IEEE SMC'99

1999 IEEE International Conference on

Systems, Man, and Cybernetics

October 12-15, 1999

Tokyo International Forum,

Tokyo, JAPAN

Sponsored by

IEEE Systems, Man, and Cybernetics Society
Science Council of Japan
The Society of Instrument and Control Engineers
The Robotics Society of Japan
The Japan Society of Mechanical Engineers

Conference Theme:

Human Communication and Cybernetics

IEEE - Catalog Number 99CH37028C

ISBN: 0-7803-5734-5

An EMG Controlled Pointing Device Using a Neural Network

Osamu FUKUDA, Toshio TSUJI and Makoto KANEKO
Industrial and Systems Engineering, Hiroshima University,
Higashi-hiroshima, Japan

Abstract

In this paper, we argue that myoelectric signals (EMG) measured from surface electrodes can be utilized as an interface tool for the handicapped. The EMG signal contains information about the operator's intended motion as well as the force level of the muscles and may be suitable as an input signal for a new interface tool. This paper proposes an EMG controlled pointing device using a neural network and develops a prototype system. In the proposed device, an operator's intended direction of the pointer is estimated using the finite number of base directions which are set on the computer display. The neural network has to estimate the probability that the pointer will move to each base direction, so that the heavy learning calculation and the huge network structure are not neccessary. Through experiments, it is shown that the direction and the velocity of the pointer movement can be controlled by using the EMG signals.

1 Introduction

Up to the present, various pointing devices have been proposed as an interface tool for computers and virtual reality (VR). In particular, a mouse invented by Engelbart in 1964 has been used by many people as a standard pointing device [1]. Without using a pointing device, it is almost impossible to utilize a computer efficiently.

Many researchers have tried to develop new pointing devices such as a gesture recognition system using a computer vision [2] and a motion tracking system which traces eye movement [3] in order to realize easy operations. Also, in the research area of VR, the equipment which can measure 3D position by using electromagnetic fields is often used. However, in order to use such devices, human body movements are indispensable, and it is impossible to measure invisible information such as internal force, motion intention and mental stress. In addition, heavy signal processing is often used in the vision system, which presents another difficulty.

Let us consider the case that a user of these pointing devices is a physically handicapped person. In recent years, personal computers and Internet technologies have supported the social integration of the handicapped and improved their Quality Of Life (QOL) through various communications and by providing useful information [4], [5]. The pointing device for them must serve as a part of their body. Generally, the handicapped often use specially designed equipments or pointing devices by simplifying their proper functions. It is difficult to say that ease of operation is sufficient in such a situation.

On the other hand, an interface tool for a handicapped person has been developed using EMG signals which are generated from his or her muscles. It is often used for generating control commands of a prosthetic hand for an amputee [6]-[11]. The EMG signal contains the information on the force level of corresponding muscles and mechanical impedance of joints such as stiffness, viscosity, and inertia in addition to the intended motions of the operator. This signal may be suitable as an input signal to a new pointing device.

In this paper, we propose a new pointing device using the EMG signals and develop a prototype system. A neural network is used as a pointer controller in the prototype system, so that the system can adapt itself to changes of the EMG patterns according to the differences among individuals, different locations of the electrodes, time variation caused by fatigue or sweat, and so on. Also the proposed method may be useful for not only the handicapped but also other people, because the EMG signal contains information on internal force among several muscles which cannot be measured by other sensors.

2 EMG Controlled Pointing Device

Figure 1 shows the concept of the EMG-controlled pointing device. This system uses the information on the EMG signals for pointer control. The operator's intended direction of the pointer movement and its velocity are estimated from the EMG signals, and natu-

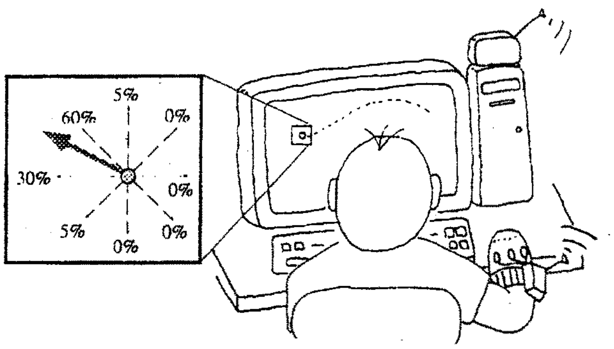

Figure 1: Concept of the EMG-based pointing device

ral interaction can be expected using this information. The desktop space is not necessary for this system.

