Motion Intention Recognition for Wearable Power Assist System using Multi-Class SVM and Kinematic Model

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Abstract: This paper is aimed at describing a framework to implement Multi-Class Support Vector Machine (MCSVM)-based motion intention recognition. To this end, we primarily constructed a wearable exoskeleton robot of lower body which is employed as an experimentation platform to test the MCSVM-based motion intention recognition. Having disclosed prototype development and MCSVM, experimental results of motion intention recognition of standing up and seating are presented. We examined the accuracy of method of motion intention recognition based on MCSVM. We also examined utility of adding information of kinematic model to training data.

1 Introduction

Power assist system is a technology or a device that amplifies the human ability to exercise, and can be done to aid the movement expanded. When we wear power assist system, it is possible to use it in our everyday life and we can exert. It is expected to be used in many areas, for example a work site, a medical front or a disaster site. In the work site, it helps to reduce the burden of workers. In the medical front, it helps rehabilitation of the patient. Some have been studied as military for transport.

Recently, the wearable power assist system has been studied by many colleges and companies. In the studies, one of the most famous wearable power assist system is HAL[1] which has been developed by Sankai and his team in university of Tsukuba. It has been developed to help practicing walking. As a development stage, it has been lease for welfare. Another famous study is Bleex[2] for labor support which has been developed by H. Kazerooni, R. Steger and their team in university of California, Berkeley.

In wearable power assist system, to develop an accurate recognition method estimating wearer 's motion intention is particularly important. To achieve this purpose, phase-sequence method based on multiple threshold values of multiple sensors has been widely used in the conventional studies, e.g. see [1]. However, the tuning of the multiple threshold values of sensors needs try and error and is time-consuming. Such threshold value tuning is also sensitive to the wearer's situation and needs re-tuning for each wearer. In order to avoid such time-consuming and sensitive procedures, we propose a phase sequence method based on multi-class support vector machine(MCSVM) [3]-[7] (Method 1). We also propose an improved recognition method applying both MCSVM and kinematic model of the exoskeleton mechanism. The effectiveness of the proposed methods is confirmed by experiments.

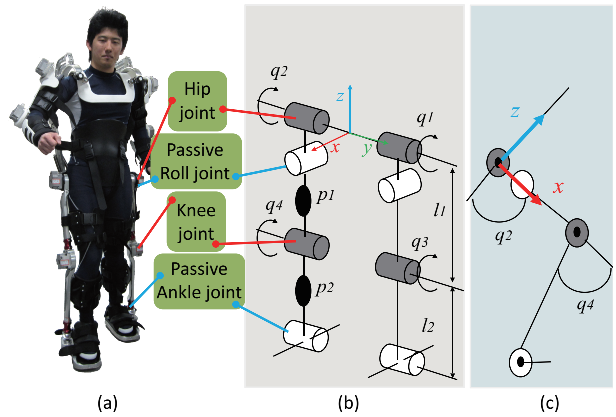

Figure 1: (a) TTI-Exo, being worn by an able-bodied subject. (b) Schematic of lower body. (c) System of coordinates with their origin at the center of hip joint.

2 Experimental system

In order to investigate the usefulness of power assist system, we built an electrically-actuated whole-body exoskeleton, named TTI-Exo. Its upper body is previously utilized for upper body rehabilitation and system with an able-bodied wearer and joint power augmentation tasks [8]. Figure.1 shows the actual configurations.

Each leg is powered via 2 electrically-actuated active DoF (degrees of freedom) in hip and knee joints.

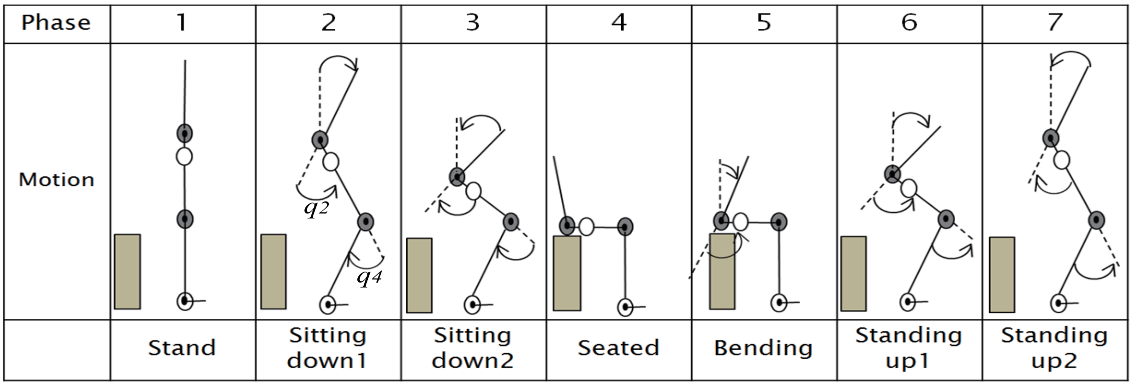

Figure 2: Dividing of motion

Table 1: Structure of data

Without kinematic model	$\overline{\boldsymbol{x}}_i = (q_2, q_4, \dot{q_2}, \dot{q_4}, p_1, p_2)$
With kinematic model	$\overline{\boldsymbol{x}}_i = (q_2, q_4, \dot{q_2}, \dot{q_4}, p_1, p_2, x_k, z_k, x_a, z_a)$

Therefore, the robot has no inherent balancing ability. TTI-Exo is equipped with passive hip joints about roll axis to allow lateral leg movements. The system is attached to the wearer using straps and C-shaped braces. The weight of exoskeleton is supported by sole. Link lengths are also adjustable for different wearers in a way to align robot and human joints.

