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Upper-Body Motion Mode Recognition Based on IMUs for a Dynamic Spine Brace

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Abstract— **This paper presents an upper-body motion mode recognition method based on inertial measurement units (IMUs) using cascaded classification approaches and integrated machine learning algorithms. The proposed method is designed to be applied on a dynamic spine brace in the future to assess its usability. This study focuses on the problem of classifying upper-body motion modes by using four IMUs worn on the upper-body of the subjects. Six locomotion modes and ten locomotion transitions were investigated. A quadratic discriminant analysis (QDA) classifier and a support vector machine (SVM) classifier were deployed in our study. With selected cascade classification strategies, the system is demonstrated to achieve a satisfactory performance with an average of 96.77%(QDA) and 97.64%(SVM) recognition accuracy. The obtained results prove the effectiveness of the proposed method.**

I. Introduction

Wearable robotics is a promising and challenging field of robotic research. As rehabilitation is a key application of wearable robotics, orthoses and exoskeletons have gained increasing research interests recently [1]–[3]. Exoskeletons for rehabilitation have been developed in different types of mechanical structures, actuators and interfaces [1].

Generally, wearable exoskeletons are classified according to the human segments on which the robot kinematic chains are applied. Thus, robotic exoskeletons can be classified as upper limb, lower limb and full-body exoskeletons [4]. Although rehabilitation robots have different forms and functionality, most current research still focus mainly on limbs or full-body suits. There are only few studies concerning robotic spine exoskeletons. For example, a SpineCor brace was designed using a series of elastic straps to provide spine correction [5]. However, the force application of this brace is still passive and requires extensive training.

A dynamic spine brace was recently proposed by the Robotics and Rehabilitation Laboratory in Columbia University [6]. It is a wearable upper-body suit that can provide dynamic controlled forces on different regions of spine to help correct abnormal postures (shown in Fig. 1(a)). There is a potential need for this functionality in rehabilitation of adolescents with idiopathic or neuromuscular scoliosis. Compared to passive spine braces that apply rigid and passive support, the dynamic spine brace is able to actively control the motion of different regions of the spine by using three rings where the motion of successive rings is controlled by using six parallel actuators. The novel design of the dynamic spine brace ensures its functionality in modifying the spine posture. In addition, it does not restrict mobility in the daily activities of the user.

However, for the dynamic spine brace, there are still challenges in achieving responsive human-robot interaction through this interface. One of the most difficult challenges is to provide the robotic system with sensors and appropriate software to allow it to respond to the environment, and react intuitively to human motion with both accuracy and immediacy. This is especially pertinent for situations where the interface must compensate with unexpected sudden changes in human intention. Therefore, motion mode recognition holds an important role in the high level decision making and this is one of the factors that may potentially differentiate and make this system more usable.

Recent studies have demonstrated human motion recognition techniques by using wearable sensors combined with machine learning algorithms. Inertial Measurement Units (IMUs) are widely used in upper-limb and lower-limb motion detection [7], [8]. Other studies have chosen surface electromyograph (sEMG), capacitive sensing or multi-sensor fusion strategies for lower-limb motion detection [9]–[11]. Though these studies have focused on different motion sensing methods, they are typically looking at motion of individual limbs instead of the complex coordinated motions of the upper-body. Only a few studies are addressing upper-body motion recognition, e.g. [12].

In this study, we utilized upper-body motion mode recognition methods in order to implement on the dynamic spine brace for improved active motion adaptation and response. Four IMUs were used to detect upper-body motions. We designed several upper-body motion tasks that can utilize up to sixteen locomotion modes. Three able-bodied subjects participated in the experiments. By using cascaded classification methods and integrated machine learning algorithms, an effective motion mode recognition method was designed which will be applied to the dynamic spine brace in the future.

The rest of this paper is organized as follows. Section II shows the method for upper body motion mode recognition. Section III shows the results and related discussion. We conclude in Section IV.

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II. Method

A. Experimental protocol

Three subjects (all male; aged between 21 and 23 years) volunteered to participate in the study and provided written consent prior to testing. The sensing system consists of four wireless IMUs at a sample rate of 100Hz. Each IMU sensor records three sets of kinematic information, including three-axis acceleration, three-axis angular velocity, and three-axis Euler angles (yaw, roll, pitch).

