FATIGUE RECOGNITION USING EMG SIGNALS AND STOCHASTIC SWITCHED ARX MODEL

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Abstract: The man-machine cooperative system is attracting great attention in many fields, such as industry, welfare and so on. The assisting system must be designed so as to accommodate the operator's skill, which might be strongly affected by the fatigue. This paper presents a new fatigue recognizer based on the Electro Myo-Gram (EMG) signals and the Stochastic Switched ARX (SS-ARX) model which is one of the extended model of the standard Hidden Markov Model (HMM). Since the SS-ARX model can represent complex dynamical relationship which involves switching and stochastic variance, it is expected to show higher performance as the fatigue recognizer than using simple statistical characteristics of the EMG signal and/or standard HMM. The usefulness of the proposed strategy is demonstrated by applying to a peg-in-hole task.

1 INTRODUCTION

The man-machine cooperative system is attracting great attention in many fields, such as manufacturing, medicine, welfare and so on. The main purpose of assisting system is to reduce physical burden of the operator. Since a human skill is strongly affected by fatigue of the operator, the assisting system must be designed so as to accommodate with the change of skill characteristics caused by fatigue. To meet this requirement, fatigue must be detected and evaluated based on some quantitative manner. One of the basic ideas to evaluate the degree of fatigue is to measure physiological signals, such as the density of lactic acid in blood. This approach, however, requires the operator to stop the task, to take special examination and to be injured for sampling.

Recently, Electro Myo-Gram (EMG) signal is recognized as a promising one to measure the degree of physical fatigue without any special examination. EMG signal can be easily detected by only putting the probe on surface of the corresponding muscle. The relationship between the fatigue and the change of features such as Muscle Fiber Conduction Velocity (MFCV), magnitude, spectrum of EMG and so on are reported (Sadoyama and Miyano, 1981; Lippold et al., 1960; Arendt-Nielsen and Mills, 1988; D. K. Kumar and Bradley, 2003). Although these previous researches enable us to characterize the relationship between fatigue and the statistical characteristics of the EMG signal, their applications have been restricted in simple monotonous motion because those measures are developed under the Maximal Voluntary Contraction (MVC) condition. If the target task is more complex, fatigue recognition based on these features turns difficult cause of large variance of the measured signals in dynamic motion. To overcome this problem, a model-based approach, which can reflect the effect of the dynamic motion, must be exploited for the fatigue recognition.

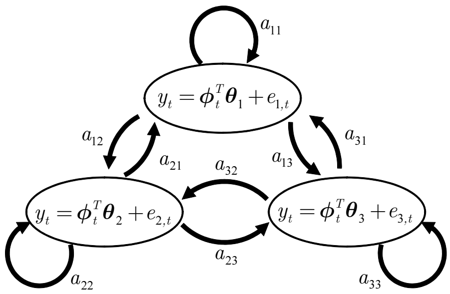

Figure 1: SS-ARX model (three states).

This paper presents a new fatigue recognizer based on the EMG signals and the Stochastic Switched ARX (SS-ARX) model. The SS-ARX model (Sekizawa et al., 2007) can be regarded as an extension of standard Hidden Markov Model (HMM) wherein each Auto Regressive eXogenous (ARX) model is embedded in each discrete state of the

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HMM. In the proposed framework, we pay attention not only to the measured signal itself but also to the dynamic relationship between the EMG signals and motion, i.e. movement of the tool. Since the SS-ARX model can represent complex dynamics, which involves switching and stochastic variance, it is expected to show higher performance as the fatigue recognizer using standard HMM. This advantage is more emphasized when the target task becomes much more complex. Furthermore, we demonstrate the usefulness of the proposed strategy by applying to a peg-in-hole task. A comparison with standard HMM is also discussed.

2 STOCHASTIC SWITCHED ARX MODEL

SS-ARX model is defined as the system wherein one autoregressive exogenous (ARX) models is switched to the other one according to the state transition probability(Sekizawa et al., 2007). Figure 1 shows the SS-ARX model with three states.

