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Intent recognition of torso motion using wavelet transform feature extraction and linear discriminant analysis ensemble classification

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ABSTRACT

In this paper, a multi-sensor, multi-classifier approach for intent recognition of human torso motion is presented. A linear discriminant analysis based classifier is used, and the extraction of time-frequency domain features through the use of the wavelet transform is discussed. In addition, a weighted multi-classifier combination method for combining outputs of multiple classifiers into a single coherent output is implemented. The approach was evaluated on physiological data collected from three human participants. Results show up to 97% accuracy in classifying flexion and extension motions of the torso.

1. Introduction

Intent recognition of activities and motions performed is an open research problem for the control of systems in bio-robotics, wearable sensing, robotic prostheses and assistive devices [1–3]. In these applications, intent recognition is predominantly driven by physiological surface electromyogram (sEMG) signals from the user's body, and inertial sensors mounted either on the body or the device [4–9]. A survey of the current literature points to a majority of sEMG sensors used for detecting user intent [7–16], followed by inertial sensors [2,3,5,17,18]. Some of the works have highlighted the limitations of solely using sEMG sensors and have presented approaches using a combination of sEMG and inertial sensors [4,19,20]. With multiple streams of data available from physiological sensors, the problem of recognizing intent from physiological data can then be re-defined as a problem of extraction, identification, and classification of patterns occurring in the sensor data [18]. Machine learning based methods of pattern classification are among the most useful tools available for addressing such problems. With signals obtained from a user's body, implementing an intent recognition system involves running a pattern classification scheme [14,21], to classify and interpret patterns in the signals that correspond to intent and motion.

Among contemporary research approaches, the use of linear methods such as linear discriminant analysis (LDA) for classifying human physiological data to infer intent, was demonstrated in [5,6,12,22], with classification accuracies ranging from 82%-92%. Linear discriminant analysis (LDA) is a sample-based method of classification, and this method has been shown to be computationally efficient, mostly unsusceptible to overfitting [23,24], and is among the preferred linear classifiers [20]. Additionally, it has been shown that the accuracy of classification obtained from LDA can be improved by using multiple classifiers. Using multiple classifiers and combining them using a classifier fusion approach has been shown to deliver better results with a combined accuracy far better than any single classifier [25,26]. Therefore, the adoption of a multi-classifier fusion based approach, specifically majority voting based fusion is proposed in this paper to improve upon the classification performance of traditional LDA.

Closely associated with the classification methods are the features used for extracting patterns from sEMG and other sensor data. Signals sampled from a physical system in the form of a time-series do not always reflect the entire information content of the measurement. Particularly, discriminating information that displays a large degree of separability between two measurements corresponding to two different states is not always easily accessible from the raw data, and needs to be extracted from the mathematical and statistical properties of the signal data. Feature extraction is the most domain dependent aspect of a classification system, and this makes it possible to closely tailor a solution to a particular problem through the use of targeted, domain specific features [23,27]. Traditionally, time-domain and frequency-domain were the most commonly used features [9,28]. However, human motion and sEMG data have been shown to be non-stationary in nature,

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and combined time-frequency domain features have been shown to be more representative of these types of data [29–33]. Increasing acceptance of time-frequency domain methods of analyses has led to wider adoption of time-frequency domain features, extracted using the wavelet transform [29,34,35]. Of particular interest to this work, is the selection of suitable wavelets for time-frequency domain feature extraction. Among the many families of wavelets, the Daubechies family of wavelets has been found to be particular effective in analyzing sEMG recordings [21,31,35–37]. Multiple studies have pointed to the utility and effectiveness of multiple Daubechies wavelets from db-2 to db-8, and all the way up to db-20 [29,30,34,38].

This paper discusses a pattern classification based method of intent recognition, focused on intent recognition of torso movements. The study of intent recognition of torso movements finds applicability in assistive devices for the upper body and is motivated in part by the need for a safe, efficient, and reliable control and interface system for a powered, assistive device for the back and upper body. The design of such a device was introduced by the authors in a previous publication, and research on realizing the device is ongoing [39]. The device is intended to provide strength augmentation and injury protection to healthy users, to help carry heavy loads. In addition, the device is also intended to have healthcare applications, such as restoring mobility and motion after stroke or spinal cord injury.