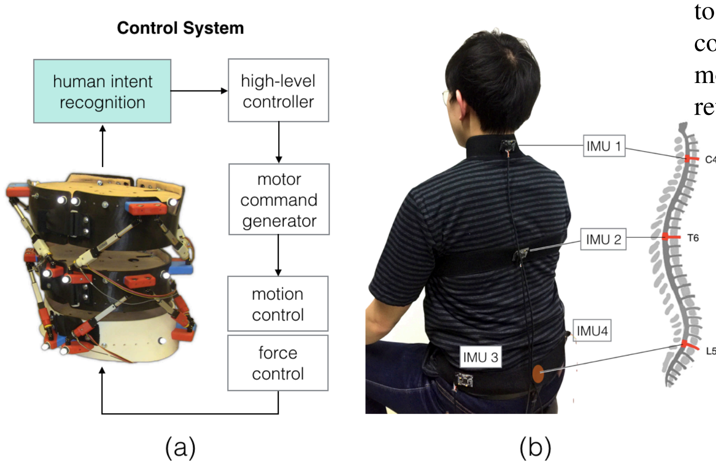

Fig. 1. (a)Human intent recognition in hierarchical control strategy for a dynamic spine brace. (b)The placement of four IMUs and their corresponding locations on human spine.

As shown in Fig. 1(b), the placement of four IMUs are as follows: one unit was placed on the neck of the subject, corresponding to the location of the fourth cervical vertebra (C4); a second unit was placed on the upper back of the subject, corresponding to the location of the sixth thoracic vertebrae (T6); while the other two units were placed symmetrically on the subject's lower back, corresponding to the height of the fifth lumbar vertebrae (L5).

All individuals were asked to perform a set of upper-body motion tasks in five different directions. These five directions were: center, right $45°$, right, left$45°$, left. The tasks selected for upper-body movement were: (1) Subject sitting on the chair, (2) stretching the arm to reach a point in front of the subject, (3) returning the arm to the initial position, (4) keeping the upper limbs in a resting position. Subjects were asked to make the first movement along the center with their right hand, then subjects used their right hand for the right side and their left hand for the left side. Subjects repeated each motion movement task fifteen times during the experiment. The reaching points were 12 inches in front of subject's feet, 27 inches on the right and left side of the the subject's shoulder, and at a height of 32 inches above the ground. An experimental observer advised subjects about the activities to perform and recorded each task.

IMU signals were captured and utilized as data sets for sixteen locomotion modes in our experiment. Each mode was labeled by the experiment observer during the operation task. Collected data of sixteen locomotion modes were categorized into static and dynamic modes in the first step of our cascaded classification (shown in Fig. 2). The static mode referred to the movement when the subject's upper-body remained static, while the dynamic mode was when the subject stretched the arm or returned to the resting position. Static mode was then divided into six static modes according to their different locations, and they were marked as S1, S2, S3, S4, S5, and S6. For the dynamic mode, two types of locomotion transitions were investigated and classified into forward mode (static to dynamic) and return mode (dynamic to static). In each transition group, there were five modes coordinating the different locomotion directions. Forward modes were marked as F1, F2, F3, F4 and F5. Similarly return modes were marked as R1, R2, R3, R4 and R5.

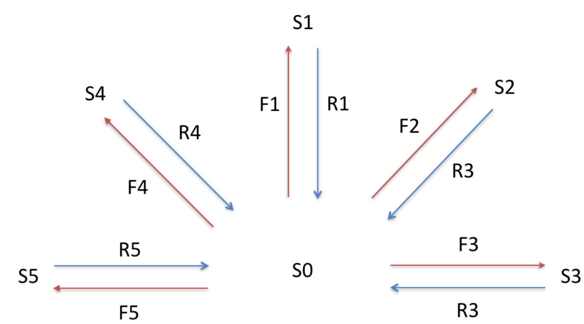

Fig. 2. S0-S5 are static modes. F1-F5, R1-R5 are dynamic modes. F1-F5 are forward locomotion transitions. R1-R5 are return locomotion transitions.

B. Data segmentation and feature set

In data segmentation stage, data streams from IMUs were gathered and then processed into segments. In our study, there were four IMUs with 9 signal channels on each unit, thus total 36 channels of signals were sampled. Even though all data in each mode was labeled manually at the beginning and at the end of locomotion activities, it was still difficult to segment a consecutive data stream without breaking its continuity. Thus, to extract data segments effectively, a sliding window over the time series data was introduced to extract data in this stage.All data was segmented into sliding windows, with overlap of 15ms for each sampling period.