This model can be regarded as the model wherein each ARX model is embedded in each discrete state of standard HMM. In the following, the definition and three important problems of the SS-ARX model are briefly reviewed (see detail in (Sekizawa et al., 2007)).

2.1 Parameters in SS-ARX Model

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

- S_i: Discrete state $(i=1,2,\cdots,N)$
- a_{ij}: State transition probability $(i=1,2,\cdots,N;\, j=1,2,\cdots,N)$
- π_i: Initial state probability $(i=1,2,\cdots,N)$
- θ_i: Parameters in ARX assigned to S_i $(i=1,2,\cdots,N)$
- σ_i: Variance of equation error $e_{i,t}$ in ARX model assigned to $S_i (i=1,2,\cdots,N)$

N denotes the number of discrete states. We denote the set of parameters in the SS-ARX model by $\lambda=(\pi_i, a_{ij}, \theta_i, \sigma_i)$.

2.2 Three Fundamental Problems

To address several fundamental problems listed below, the measured signal and its occurrence probability are defined for SS-ARX model as follows: First of all, a measured signal $o_{l,t}$ at time t is defined as combination of the output $y_{l,t}$ and the regressor $\psi_{l,t}$, that is, $o_{l,t}=(y_{l,t}, \psi_{l,t})$. Where l is index of observed sequences, i.e. the index of trials. Then, its occurrence probability $b_i(o_{l,t})$ is defined by assumption of the Gaussian distribution of the equation error, and is given by

$$b_i(o_{l,t}) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left\{ -\frac{(\theta_i^T \psi_{l,t} - y_{l,t})^2}{2\sigma_i^2} \right\}. \qquad (1)$$

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

1. Evaluation problem
The probability $P(O_l|\lambda)$ that the measured signal sequence $O_l=(o_{l,0}, o_{l,1}, \cdots, o_{l,t}, \cdots, o_{l,T})$ occurs from the model $\lambda=(\pi_i, a_{ij}, \theta_i, \sigma_i)$, that probability is called as likelihood, is calculated. This problem can be solved by applying Forward algorithm (Rabiner, 1989).

2. Decoding problem
The most likely underlying state sequence $s = (s_{l,0}, s_{l,1}, \cdots, s_{l,t}, \cdots, s_{l,T})$, which yields the measured signal sequence $O_l = (o_{l,0}, o_{l,1}, \cdots, o_{l,t}, \cdots, o_{l,T})$, is found for the model $\lambda=(\pi_i, a_{ij}, \theta_i, \sigma_i)$. This state estimation can be realized by applying Viterbi algorithm (Rabiner, 1989).

3. Estimation problem
The model parameter $\lambda = (\pi_i, a_{ij}, \theta_i, \sigma_i)$, which gives the highest occurrence probability for the measured signal sequence $O_l=(o_{l,0}, o_{l,1}, \cdots, o_{l,t}, \cdots, o_{l,T})$, is estimated.

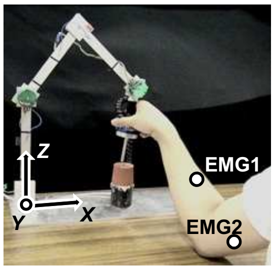


Figure 2: Data acquisition of peg-in-hole task.

The solution for problems 1 and 2 are same as ones for standard HMM. However, the parameter estimation algorithm for the SS-ARX model requires some extension to the one for standard HMM. The concrete parameter estimation algorithm for the SS-ARX model can also be derived based on the EM algorithm. The resulting parameter update law of $\boldsymbol{\theta}_i$ is given as follows:

$$\theta_i' = \left\{ \sum_{t=0}^{T} \sum_{l=1}^{L} k_l \psi_{l,t} \psi_{l,t}^T \alpha(l,i,t)\beta(l,i,t) \right\}^{-1} \times \left\{ \sum_{t=0}^{T} \sum_{l=1}^{L} k_l \psi_{l,t} y_{l,t} \alpha(l,i,t)\beta(l,i,t) \right\} \quad (2)$$

where k_l is defined by $1/P(O_l|\lambda)$, and $\alpha(l,i,t)$ and $\beta(l,i,t)$ are the forward probability and the backward probability of SS-ARX model, which resemble them of HMM respectively. Other update laws and its derivation are written in our previous study (Sekizawa et al., 2007).

