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Feature reduction for classification of daily activities through kinematic data from smartphones

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ABSTRACT

Linear acceleration and angular rotation data measured from a human body can provide insights on how a person moves. These kinematic data are typically analyzed and used to understand disease progression associated with movement disorders. Time and frequency domain features extracted from such data are often of large dimensions and not feasible for implementation on resource-constraint devices. In this paper, we propose two optimal feature selection schemes that can better characterize the kinematic measurements to distinguish the movements of a person. One of the proposed approach is based on principal component analysis and the other is based on combinatorial high frequency feature selection from multi-classification algorithms to reduce the features required to maintain high activity prediction rate. We apply three classification algorithms to differentiate the activities a subject was engaged in. Results show the features can be reduced from 561 to 15 with above 84% activity prediction accuracy.

1. Introduction

Human motion is controlled by a complex dynamic nervous system. Monitoring and tracking how humans move may provide insights on diseases that accompany with movement disorders thus encounter risks of falls. Motion capture has been used for disease monitoring, sports training, rehabilitation, and entertainment systems (Helmer, Mestrovic, Farrow, Lucas, & Spratford, 2009; Menache, 2000; Ayoub et al., 1998; Gleicher, 1999). Computer vision and inertial sensor systems are two broad approaches of motion capture. Computer vision-based systems are often considered "gold standard" for motion capture, but are limited to a confined area where subjects have to be within the line-of-sight. Recent development in wearable technology, such as (Fitbit, ; Jawbone,), and other smart wrist bands and smartphones equipped with embedded inertial sensors have been favorably considered for movement detection and tracking (Chon & Cha, 2011). It is becoming feasible to record movements and activities of people non-intrusively for a long period of time.

Kinematic data collected from inertial sensors placed on human body can be used to study chronic diseases such as Parkinson's disease (PD) and Alzheimer's disease on their progression as well as assessing the effectiveness of medical intervention (Bachlin et al., 2010). Clinicians are also interested in non-intrusive ways of monitoring the activities of daily lives of patients who may suffer from movement disorders to provide informed care solutions to improve their quality of life (Bloem, Housdorff, Visser, & Giladi, 2004). The change of the movement pattern generated from kinematic data also helps to identify fatigue and depression due to the disease or the treatment. Patients with Parkinson's disease, in particular, often experience symptoms such as slow movements, shuffling of gait, tremors which can be recognized with movement pattern changes. Non-motor symptoms due to depression such as less willingness to participate daily activities can be inferred by the movement pattern changes as well (Jankovic, 2008; Friedman et al., 2007).

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Movements and activities can be classified by observing the patterns of the kinematic data collected from different parts of the body such as wrist, ankle, and back (Yang & Hsu, 2010). Kinematic data are often captured in the format of linear acceleration, angular rotation, distance, etc. in time series. Each movement can be identified with a unique feature set in both time and frequency domain. These features can be used to identify the dynamic motion of a subject (Mannini & Sabatini, 2010).

In our previous study (Dong et al., 2015), we collected kinematic data measured from inertial sensors placed on the lower back and ankles of patients with PD and healthy subjects to study features to differentiate gait variances. We analyzed the data with adaptive fractal analysis and used power spectral density analysis to study the gait features. We found that patients with PD exhibit different gait performance when they are cued (instructed by healthcare personnels) comparing to spontaneous gait initiation. Therefore, it is of great interest to understand gait variabilities patients exhibit in a natural environment to understand disease progression and potential fall indications. A light-weight activity recognition algorithm is then needed, which can be implemented on mobile devices to provide real-time feedback to patients as well as their healthcare givers.