Time domain features, such as signal mean, maximum, difference were derived from all four sensors in sliding windows, and eventually concatenated as a 180-dimension vector IMU sensor feature set. Five time-domain features were selected and IMU signals for each sliding window were calculated. The features were defined as follows:

$$f1 = avg(X),$$
$$f2 = std(X),$$
$$f3 = max(X),$$
$$f4 = min(X),$$
$$f5 = sum(X),$$

where X stands for the N-length data vector of one analysis window. avg(X) represents the average value of X, std(X) is the standard deviation of X, diff(X) is the difference of X, a (N-1)-length vector.

C. Classification method

Cascaded classification methods combining with a quadratic discriminant analysis (QDA) classifier and a support vector machine (SVM) classifier were deployed for motion modes detection in this study (shown in Fig. 3). All data collected from the motion task experiment were divided into sixteen different modes of locomotion. First, the locomotion modes were divided into static and dynamic modes. When static mode and dynamic mode were discriminated, data of dynamic mode were imported for the next classification process. Two classifiers were trained here for the data of forward modes and the data of return modes. Finally, data sets of static mode were trained into 6 phases, and data sets of dynamic mode were trained into 5 phases respectively.

Among these sixteen modes, we categorized them into static mode and dynamic mode. The static mode refers to the phase when the subject's movement remains static, and the dynamic mode is when the subject stretches the arm and the return movement. In dynamic mode, we further distinguished the transition movement by its direction, which are forward and return. We eventually measured the data of 6 static modes and 10 locomotion transitions.

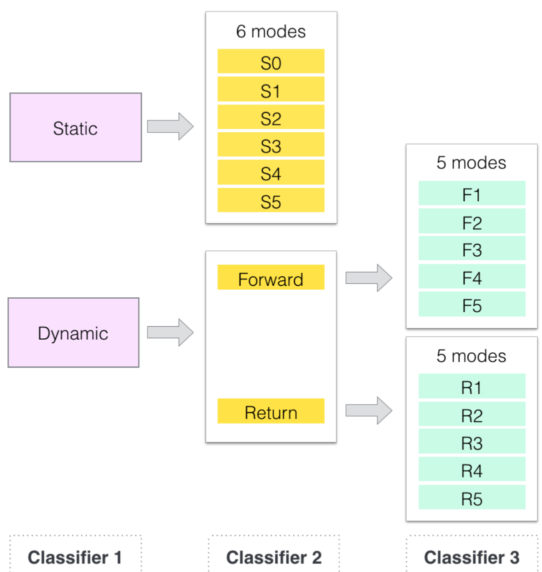

Fig. 3. Cascaded classification: (1)static and dynamic, (2)static modes and locomotion transitions, (3)forward modes and return modes.

D. Evaluation methods

In this study, 10-fold leave-one-out cross validation (LOOCV) was used for the training and testing of the classifiers. In this procedure, data of one fold was used as the testing set, and the remaining data was used as the training set. The process was repeated ten times until all group data was used as testing set. In this analysis, the overall recognition error (RE) was defined as

$$RE = N_{min}/N_{total} \times 100\% \tag{1}$$

where N_{min} is the number of wrongly recognized testing data and N_{total} is the number of all testing data. Each ambulation mode was evaluated separately. In order to understand the recognition performance of each locomotion pattern, we used a confusion matrix to present the recognition results in our dynamic mode evaluation. The confusion matrix was defined as

$$C = \begin{pmatrix} c_{11} & c_{12} & \cdots & c_{1m} \\ c_{21} & c_{22} & \cdots & c_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ c_{m1} & c_{m2} & \cdots & c_{mm} \end{pmatrix} \tag{2}$$

where each element C_{ij} was defined as

$$C_{ij} = n_{ij}/n_i \times 100\% \tag{3}$$

n_{ij} is the number of testing data in mode i but wrongly recognized as mode j. n_i is the total number of testing data in mode i.

III. Results and Discussion

A. Cascaded classification

As cascaded classification methods were applied in this study, there were recognition results of sixteen modes in three classifiers: (1) static and dynamic, (2) static modes and locomotion transitions, and(3) forward modes and return modes. First, all data was classified as either static or dynamic mode; the data of static mode was then classified into its six designated modes. Meanwhile, another classification on data of dynamic mode was deployed to determine the locomotion transition modes based on the direction of the movement (forward and return). All data of forward motion mode was classified according to the direction of motion. The same method was applied to return motion mode as well. Recognition results were calculated by a 150-ms sliding window length for classification with QDA classifier and SVM classifier. The recognition performance in the first classifier was good, with an average 98.04% $\pm$ 1.54 recognition accuracy with QDA classifier, and 98.90%$\pm$ 1.63 recognition accuracy with SVM classifier. Compared with the first layer classification, it was more difficult to distinguish the locomotion transitions(forward and return) in the second classifier. In locomotion transition mode recognition, the average recognition accuracy was 97.46%$\pm$ 1.14 with QDA classifier and 98%$\pm$ 1.47 recognition accuracy with SVM classifier.