In Figure.1(b), Gray represents the joints which are equipped with actuators and encoders. White represents freedom joints. Black ellipse represents the pressure sensors. We can get following experimental data from this system { q_2: Right hip angle, q_4: Right knee joint angle, p_1: Pressure front thigh, p_2: Pressure rear leg region }. Angular velocity is calculated by differentiating the angle { $\dot{q_2}$: Right hip joint angular velocity, $\dot{q_4}$: Right knee joint angular velocity }.

When hip joint is set at origin, x-coordinate and z-coordinate of knee joint (x_k, z_k) and ankle joint (x_a, z_a) are obtained by kinematic model of exoskeleton mechanism by Eq.(1) - (4).

$$
\begin{aligned}
x_k &= l_1 \sin q_2 && (1)\\
z_k &= -l_1 \cos q_2 && (2)\\
x_a &= x_k - l_1 \sin(q_4 - q_2) && (3)\\
z_a &= z_k - l_2 \cos(q_4 - q_2) && (4)
\end{aligned}
$$

3 Experiment

Figure.2 shows that motions of standing up and seating are divided into seven phases and labeled according to the direction of joint movement. Each motion is labeled with number from 1 to 7. We recognized these seven motions. Data were obtained by motion in order of phase with TTI-Exo on. When we got data, motors were moved passively by motion of subject. Sampling time is 0.01[s]. Discriminant functions were made by MCSVM using this data. Motion intention was recognized by simulation using discriminant function.

3.1 Multi-Class SVM

MCSVM is pattern recognition techniques and classified into multiple of n-data which present in the m-dimensional space. It is a supervised learning algorithm. We assume that a training sample of input-output pairs $S = ((\overline{\boldsymbol{x}}_1, y_1), ..., (\overline{\boldsymbol{x}}_n, y_n))$ where $\overline{\boldsymbol{x}}_i$ is training data whose structure is showed in Table.1. The difference between two types of training data is information of kinematic model.

$y_i \in \mathcal{Y} = \{1, 2, 3, 4, 5, 6, 7\}$ are label. We obtain $\boldsymbol{w}$ and ξ_i by solving Eq.(5).

$$\min_{w, \xi \geq 0} \frac{1}{2} \boldsymbol{w}^T \boldsymbol{w} + \frac{C}{n} \sum_{i=1}^{n} \xi_i \tag{5}$$

$$
\begin{aligned}
& s.t. \forall \overline{y}_1 \in \mathcal{Y}, \\
& \boldsymbol{w}^T [\Psi(\boldsymbol{x_1}, y_1) - \Psi(\boldsymbol{x_1}, \overline{y}_1)] \geq \Delta(y_1, \overline{y}_1) - \xi_1 \\
& \qquad \vdots \\
& s.t. \forall \overline{y}_n \in \mathcal{Y}, \\
& \boldsymbol{w}^T [\Psi(\boldsymbol{x_n}, y_n) - \Psi(\boldsymbol{x_n}, \overline{y}_n)] \geq \Delta(y_n, \overline{y}_n) - \xi_n
\end{aligned}
$$

$\boldsymbol{w}$ is a parameter vector and ξ_i is a slack variable and C is a constant that controls the trade-off between training error minimization and margin maximization and $\Delta(y, \overline{y})$ is a loss function and $\Psi(\boldsymbol{x_i}, y)$ is a feature vector. Discriminant functions are expressed following.

$$h_{\boldsymbol{w}}(\boldsymbol{x}_i) = \underset{y \in \mathcal{Y}}{\operatorname{argmax}} f_{\boldsymbol{w}}(\boldsymbol{x}_i, y) \tag{6}$$

$$f_{\boldsymbol{w}}(\boldsymbol{x}_i, y) = \boldsymbol{w}^T \Psi(\boldsymbol{x}_i, y) \tag{7}$$

Training data is $m \times n$ matrix where $m = 6$ for the training data without kinematic model or $m = 10$ for training data with kinematic model, and the number of training samples $n = 7500$. $\boldsymbol{x_i}$ is test data which is $m \times 1$ matrix.

3.2 Experimental Result

In this subsection we measure the performance of proposed motion intention recognition method by " Precision ", " Recall ", and " Accuracy " using cross-validation. The data consist of 4 sets of 2500 data. Note that the last 2500 data is acquisitioned from a different wearer. The cross-validation is carried using three of 4 sets of data as training data. Table.2 shows the result by MCSVM. Table.3 shows the result using both MCSVM and kinematic model. In both tables, the result on the #4 data set is the worst because the test data of the #4 data set is about the different wearer. Both tables show the proposed method with MCSVM with kinematic model can achieve reasonable and practical performance for motion intention recognition with wearable power assist system.

Table 2: Result of MCSVM

#	Precision	Recall	Accuracy
1	0.7877	0.7741	0.7752
2	0.8277	0.8268	0.9148
3	0.8164	0.8644	0.9072
4	0.5684	0.6096	0.5500

Table 3: Result of MCSVM with kinematic model

#	Precision	Recall	Accuracy
1	0.7270	0.7741	0.8368
2	0.8295	0.8212	0.9132
3	0.8298	0.8460	0.9324
4	0.5046	0.5802	0.6796

4 Conclusion

In this paper we proposed a motion intention recognition system using phase sequence method based multi-class support vector machine (MCSVM) and kinematic model of exoskeleton mechanism. Using our wearable power assist system equipped with piezoelectric pressure sensors we confirmed that the proposed method can achieve the practical performance.

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