To realize reliable GUI operation, it is necessary that the direction of pointer movement must be controlled accurately according to the intention of the user. In the proposed method, a several numbers of base directions are set on the computer display, and the operator's intended direction is estimated from the probability that the pointer will move to each base direction. For example, the direction is estimated as the bold arrow using eight base directions in the Fig. 1.

In such a way, any operator's intended directions can be estimated using the finite number of the base directions. The neural network only has to estimate the probability of the pointer movement to each base direction, so that the heavy learning calculation and the huge network structure may be avoided.

3 Structure of the System

The structure of the prototype system is shown in Fig. 2. This system consists of the EMG signal processing part, the neural network part, and the pointer control part. In the neural network part, the log-linearized Gaussian mixture network (LLGMN) proposed by Tsuji et al. [12] is used. The LLGMN can acquire the log-linearized Gaussian mixture model through learning and calculate the posteriori probability of the pointer movement to each base direction based on this model. The probability density function is expressed by the weighted sum of the Gaussian components. It enables the LLGMN to learn the complicated mapping between the operator's EMG patterns and the pointer movement.

3.1 EMG Signal Processing Part

First, the EMG signals measured from L pairs of electrodes (Web5000: NIHON KOHDEN Corp.) are rectified and filtered out through the second-order Butterworth filter (cut-off frequency : 1 [Hz], UAF42, BURR-BROWN Corp.), and they are digitized by an A/D converter (sampling frequency, 10 [Hz]; and quantization, 12 [bits]). These sampled signals are defined as $EMG_i(n)$ $(i = 1, \cdots, L)$, and the following equation is calculated:

$$\alpha(n) = \frac{1}{L}\sum_{i=1}^{L}\frac{EMG_i(n) - EMG_i^{st}}{EMG_i^{max} - EMG_i^{st}}, \tag{1}$$

where EMG_i^{st}, EMG_i^{max} are the mean values of $EMG_i(n)$ while relaxing the arm and keeping the maximum voluntary contraction (MVC), respectively. The $\alpha(n)$ indicates the ratio of the muscular contraction level to the MVC. The velocity of the pointer movement can be regulated according to this ratio.

Next, $EMG_i(n)$ are normalized to make the sum of L channels equal 1:

$$x_i(n) = \frac{EMG_i(n) - EMG_i^{st}}{\sum_{i'=1}^{L}(EMG_{i'}(n) - EMG_{i'}^{st})}, \tag{2}$$

where $x_i(n)$ is an element of the feature vector $\boldsymbol{x}(n) = [x_1(n), x_2(2), \cdots, x_L(n)]^{\mathrm{T}} \in \Re^L$ for the input of the neural network part. Also, the square sum of the $EMG_i(n)$ is calculated for the detection of the pointer movement: when this value is over the prespecified threshold, it is determined that the movement has occurred.

3.2 Neural Network Part

In the neural network part, the probability of pointer movement to each base direction is estimated from the EMG pattern $\boldsymbol{x}(n)$ which is extracted in the EMG signal processing part.

First, the input vector $\boldsymbol{x}(n) \in \Re^L$ is preprocessed and converted into the modified input vector $\boldsymbol{X}(n) \in \Re^H$ as follows:

$$\begin{aligned}\boldsymbol{X}(n) \;=\; & [1, \boldsymbol{x}(n)^{\mathrm{T}}, x_1(n)^2, x_1(n)x_2(n), \cdots, \\ & x_1(n)x_L(n), x_2(n)^2, x_2(n)x_3(n), \\ & \cdots, x_2(n)x_L(n), \cdots, x_L(n)^2]^{\mathrm{T}}. \end{aligned} \tag{3}$$

The first layer consists of $H = 1 + L(L+3)/2$ units corresponding to the dimension of $X(n)$ and the identity function is used for an output function of each unit.

