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Activity recognition of the torso based on surface electromyography for exoskeleton control

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ABSTRACT

This paper presents an activity mode recognition approach to identify the motions of the human torso. The intent recognizer is based on decision tree classification in order to leverage its computational efficiency. The recognizer uses surface electromyography as the input and CART (classification and regression tree) as the classifier. The experimental results indicate that the recognizer can extract the user's intent within 215 ms, which is below the threshold a user will perceive. The approach achieves a low recognition error rate and a user-unperceived latency by using sliding overlapped analysis window. The intent recognizer is envisioned to a part a high-level supervisory controller for a powered backbone exoskeleton.

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1. Introduction

Recent technological advances in robotics make possible the development of an exoskeleton that can act as an extension of themselves. Augmenting the upper and lower limbs has been the primary focus of exoskeleton research to-date [1–9]. A powered backbone component of an exoskeleton can increase the load carrying capacity of a person and can potentially benefit a wide array of people, ranging from people bringing groceries into their homes, to people suffering from disabilities such as: paraplegia and hemiplegia, since daily activities such as flexion or extension can prove to be very challenging for them. In these respective cases, the benefits could result in improved load carrying capacity and an ability to stand and walk freely. Intuitive control of the device is paramount so that the user does not need to worry about operation and can be more concerned about participating in activities of daily life. But current exoskeleton technology still limits the natural motions of the torso and activities that users are able to participate in since the connection between the upper and lower limbs is a rigid spine. Two methods for inferring user intent are through mechanical sensors embedded in the device such as joint and inertial measurements and surface electromyography (sEMG). sEMG signals are detected over the skin surface and are generated by the electrical activity of muscle fibers during contraction. Multi-channel EMG signals, collected by electrodes placed on the involved muscles, can be used to identify the user's intent activity mode since each activity corresponds to a specific pattern of activation of several muscles. Therefore, sEMG signals are a significant control input for powered prostheses, exoskeleton and rehabilitation robots. Some prior works exist on developing sEMG pattern recognition-based control approach for many other kinds of powered prostheses, such as: A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses is described in [1]. A volitional control approach of a prosthetic knee using surface electromyography is described in [2]. Other researchers emphasize on describing the development of pattern recognition approach based on EMG signal, such as: An EMG-based pattern recognition approach for identifying locomotion modes by using artificial neural networks (ANN) and linear discriminant analysis (LDA) is presented in [3]. A robust, real-time control scheme for multifunction myoelectric control is presented in [4]. An EMG-based hand gesture recognition approach for real-time biosignal interfacing is described in [5].

Current prosthetic devices predominantly utilize sEMG signals from the user's body, in addition to pressure and force sensors, mounted at various locations on the device and along the body. As part of efforts to identify a suitable sensor set to recognize user intent, this paper presents an approach based on a sEMG and uses inertial measurements to classify the training data. EMG signals from the user's body correspond to a local, area specific level, and play the most important role in pattern classification, while inertial measurements correspond to a more holistic and generalized way of intent recognition. Related prior research works include a

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multimodal interpretation of muscular activities using a body sensor network with electromyogram and inertial sensors [6]. Also, an automatic recognition method of sign language sub-words based on portable accelerometer and EMG sensors is described in [7]. A rule-based control approach of walking by using decision trees and practical sensors is designed in [11]. The objective in our research is to develop a real-time intent recognition system for intelligent, powered backbone exoskeleton. This paper will focus on the activity mode intent recognizer, which is a high-level supervisory controller and its function is to distinguish between the intent activities modes of subject, such as flexion, extension and twisting.

2. Methodology

Intent recognition, also called goal recognition, is the task of recognizing the intents of a subject by analyzing some or all of their actions and/or analyzing the changes in the state resulting from their actions based on certain classifier. In this research, a classifier was designed and trained with appropriate database in order to be used for real time intent recognition. Appropriate set of sensors, appropriate window length for sensor data streams, and appropriate set of features to extract from each window need to be determined in order to train and use the classifier. Further, an appropriate data dimension reduction method was needed for real-time implementation. Once the decision tree classifier was implemented, it was used in real time to determine which activity was most probable at a certain instant in time. Finally, the result was essentially low-pass filtered by a majority voting system in order to filter out noise and increase classification accuracy. The specific procedure adapted from [10] is described below.

