_{F1,t}, z_{F2,t}, d_{F,t})^T \quad (35)$$

$$\boldsymbol{\psi}_{\rho,t} = (\rho_{F0,t}, \rho_{F1,t}, \rho_{F2,t}, d_{F,t})^T. \quad (36)$$

4.2.3. Stochastic switched impedance model We consider the left-to-right model with five discrete states as the model for peg-in-hole task (Fig. 5).

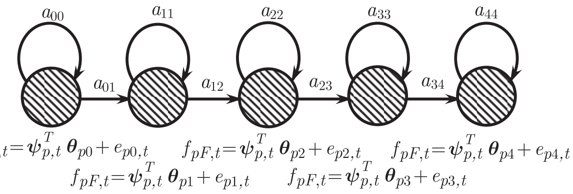

Fig. 5. Stochastic switched impedance model (left to right)

4.3 Acquisition of data and result of parameter estimation

4.3.1. Acquisition of data The operator manipulated the data acquisition tool shown in Fig. 6. The position (x[mm], z[mm], ρ[rad]) and interactive force (f_x[N], f_z[N], m_y[Nm]) are measured by three potentiometers and force sensor. Sampling interval was set to be 2[msec], it took about 5[sec] to complete the task.

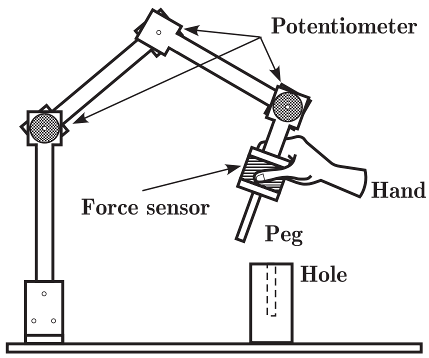

Fig. 6. Data acquisition tool

4.3.2. Results of parameter estimation The estimated impedance parameters at each discrete state (M_{xi}, M_{zi}, $M_{\rho i}$, C_{xi}, C_{zi}, $C_{\rho i}$, K_{xi}, K_{zi}, $K_{\rho i}$, D_{xi}, D_{zi}, $D_{\rho i}$) are shown in Figs.7 to 9 (upper figures). Also, the interactive force was calculated based on the estimated model, switching points (obtained by applying Viterbi algorithm) and the filtered measured position data in (29) in order to verify the parameter estimation. The calculated force profiles are depicted in lower figures in Figs.7 to 9 together with the estimated switching points represented by vertical dash lines. The profiles of the real force data also represent the data obtained by applying the low-pass filter $1/(1+\nu^2)$ to the original measured force data. In these figures, the real and calculated force data agree well with each other. This implies that the proposed estimation technique works well.

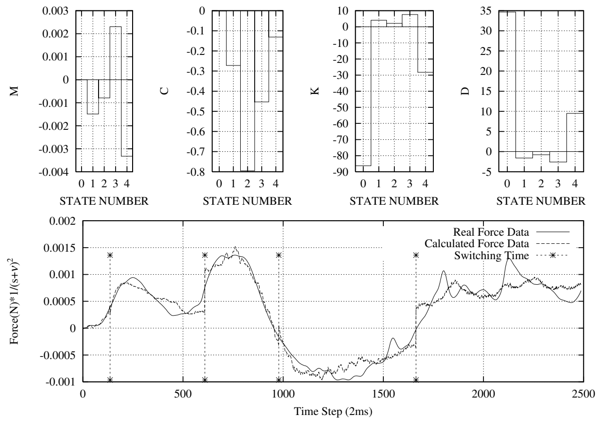

Fig. 7. Estimated parameter and comparison of real force and calculated force (X-axis)

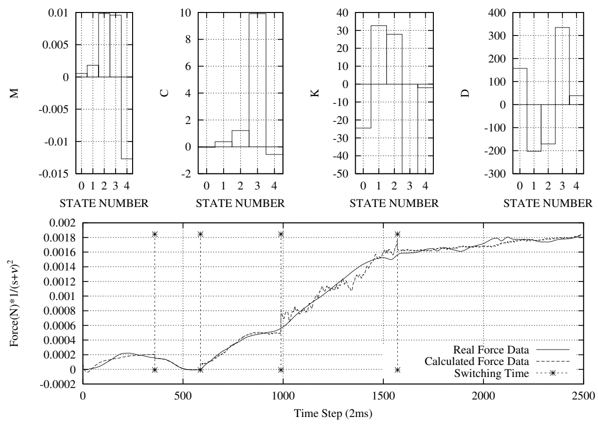

Fig. 8. Estimated parameter and comparison of real force and calculated force (Z-axis)

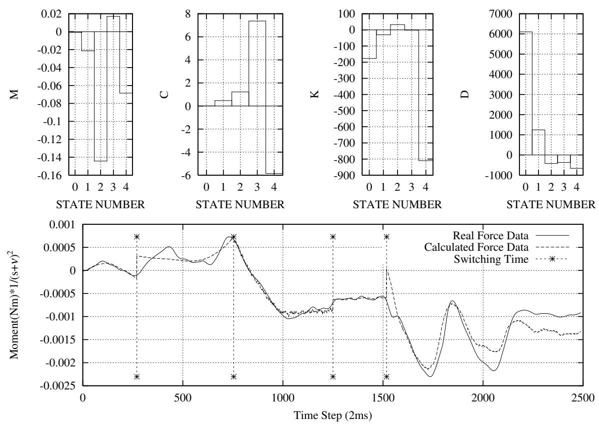

Fig. 9. Estimated parameter and comparison of real force and calculated force (around Y-axis)