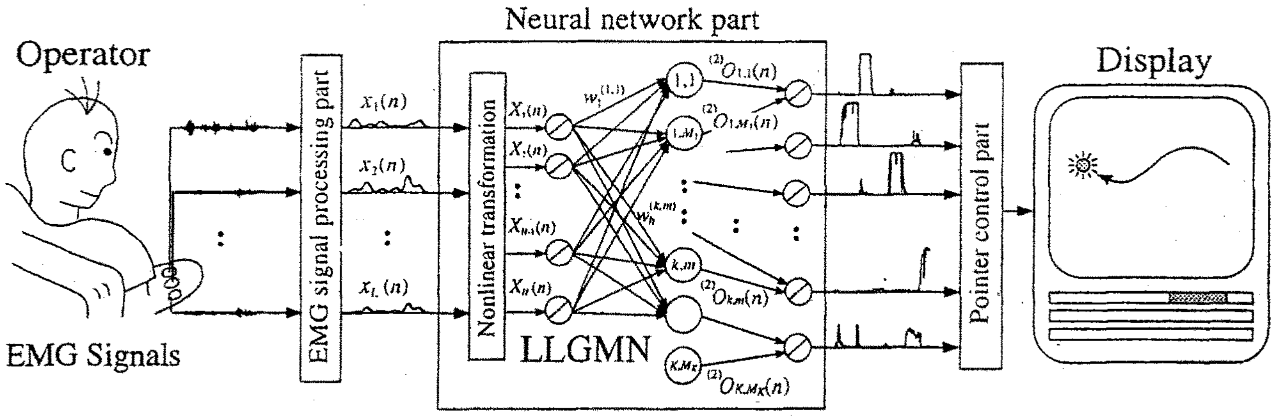

Figure 2: Structure of the prototype system

Each unit of the second layer receives the output of the first layer ${}^{(1)}O_h(n)$ weighted by the coefficient $w_h^{(k,m)}$ and outputs ${}^{(2)}O_{k,m}(n)$ as follows:

$$ {}^{(2)}O_{k,m}(n) = \frac{1}{\sum_{k'=1}^{K}\sum_{m'=1}^{M_{k'}} \exp[{}^{(2)}I_{k',m'}(n) - {}^{(2)}I_{k,m}(n)]}, \tag{4} $$

$$ {}^{(2)}I_{k,m}(n) = \sum_{h=1}^{H} {}^{(1)}O_h(n) w_h^{(k,m)}. \tag{5} $$

It should be noted that (4) can be considered as a kind of generalized sigmoid function. The third layer consists of K units corresponding to the number of the base directions. The unit k integrates the outputs of M_k units $\{k,m\}$ $(m = 1, \cdots, M_k)$ in the second layer. The relationship between the input and the output is defined as:

$$ {}^{(3)}O_k(n) = {}^{(3)}I_k(n), \tag{6} $$

$$ {}^{(3)}I_k(n) = \sum_{m=1}^{M_k} {}^{(2)}O_{k,m}(n). \tag{7} $$

This output ${}^{(3)}O_k(n)$ indicates the posteriori probability of pointer movement to the base direction k.