Note that this model is applicable not only to the linear dynamics but also to a certain class of nonlinear dynamics, which may include switching mechanism. This benefit strongly motivates us to apply to the modeling and recognition of complex human skill.

3 EXPERIMENT SETUP AND DATA ACQUISITION

The fatigue recognizer is realized using SS-ARX model, and applied to the peg-in-hole task shown in Fig. 2. The peg-in-hole task is widely known as the typical skill which involves the switching in the dynamics caused by change of the contact configuration (Hirana et al., 2004; Ricker et al., 1996). In this work, the peg is supposed to move only on $X-Z$ plane. The mechanical arm in Fig. 2 provides no assisting force. As shown in Fig. 2, examinee holds the peg by grasping the end of the arm. There is no clearance between the rubber hole and peg. This implies that much force is required to accomplish the peg insertion. The examinees execute the task following the scenario depicted in Figure 3.

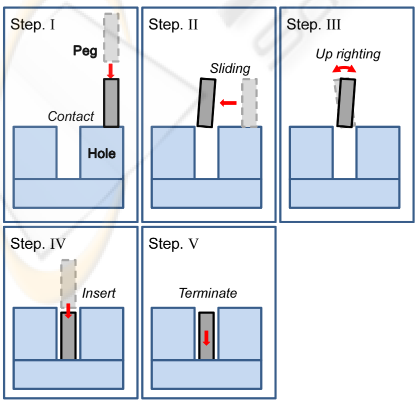


Figure 3: Typical motion of peg.

Table 1: Model parameters of examinee A (case of non-fatigue).

State transition probability				
a_{ij}	$i=1$	$i=2$	$i=3$	$i=4$
$j=i$	0.962	0.956	0.959	1
$j=i+1$	0.038	0.044	0.041	0

ARX-model parameters					
	θ_{i1}	θ_{i2}	θ_{i3}	θ_{i4}	σ_i
state1	0.404	0.134	0.042	0.549	0.005
state2	0.466	-0.166	0.031	0.472	0.006
state3	0.961	-0.088	0.006	-0.012	0.010
state4	0.189	-0.008	-0.014	0.014	0.004

Table 2: Model parameters of examinee A (case of fatigue).

State transition probability				
a_{ij}	$i=1$	$i=2$	$i=3$	$i=4$
$j=i$	0.978	0.923	0.950	1
$j=i+1$	0.022	0.077	0.050	0

ARX-model parameters					
	θ_{i1}	θ_{i2}	θ_{i3}	θ_{i4}	σ_i
state1	0.945	-0.091	0.006	0.052	0.007
state2	1.071	0.347	0.229	-0.200	0.013
state3	0.984	0.029	-0.056	-0.021	0.005
state4	0.180	0.002	0.040	0.003	0.003

Step. I The peg goes down vertically until it contacts with the surface of stage.

Step. II The peg slides to top of hole on the surface with keeping contact.

Step. III The operator uprights the peg for preparing the insertion.

Step. IV The peg is inserted firmly to the end of the hole.

Step. V Terminate.

Furthermore, the operators are well trained so as to be able to ignore the effect of experiences. The data for parameter estimation and recognition are acquired by the procedure shown in Fig. 4.

As a whole, twenty five data are acquired for verification of recognition. Examinees are expected to be more fatigued in the latter trials. Three examinees followed this procedure.