1. ***Data streams:*** EMG sensors on the flexor and extensor muscles of the back and abdomen, motion capture markers at multiple locations on the back to provide inertial measurements. The raw data streams were preprocessed by some commonly used methods include: high-pass filtering, low-pass filtering, rectification and normalization
2. ***Feature selection and extraction:*** Features were selected from sliding windows in our project since a relatively long window can be condensed into few information-rich features. Both sliding disjoint and overlapped windows [4] were used in order to compare their classification accuracy rate and delay time, respectively. The real-time nature of intent recognition system requires that the features selected should have low computational cost, such as mean absolute value or standard deviation. For each sensor channel, four features will be selected and then a feature space can be obtained after computing.
3. ***Dimension reduction:*** The feature space dimension needs to be reduced in order to keep the most important information, decrease the time requirement for training the classifier and facilitate the real-time system implementation. A previous research work on myoelectric pattern classification for upper limb prostheses [9] shows that principal component analysis (PCA) dimension reduction algorithm can fulfill the target successfully and also improve classification accuracy. So in this project PCA was considered for dimension reduction.
4. ***Classification:*** CART (classification and regression tree) was chose as the decision tree classifier [11]. It is computational efficiency to implement, which is very important for real-time recognition system to ensure a fast response. CART provides a general framework that can be instantiated in various ways to produce different decision trees. The fundamental principle of tree creation is very simple: decisions that lead to a simple, compact tree with few nodes should be preferred. This is a version of Occam's razor, that the simplest model that explains data is the one to be preferred. Therefore, a term called "impurity" should be defined in order to make sure the data reaching the immediate descendent nodes as pure as possible. Let $i(N)$ denotes the impurity of a node N. In all cases, $i(N)$ should be 0 if all of the patterns that reach the node bear the same category label, and to be large if the categories are equally represented. The most popular measure is the *entropy impurity*:

$$i(N) = -\sum_{j} P(\omega_j)\log_2 P(\omega_j) \tag{1}$$

where $P(\omega_j)$ is the fraction of patterns at node N that are in category ω_j. The algorithm constructs the CART by making recursive binary splitting of the training data set. The data are partitioned into smaller and smaller subsets which are represented as the nodes in the tree until all of the nodes are pure. Gini impurity was used as split criterion:

$$i(N) = \sum_{i \neq j} P(\omega_i)P(\omega_j) = 1 - \sum_{j=1}^{k} P^2(\omega_j) \tag{2}$$

where $i(N)$ denote the impurity of a node N, $P(\omega_j)$ is the fraction of patterns at node N that are in category ω_j. After training the binary decision tree, a 10-fold cross validation (CV) [8] method was utilized to prune the tree in order to avoid overfitting. Therefore, the classifier can show strong generalization when applied to the unknown data.
5. ***Majority voting scheme:*** The classification accuracy of the real-time intent recognizer can be improved by implementing a low-pass filter. For this work, a majority voting scheme [1] is used which requires a majority agreement over a frame of activity mode decisions coming from the previous step in order to decide whether the high-level controller needs to switch activity mode or not. Such an approach can filter out noise and increase classification accuracy, but at the cost of increased delay time. Thus the tradeoff between classification accuracy and switching latency based on certain requirement for an application should be estimated.

3. Approach

3.1. Experimental design

The study involved collecting measurements of surface electromyogram (sEMG) activity corresponding to specific motions of a human participant as inputs, and measurement of inertial data (position, velocity, acceleration) corresponding to these specific motions as outputs. The inertial measurements were emulated from motion capture data recorded from a high-speed motion capture system (Qualisys™—Oqus), and the sEMG signals were recorded using a commercial sEMG measurement system (Delsys™ Myomonitor-IV). The two systems were synchronized in order to ensure a common time-stamp on all the recordings. The motion capture system sampled motion at 240 Hz and used groups of reflective markers placed at anatomical locations on the participant's body, to define points of interest. Principal marker placement was at the sacrum, and at the L1, T7, T4 and C7 vertebrae. These vertebral locations were used to divide the back into four distinct segments that were assumed to be rigid body segments for the purpose of studying motion [12]. The lumbar segment was defined from the sacrum to the L1 vertebra, the region between the L1 and T7 vertebrae was designated the lower thoracic segment, the region between the T7 and T4 vertebrae was designated the mid-thoracic segment, and the T4 and C7 vertebrae demarcated the upper thoracic segment. Rigid planar clusters of markers, as shown in Fig. 1, were placed on each of the segments to accurately define and track

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