3.3 Pointer Control Part

The direction of the pointer movement is estimated using the output of the neural network part. The output of the LLGMN ${}^{(3)}O_k(n)$ indicates the posteriori probability that the pointer will move to each base direction k shown in Fig. 3. Therefore the vector of the

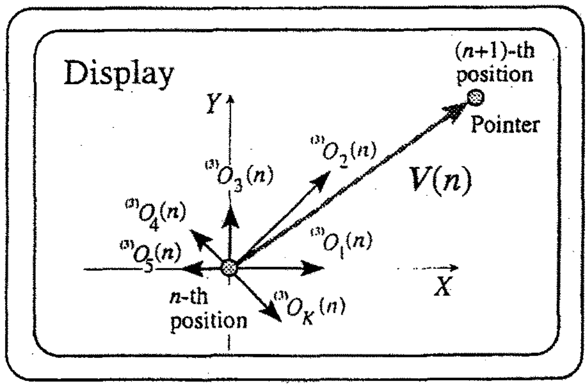

Figure 3: Moving direction of a pointer

pointer movement $\boldsymbol{V}(n) = (V_X(n), V_Y(n))^{\mathrm{T}}$ for nth input pattern is calculated as follows:

$$ V_X(n) = \frac{\Delta(n)e_x(n)}{\sqrt{e_x^2(n) + e_y^2(n)}}, \; V_Y(n) = \frac{\Delta(n)e_y(n)}{\sqrt{e_x^2(n) + e_y^2(n)}}, \tag{8} $$

where $\Delta(n)$ is a velocity gain of the pointer movement, and $e_x(n), e_y(n)$ are defined as:

$$ e_x(n) = \sum_{k=1}^{K} {}^{(3)}O_k(n)\cos(2\pi(k-1)/K), \tag{9} $$

$$ e_y(n) = \sum_{k=1}^{K} {}^{(3)}O_k(n)\sin(2\pi(k-1)/K). \tag{10} $$

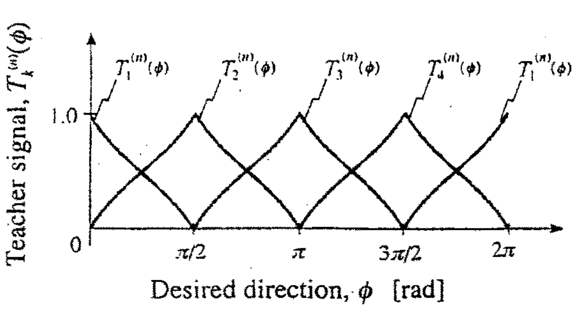

Figure 4: Teacher signals of the LLGMN

4 Learning Rule

Before the operation, the LLGMN must be trained the nonlinear mapping between the EMG patterns and the pointer movement. Then the LLGMN can estimate the pointer movement based on the statistical model.

Here the learning method is explained. In the learning process, the desired direction of the pointer movement is shown in the display. The user generates the EMG signals according to this direction. Then the pair of the desired direction ϕ and the EMG pattern $\boldsymbol{x}(n)$ are used as the learning data. The order of presenting the desired direction ϕ is random, where ϕ is defined as 0 in the positive direction of X-axis and increases counterclockwise in Fig. 3.

In the case that the number of the base directions is K, the teacher signal $T_k^{(n)}(\phi)$ $(k = 1, \cdots, K)$ is calculated as follows:

$$T_k^{(n)}(\phi) = \begin{cases} \frac{\cos(|\phi-\phi_{\mathrm{base1}}|)-\cos(|\phi_{\mathrm{base2}}-\phi|)\cos(\frac{2\pi}{K})}{[\cos(|\phi-\phi_{\mathrm{base1}}|)+\cos(|\phi_{\mathrm{base2}}-\phi|)][1-\cos(\frac{2\pi}{K})]} & \\ & (\frac{2\pi(k-2)}{K} < \phi < \frac{2\pi k}{K}) \\ 0 & (other), \end{cases} \tag{11}$$

where ϕ_{base1}, ϕ_{base2} are defined as:

$$\phi_{\mathrm{base1}} = \frac{2\pi(k-1)}{K}, \quad \phi_{\mathrm{base2}} = \frac{2\pi k}{K}. \tag{12}$$

For example, the teacher signals for four base directions which corresponds to the up, down, right, and left directions are shown in Fig. 4. When the desired direction ϕ does not agree with the base direction, two units in the third layer which are close to ϕ are selected, and the teacher signals are given to them as shown in the figure. The teacher signal $T_k^{(n)}(\phi)$ is determined according to the projection of the unit vector in the desired direction ϕ on the kth base direction. It should be noted that $\sum_{k=1}^{K} T_k^{(n)}(\phi) = 1$.