During the experiment, the position of the peg p_Z and two EMG signals at different locations shown in Fig. 2 (Extensor carpi ulnaris and Triceps brachii muscle) are measured every 1[msec]. The reason why these muscles are chosen is that these are well related with a force along with direction of peg insertion. The

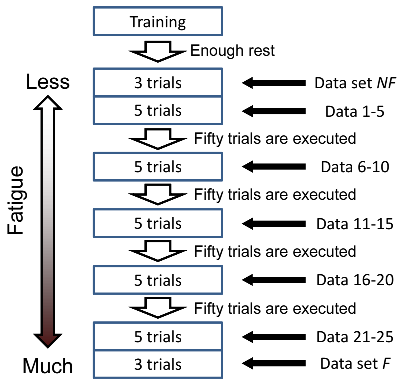


Figure 4: Data acquisition procedure.

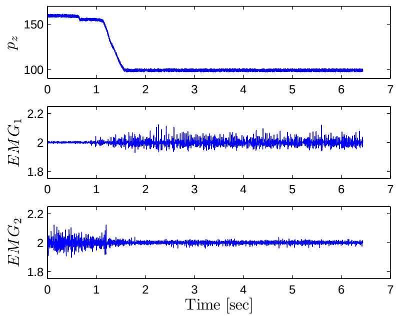
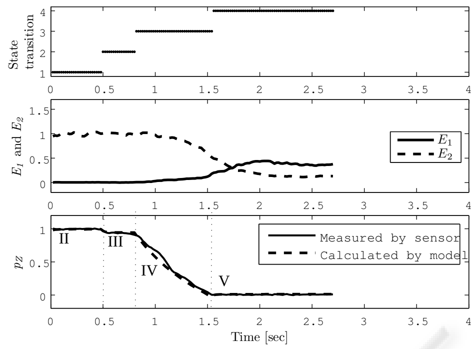
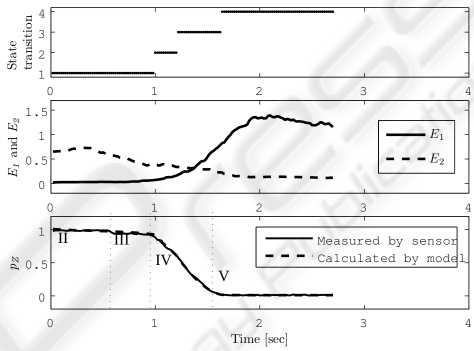


Figure 5: Example of signals EMG_1, EMG_2 and p_Z (examinee A, case of non-fatigue).



(a) Case of non-fatigue



(b) Case of fatigue

Figure 6: State transition, feature value of EMG, and p_Z(examinee A).

EMG signals are amplified with a gain of 1000 (Biometrics Ltd; SX230). Examples of measured EMG signals are shown in Fig. 5 together with p_Z.

In addition, the EMG signals are transformed to feature values by using the moving integral and normalized using the minimum and maximum values in trial 1 of Dataset NF, and also decimated by 20. In the following, E_1 and E_2 are used to denote the normalized feature values of the EMG_1 and EMG_2, respectively.

4 PARAMETER ESTIMATION RESULTS

In this section, the parameters of SS-ARX model are estimated based on learning data and the parameter update algorithm described in section 2. First of all, the signals and parameters appearing in the ARX model in the state k are defined as follows:

$$y_t = p_Z(t) \quad (3)$$

$$\psi_t = \{p_Z(t-1), E_1(t-1), E_2(t-1), 1\} \quad (4)$$

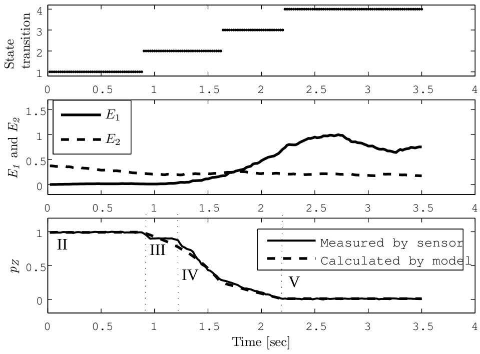
$$\theta_k^T = \{\theta_{k1}, \theta_{k2}, \theta_{k3}, \theta_{k4}\} \qquad (k = \{1, 2, \cdots, N\}) \quad (5)$$

$\boldsymbol{\theta}_k$ is the coefficient vector in the ARX model at state k. For reduction of the computational burden and complexity, the analysis is restricted in the motion along Z-axis which requires much more muscle force than other direction in the insertion task. Furthermore, the number of states is set to be $N = 4$ by try and error, and the left-to-right SS-ARX model is adopted.