4.4 Discussion and application

We can see the several interesting properties among obtained parameters. First of all, estimated switching points seem to coincide with the instance of change of geometrical constraints for the peg. As for the impedance parameters, although some parameter show negative value, the task was performed safely. This can be explained as follows: The stability of the task is specified by overall closed-loop dynamics given by Fig.10. In

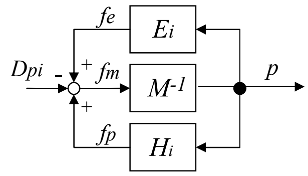

Fig. 10. Block diagram of whole system

Fig.10, each block is given by

$$M = M_m s^2 \tag{37}$$

$$H_i = M_{pi} s^2 + C_{pi} s + K_{pi} \tag{38}$$

$$E_i = C_{ei} s + K_{ei} \tag{39}$$

where H_i indicates ith dynamics of human skill (estimated in the previous subsection) , M represents the mass of the handling tool, i.e. the peg and force sensor, and E_i represents the dynamics of the environment at ith discrete state which consists of the dynamics of hole and force sensor. p represents the coordinate (x, z and ρ). This consideration allows us to have negative impedance parameter in realization of stable peg insertion.

The direct application of the obtained results is an implementation of the target impedance models for the industrial robot together with the switching scenario of them. This kind of 'Skill transfer' is one of the most promising idea to realize the dexterous manipulation. The other interesting application is a quantitative evaluation (recognition) of the skill based on the similarity measure for the stochastic processes. This kind of measure can be a criterion for the design of artificial skill [Nechyba,1997][Hirana,2004].

Also, it will be quite interesting to investigate the obtained impedance parameters for understanding of physical meaning of human skill. Our developed strategy can be a good first step to tackle this problem.

5. CONCLUSIONS

In this paper, first of all, a Stochastic Switched AutoRegressive eXogenous (SS-ARX) model was introduced and its parameter estimation algorithm has been derived.. Then, we have developed the modeling and analysis strategy of human skill based on the stochastic switched impedance model which can be regarded as one of the SS-ARX model. Finally, the developed strategy was applied to peg-in-hole task which involves interesting dexterous human skill, and the effectiveness of the proposed strategy was discussed.

REFERENCES

[Nechyba,1997] *M.C. Nechyba and Y. Xu : Human Control Strategy: Abstraction, Verification and Replication, IEEE Control Systems Magazine, vol. 17, no. 5, pp. 48-61, 1997*

[Hannaford,1991] *B.Hannaford and P.Lee: Hidden Markov Model Analysis of Force/Torque Information in Telemanipulation, The Int. J. of Robotics Research, 10-5, 528/539, 1991*

[Hirana,2004] *K.Hirana, T.Suzuki, et.al: Quantitative Evaluation for Skill Controller Based on Comparison with Human Demonstration, IEEE Trans. on Cont. Syst. Tech., Vol.12, No.4, pp.609-619, 2004*

[Sjoberg,1995] *J.Sjoberg, Q.Zhang, et.al : Nonlinear Black-Box Modeling in System Identification: a Unified Overview, Automatica, vol.31, no.12, pp.1691-1724, 1995*

[Narendra,1990] *K.S.Narendra and K.Pathasarathy: Identification and Control of Dynamical Systems Using Neural Networks, IEEE Trans. on Neural Networks, vol.1, no.1, pp.4-27, 1990*

[Ferrari,2003] *G.Ferrari-Trecate, M.Morari et.al; A clustering technique for the identification of piecewise affine systems, Automatica, 39, pp.205-217, 2003*

[Bemporad,2004] *J.Roll, A.Bemporad, et.al; Identification of piecewise affine systems via mixed-integer programming, Automatica, 40, pp.37-50, 2004*

[Kim,2005] *J.H.Kim, S.Hayakawa, T.Suzuki, et.al; Modeling of Driver's Collision Avoidance Maneuver based on Controller Switching Model IEEE Trans. of Syst. Man and Cyber., Vol.35, No.6, pp.1131-1143, 2005*

[Suzuki,2005] *T.Suzuki, S.Yamada, et.al: Modeling of Drivers Collision Avoidance Behavior based on Hybrid System Model -An Approach with Data Clustering- Proc. of IEEE Int. Conf. on Syst. Man and Cyber. pp.3817-3822, 2005*

[Rabiner,1989] *L.R.Rabiner; A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition, IEEE, Vol.77, 1989*

[Wada,1993] *S.Sagara, Z.J.Yang, K.Wada; Identification of Continuous Systems Using Digital Low-pass Filters, Int.J.Syst.Sci.,22-7,1159-1176, 1991*

[Kim,2004] *J.H.Kim, S.Hayakawa, T.Suzuki et.al; Modeling of Human Driving Behavior based on Expression as Hybrid Dynamical System, Trans.of SICE, Vol.40, No.2, pp.180-188, 2004*

[Balakrishnan,2004] *H.Balakrishnan et.al; Inference Methods for Autonomous Stochastic Linear Hybrid Systems" LNCS2993, HSCC 2004, pp.64-79, 2004*