As the energy function for learning, we use:

$$\begin{aligned} J &= \sum_{n=1}^{N} J_n, \\ J_n &= I_K(T^{(n)}(\phi); {}^{(3)}O(n)) \\ &= \sum_{k=1}^{K} T_k^{(n)}(\phi) \log T_k^{(n)}(\phi) \\ &\quad - \sum_{k=1}^{K} T_k^{(n)}(\phi) \log {}^{(3)}O_k(n), \end{aligned} \tag{13}$$

where I_K represents the difference between two probability distributions, which is defined as the Kullback-Leibler divergence. The learning is performed to minimize J.

5 Experiments

In order to examine the availability of the proposed method, the experiments have been conducted. The subject is a graduate student: male, age 29 in a healthy condition. In the experiments, the direction of the pointer movement is controlled according to the EMG signals when the operator bends his wrist joint to the intended direction.

5.1 Example of the Pointer Control

Figure 5 shows an example of the pointer control. In this figure, the traces of the pointer, the EMG signals, the square sum of $EMG_i(n)$, the muscular contraction level $\alpha(n)$, the output of the LLGMN and the estimated direction are shown. Six electrodes, four base directions and 500 learning data (100 random directions × 5 samples) were used in the experiment. The traces of the pointer are plotted every 0.1[sec] and two arrows indicate the pointer movement. The velocity gain of the pointer movement $\Delta(n)$ was regulated from 0 to 40 [pixels/sec] in proportion to $\alpha(n)$. It can be seen that the direction and the velocity of the pointer movement can be controlled using the EMG signals.

Next, the subject tried to draw a rectangle, a triangle and a circle shown in Fig. 6. Six electrodes and four base directions and 500 learning data (100 random directions × 5 samples) were used in the experiment. The velocity gain of the pointer movement $\Delta(n)$ was fixed with 30 [pixels/sec]. The pointer could be controlled approximately according to the desired