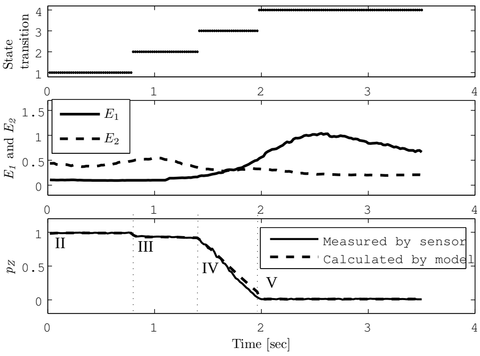
The parameters of SS-ARX model of non-fatigue case, λ_{NF} is estimated using Data set NF. On the other hand, the parameters of SS-ARX model of fatigue case, λ_F is estimated using Data set F. 500 sets of initial parameters for the SS-ARX model were tested in the parameter estimation algorithm to find semi-optimal parameters. The parameter estimation results are shown in Tables 1 and 2.

Although we can see big difference in parameters between two models, this is partly because the physical meaning of the state in each model differs.

In Figs. 6 and 7, the estimated state transition, normalized feature values of EMG signals, and the comparison between the observed p_Z and calculated one using the estimated model are depicted from the top. The top figure represents the estimated state transition using Viterbi algorithm (Note that the state transition is not measured explicitly in our framework). The bottom figure indicates that the observed output



(a) Case of non-fatigue



(b) Case of fatigue

Figure 7: State transition, feature value of EMG, and p_Z(examinee B).

agree well with the calculated output. Thus, the accuracy of the SS-ARX model can be verified.

Also, the steps in the motion of the peg (II to V) are superimposed in the bottom figure. Intuitively, the state transition scenario must be associated with the switching occurred in the real task. Thus, we can see that the state definition of λ_F is different from one of λ_{NF}. In addition, we can see the big difference in the profiles of the E_1 and E_2 in the case of examinee A, however, the differences are not clear in the case of examinee B as shown in Fig. 7. In this case, it seems almost impossible to discriminate fatigue and non-fatigue cases only by looking at the profiles of E_1 and E_2 and the state transition in each case. However, Since the SS-ARX model explicitly includes the dynamic relationship between E_1, E_2 and p_Z, the fatigue recognition can be realized even in such a case as shown in the next section.

5 FATIGUE RECOGNITION

In this section, fatigue is recognized using the two models estimated in the previous section. The log-likelihood values of the measured data over the two

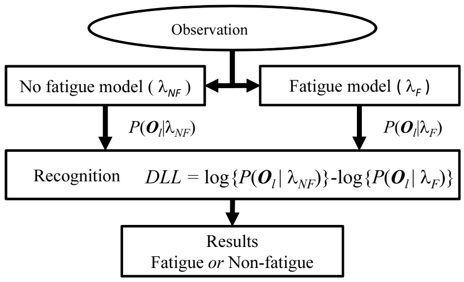


Figure 8: Proposed Recognition Scheme

models are computed and compared to recognize the degree of fatigue of examinee. The illustrative diagram of the proposed scheme is shown in Fig. 8. The degree of fatigue of each examinee is evaluated by the difference of two log-likelihood values (denoted by *DLL*) given as follows:

$$
\begin{aligned}
DLL &= \log\left\{\frac{P(O_l|\lambda_{NF})}{P(O_l|\lambda_F)}\right\} \\
&= \log\{P(O_l|\lambda_{NF})\} - \log\{P(O_l|\lambda_F)\} \quad (6)
\end{aligned}
$$

where O_l is the measured sequence. $\log\{P(O_l|\lambda)\}$, which is log-likelihood of the measured sequence over the model, can be easily calculated by using Forward algorithm introduced in section 2.