The contribution of this paper is a multi-classifier intent recognition approach that uses Linear Discriminant Analysis (LDA) for pattern classification using data from two sensor types. The paper also discusses the identification and extraction of time-frequency domain features using wavelet transform methods that can help deliver improved classification accuracy. Building upon traditional LDA, a multi-classifier method of classification is presented, which utilizes multiple classifiers that are combined using a majority voting classifier fusion scheme. Section 2 briefly discusses the theory pertaining to classification, LDA and time-frequency domain feature extraction. Section 3 details the methods employed for data collection, feature extraction, and classifier design. Section 4 presents the evaluation of these features and classifiers and conclusions are drawn in Section 5.

2. Background

2.1. Pattern classification for intent recognition

The problem of recognizing intent from sensor data is essentially one of classifying patterns occurring in sensor data. In this scenario, pattern classification primarily pertains to assigning predefined labels to objects in a data set [27]. The objects themselves can be defined by a set of measurements, attributes or features, and the objective here is to construct a discriminant or prediction rule for assigning labels to objects [40]. Such a discriminant rule is a projection method that looks to maximize the separability between different objects in a data set.

Among the various discriminant analysis methods, sample-based linear methods are appealing to us because of their simplicity of implementation. Some additional advantages of following sample-based, linear methods of discriminant analysis are that they can be purely data driven, do not require any prior information about the data, and allow minimum assumptions to be made about the nature of the data. Fisher's Linear Discriminant Analysis (LDA) is one such linear method of generating discriminants that seeks to project data in a manner such that separability between different objects in a data set is maximized [15]. In addition, while seeking maximum separability, it also seeks a projection that minimizes the variance of a particular feature within the dataset.

2.1.1. Linear discriminant analysis (LDA)

The Fisher's linear discriminant is constructed by seeking a function w, that projects data x, consisting of a number of classes n, onto *(n-1)* lines y, such that maximum separation is achieved between the classes [15], as shown in (1).

$$y = w^T x \tag{1}$$

The measure used to separate the classes is the mean of the classes, μ_i, shown in (2), where N_i is the number of samples in each class.

$$\mu_i = {}^{1}\!/\!{N_i} \sum_{x \in \omega_i} x \tag{2}$$

This separation is achieved by maximizing a function w, which represents the difference between the means of the classes normalized by the variance in the classes. This maximization can be solved as an eigenvalue problem dependent on the scatter within the classes S_W, and the scatter between the classes S_B. This is an eigenvalue problem that essentially reduces to the expression in (3).

$$S_W{}^{-1} S_B w = \lambda w \tag{3}$$

The variance of each class can be quantified by the scatter of the class and is defined in (4).

$$S_i = \sum_{x \in \omega_i} (x - \mu_i)(x - \mu_i)^T \tag{4}$$

The summation of the scatter of all classes gives the 'within-class scatter', S_W, and is expressed in (5).

$$S_w = \sum_i S_i \tag{5}$$

The variance between the classes is quantified by the 'between-class scatter', S_B. For data that contains m classes, it is expressed as in (6).

$$S_B = \sum_{i=1}^{m} N_i (\mu_i - \mu)(\mu_i - \mu)^T \tag{6}$$

The eigenvectors obtained from (3) yield the projections, w, which are the classifiers used to separate the data. This projection is called Fisher's linear discriminant [15] and gives the directions for projecting the data such that maximum separation is achieved between classes.

2.1.2. Multiple classifiers

The accuracy of classification obtained from LDA can be improved by using multiple classifiers. The advantages of using multiple classifiers are threefold [27]. From the statistical point of view, combining multiple classifiers helps to average the outputs of multiple classifiers and avoid having to select a single best classifier that might not be adequate by itself. From the computational viewpoint, combining multiple classifiers can help avoid possible local optima. Thirdly, from the representational point of view, there is a possibility that the solution space of a particular problem might not encapsulate the optimal classifier. In such a case, multiple classifiers can approximate the solution more accurately.

Multiple classifiers can be combined using two major strategies. These are classifier fusion and classifier selection. Classifier fusion utilizes approaches such as averaging or majority voting to obtain classification accuracy that is better than that can be obtained from the individual classifiers. Classifier selection involves choosing the best classifier out of a set of multiple classifiers. When it comes to biomechanical signals, it has been shown that fusion based approaches deliver better results with a combined accuracy that