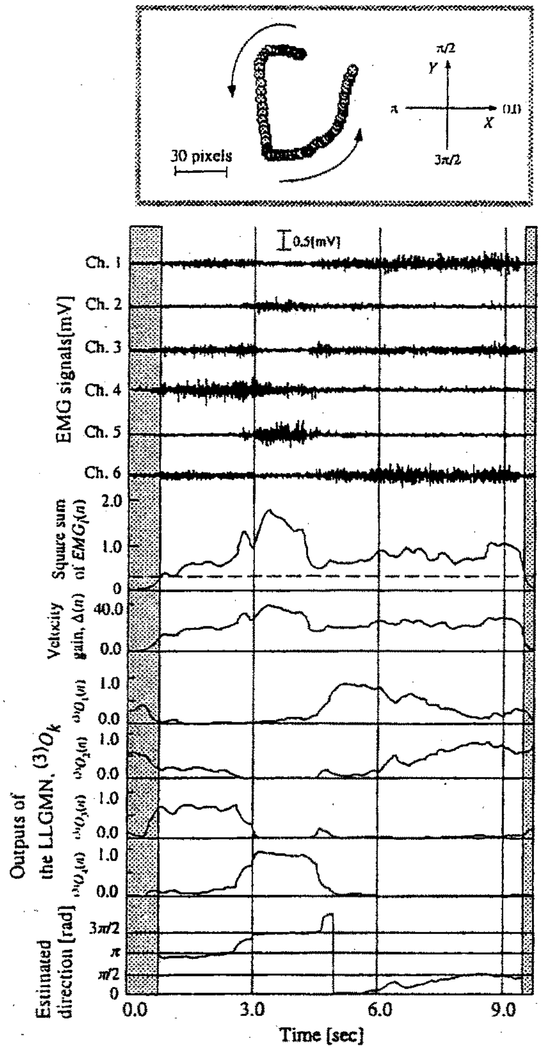

Figure 5: An example of the pointer control

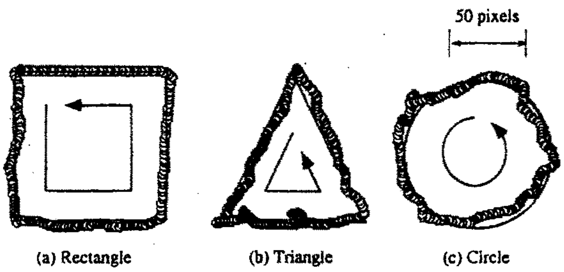

Figure 6: Results of the drawing experiments

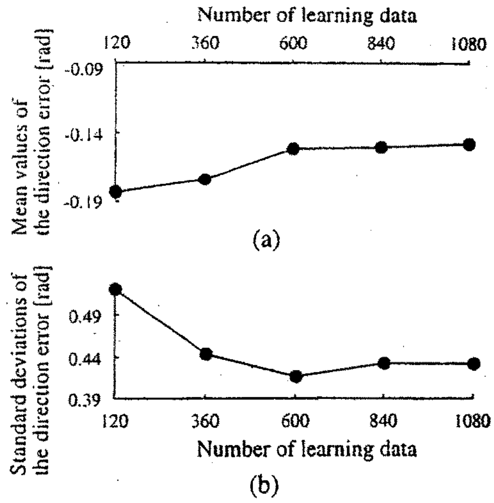

Figure 7: Accuracy of the estimated direction depending on the number of learning data

line although many errors of the direction were observed. It took about 10 seconds to draw each figure.

5.2 Accuracy of the Estimated Direction

The estimation ability of the operator's intended direction is examined using the proposed method. The number of learning data and base directions are changed from 120 to 1080 (10, $\cdots$, 90 samples for 12 learning directions) and from 4 to 12, respectively. In the experiments, the desired direction of the pointer movement is shown in the display. The subject bends his wrist joint according to this direction and the EMG signals are measured from six electrodes for estimation. The number of trials for estimation are 3600 (100 samples for every 10 degrees) and the order of presenting the desired directions is random.

The accuracy of the pointer movement depending on the number of learning data is shown in Fig. 7. Each plot shows: (a) The mean values and (b) the standard deviation of the direction error for all trials. The number of learning data was changed from 120 to 1080 (10, $\cdots$, 90 samples for 12 learning directions) and four base directions were used in this experiment. The accuracy of the pointer movement improves depending on the increase of the number of learning data. It seems that 600 learning data are sufficient in this case.

Next, the accuracy of the pointer movement depending on the number of the base directions were examined. The mean values and the standard deviations of the direction error for all trials are shown in Fig. 8(a), (b). The number of the base directions was

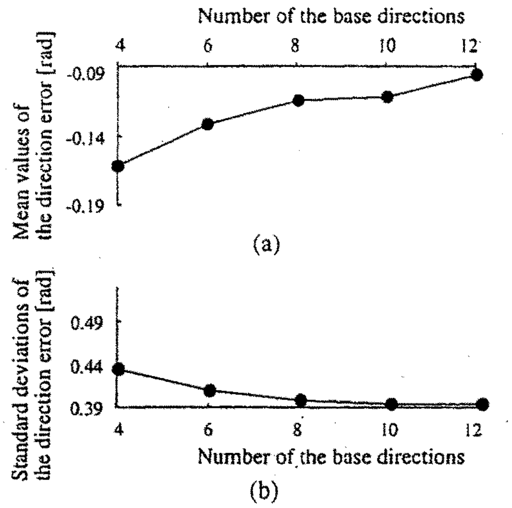

Figure 8: Accuracy of the estimated direction depending on the number of the base direction

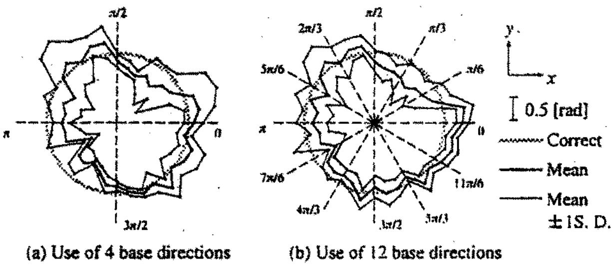

Figure 9: Accuracy of the estimated direction

changed from 4 to 12, and 600 learning data were used. It can be seen that the accuracy improves depending on the increase of the number of the base directions, although a large number of the base directions requires much longer learning time.