We can see the clear tendency that the *DLL* goes down according to increase of the trial number. In addition, the trial when the *DLL* across zero is regarded as the turning point from 'non-fatigue trial' to 'fatigue trial'. Thus, the degree of fatigue of the examinee can be evaluated in quantitative manner.

Table 3: Correlation r between the *DLL* and trial number.

Exam.	SS-ARX	HMM
Exam.A	-0.80	-0.77
Exam.B	-0.83	-0.25
Exam.C	-0.77	-0.62
Exam.D	-0.62	-0.65
Exam.E	-0.93	-0.85

Finally, some discussions on the comparison with the standard HMM are given in the following. For the comparison, the number of states of the HMM were set to 8 (left-to-right structure), although the proposed SS-ARX model has 4 states. In the numerical experiments, the 4-state HMM did not work at all as the fatigue recognizer. The measured signals E_1, E_2 and p_Z were vector quantized by using 32 symbols. Here, a correlation of five examinees between the *DLL* and data number, which is regarded as a typical index to evaluate the relationship between the *DLL* and degree of fatigue, is calculated and shown in Table 3. This result implies that the growth of *DLL* calculated by

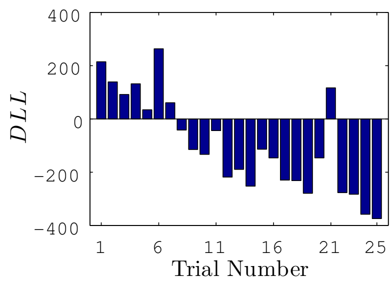


Figure 9: *DLL* of examinees A.

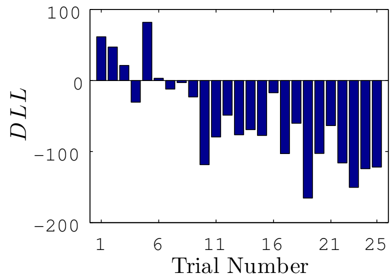


Figure 10: *DLL* of examinees B.

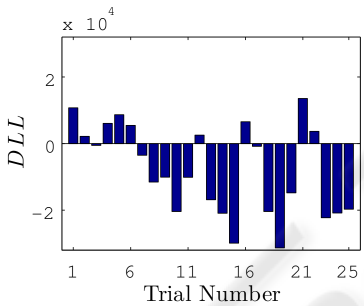


Figure 11: *DLL* of examinee B(in the case of HMM).

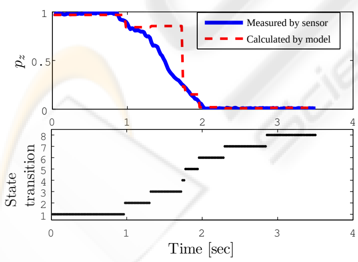


Figure 12: p_Z and state transition of trial 1 of examinee B(in the case of HMM).

SS-ARX has stronger correlation with the increase of trial number compared with that of standard HMM (except examinee D.) This comes from the fact that the HMM cannot capture the accurate dynamic characteristics underlying the measured signals compared with the SS-ARX model.

The recognition performances of the standard HMM and the SS-ARX model are compared using the profile of examinee B in the following. The recognition result of the HMM of examinee B is shown in Fig. 11. Also, the calculated p_Z and estimated state transition obtained by Viterbi algorithm are shown in Fig. 12.

In Fig. 11, obtained *DLL* does not related to trial number apparently. According to this result, it is almost impossible to discriminate between fatigue trials and non-fatigue trials. Therefore, the degree of fatigue does not seem to be recognized by standard HMM for examinee B.

6 CONCLUSIONS

This paper has presented a new fatigue recognizer based on the EMG signals and the stochastic switched ARX (SS-ARX) model. Since the SS-ARX model can represent complex dynamics which involves switching and stochastic variance, high performance as the fatigue recognizer was achieved. And the usefulness of the proposed strategy was demonstrated by applying to a peg-in-hole task. The design of adaptive assisting system which can accommodate with the change of skill characteristics caused by fatigue is our future work.

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