B. Classification of each mode

In static mode recognition, the accuracy rate could reach up to 100%, which points out that all six static modes were recognized accurately. On the other hand, the results of each locomotion transition mode has a high accuracy with average 99.98%$\pm$ 0.01 and 99.34%$\pm$ 0.38 for forward transition mode and return transition mode, respectively. The recognition performance of each locomotion transition mode is shown in Table I and Table II. There were no errors in classification of right and left side motion. The reason why F4 had 0.14% misclassification error with QDA classifier and

0.63% misclassification error with SVM classifier was due to its adjacent location to F1. This reason also applied on the errors of R1 as R3 (2.63% with QDA classifier and 0.61% with SVM classifier), and R5 as R4 (1.92% error rate).

TABLE I
RECOGNITION ACCURACY COMFUSION MATRIX

Forward	F1	F2	F3	F4	F5
F1	100%	0%	0%	0%	0%
F2	0%	100%	0%	0%	0%
F3	0%	0%	100%	0%	0%
F4	0.14%	0%	0%	99.86%	0%
F5	0%	0%	0%	0%	100%
Return	R1	R2	R3	R4	R5
R1	97.37%	0%	2.63%	0%	0%
R2	0%	100%	0%	0%	0%
R3	0%	0	100%	0%	0%
R4	0%	0%	0%	100%	0%
R5	0%	0%	0%	1.92%	98.08%

TABLE II
RECOGNITION ACCURACY COMFUSION MATRIX WITH SVM CLASSIFIER

Forward	F1	F2	F3	F4	F5
F1	100%	0 %	0 %	0 %	0%
F2	0%	100%	0%	0 %	0%
F3	0%	0 %	100%	0%	0%
F4	0.63 %	0 %	0%	99.37%	0%
F5	0%	0 %	0 %	0 %	100%
Return	R1	R2	R3	R4	R5
R1	99.39%	0%	0.61%	0%	0%
R2	0 %	100%	0%	0 %	0%
R3	0 %	0 %	100%	0%	0%
R4	0 %	0 %	0%	100%	0%
R5	0%	0 %	0%	0%	100%

C. Overall recognition accuracy

The results of recognition accuracy of each mode of locomotion and transitions were satisfactory (100% in static mode, 99.98%± 0.01 in forward mode and 99.34%± 0.38 in return mode). The recognition accuracy of static and dynamic modes was 98.04% ± 1.54 (QDA) and 98.90%± 1.63 (SVM). The recognition accuracy of locomotion transition modes was 97.46%± 1.14 (QDA) and 98%± 1.47 (SVM). Since a three-layer cascaded classifier was applied, the overall recognition accuracy was calculated by gathering the final results of each mode.The recognition accuracy of three-cascade classification was 96.77%±1.25 with QDA classifier and 97.64%± 2.08 with SVM classifier. Results show that using SVM classifiers could boost the recognition accuracy, even though the recognition accuracy was slightly higher than the recognition accuracy from QDA classifier. However, it required much longer time in training models for SVM classifier (compared to QDA classifier) due to its complexity of the algorithm. To sum up, our experimental results show that our improved recognition method obtained a high accuracy in upper-body motion mode recognition.

IV. CONCLUSION

Upper-body motion mode recognition is an important consideration in the use of a robotic spine exoskeleton. Motivated by mobility and safety of human motion, we utilized an integrated motion sensing method with improved machine learning techniques that can be applied on a dynamic spine brace to enhance its usability. Six locomotion modes and ten locomotion transitions were investigated. With selected cascade classification strategies, the system achieved good recognition performance among these sixteen modes. The overall recognition accuracy were 96.77%±1.25 and 97.64%± 2.08 corresponding to QDA classifier and SVM classifier. Future work will focus on real-time motion mode recognition and integration of the proposed method in the actual control of the dynamic spine brace. More upper-body motion recognition experiments will be conducted with different parameters and sensing systems.

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