Figure 9(a), (b) show the accuracy of the pointer movement depending on the direction. This radar chart indicates the mean values and the standard deviations of the direction error for 3600 trials (100 samples for every 10 degrees). The number of the base directions which are shown in the figure as dotted lines is (a) 4, (b) 12, respectively, and 600 learning data were used. In case of (a), the error becomes large when the desired direction differs from the base direction. On the other hand, the error is almost constant for each desired direction in (b). Also, the error in (b) is smaller than that in (a).

6 Conclusion

In this paper, we propose a new pointing device using the EMG signals, and develop a prototype system. By experiments, it is shown that the direction and the velocity of the pointer movement can be controlled by using the EMG signals.

In the future, we wish to conduct the experiment with many subjects in order to make clear the effectiveness and the problems of this system.

Acknowledgment A part of this work was supported by the Scientific Research Foundation of the Ministry of Education, Science, Sports and Culture, Japan (11555113 and 11650450).

References

[1] D. C. Engelbart : "A Conceptual Framework for the Augmentation of Man's Intellect," Vistas in Information Handling, Vol 1, ed. Howerton and Weeks, pp.1-29, Spartan Books. Washington D. C., 1963.

[2] R. A. Bolt : "'Put-That-There': Voice and Gesture at the Graphics Interface." Computer Graphics 14(3), pp. 262-270, 1980.

[3] R. A. Bolt : "Gaze-Orchestrated Dynamic Windows." Computer Graphics 15(3), pp. 109-119, 1981.

[4] http://www.ibm.co.jp/kokoroweb/

[5] http://www.eskimo.com/ jlubin/disabled.html

[6] I. Kato, E. Okazaki, H. Kikuchi and K. Iwanami : "Electro-Pneumatically Controlled Hand Prosthesis Using Pattern Recognition of Myu-Electric Signals," Digest of 7th ICMBE, P. 367, 1967.

[7] R. B. Jerard, T. W. Williams and C. W. Ohlenbusch : "Practical Design of an EMG Controlled Above Elbow Prosthesis," Proceedings of 1974 Conf. Eng. Devices for Rehabilit., Tufts Univ. School of Med., Boston, MA, 1974.

[8] S. C. Jacobson, D. F. Knutti, R. T. Johnson and H. H. Sears : "Development of the Utah Artificial Arm," IEEE Transactions on Biomedical Engineering, 29(4), pp. 249-269, 1982.

[9] K. Ito, T. Tsuji, A. Kato and M. Ito : "An EMG Controlled Prosthetic Forearm in Three Degrees of Freedom Using Ultrasonic Motors," Proceedings of the Annual International Conf. of the IEEE Engineering in Medicine and Biology Society, Vol.14, pp. 1487-1488, 1992.

[10] O. Fukuda, T. Tsuji, A. Otsuka and M. Kaneko : "EMG-based Human-Robot Interface for Rehabilitation Aid," Proceedings of IEEE International Conference on Robotics and Automation, pp. 3492-3497, 1998.

[11] O. Fukuda, T. Tsuji, A. Otsuka and M. Kaneko : "An EMG-based Rehabilitation Aid for Prosthetic Control," Proceedings of IEEE International Workshop on Human and Robot Communication, Vol. 1, pp. 214-219, 1998.

[12] T. Tsuji, H. Ichinobe, O. Fukuda and M. Kaneko : "A Maximum Likelihood Neural Network Based on a Log-Linearized Gaussian Mixture Model," Proceedings of IEEE International Conference on Neural Networks, pp. 2479-2484, 1995.