In this study, we use a UCI dataset, which includes 561 features in both time domain and frequency domain to investigate feature reduction algorithms to differentiate activities. The number of features indicates the dimension of a dataset for classification. Finding the appropriate features is the success of a classification model to differentiate activities (Kohavi & John, 1997; Dash & Liu, 1997). Large feature dimensions are associated with high computational cost, not intuitive for interpreting the results, and often cause overfitting (Dash & Liu, 1997). The mass of the data distribution often deviates from the mean for high dimensional data, which is challenging for machine learning algorithms to project from one vector space to another (Domingos, 2012).

In this paper, we propose two optimal feature reduction algorithms to extract features from kinematic data collected from inertial sensors to differentiate activities a subject was engaged in. We define the "optimal" feature sets as a subset of the features from the original feature set, with significant smaller feature size set while still achieving high activity prediction accuracy. When implementing machine learning algorithm on a resource-limited device, it is important to find the appropriate features that are representative of daily activities which can provide activity prediction accuracy. The tradeoff between the number of features and prediction accuracy ensures a portable and reliable solution for mobile health monitoring.

The proposed schemes are based on principal component analysis (PCA) and combinatorial high frequency feature selection, respectively, to reduce feature dimension while maintaining high activity prediction accuracy. Classification is done using three popular classification algorithms, *k*NN, Random Forest, and Multi-class SVM. As correlation may exist among the features provided in the dataset, redundancies and dependencies among the features may be reduced (Hall, 1999; Guyon & Elisseeff, 2003). The objective of this study is to remove the irrelevant or redundant features in the classification process in order to improve efficiency and study the trade off between prediction accuracy and the numbers of features used for classification.

The organization of the paper is as follows. Section 2 presents related work. Section 3 introduces the data set, features and classification algorithms used in this study. Section 4 presents the two proposed feature reduction schemes. Section 5 presents the results and discussion. Section 6 presents our conclusions.

2. Related work

Human movement analysis has attracted much research attention in recent years. Long-term movement monitoring and analysis of people suffering from motor dysfunctional diseases has shown promise to provide insights in the disease progression (Dong et al., 2015; Benabid et al., 1991). Feature selection is an important tool to extract relevant features, which could characterize the behavior among different movements efficiently. Several studies focus on the feature selection and extraction on posture analysis with specific subjects such as people with Alzheimer disease, PD, and the elderly (Hughes, Ben-Shlomo, Daniel, & Lees, 1992; Palmerini, Rocchi, Mellone, Valzania, & Chiari, 2011; Mancini et al., 2012; Zhang & Sawchuk, 2013; Gupta & Dallas, 2014; Zach et al., 2015). Surveys on human activity recognition methods were reviewed in Avci et al. (2010), Lara and Labrador (2013).

Postural sway is commonly measured through the pressures of a force plate on which a subject stands (Mancini et al., 2012). Accelerometer worn on the lower back of a subject has been used to study postural sway (Palmerini et al., 2011). These studies examine features observed in the measurement to differentiate a subject with PD from a healthy subject. Mancini et. al. compared sway from force platform to inertial sensors with 13 subjects with early, untreated PD and 12 age-matched control subjects using 13 features extracted from acceleration measurements (Mancini et al., 2012). Results show that time-domain features such as JERK, root mean square (RMS) amplitude and mean velocity, frequency-domain feature such as centroidal frequency, are valid and reliable measures of balance control.

Zhang et. al. experimentally validated the effectiveness of sparse representation-based approach by recognizing 9 most common human daily activities performed by 14 subjects (Zhang & Sawchuk, 2013). The results show a maximum recognition rate of 96.1% using 110 features.

Gupta and Dallas (2014) experimented with two subjects performing six activities to study features and classifiers. They computed 31 features using a 6-second window for acceleration data collected for each axis of a triaxial accelerometer. They tested on seven subjects with leave-one-out classification and showed an overall accuracy of about 98% for the classifiers. And the accuracy for identifying each activity is more than 95%. However the group size of subjects and data size of features are small for general adoption of the model.

Zach et al. (2015) focused on the detection of freezing of gait (FOG), a phenomenon of not being able to move while initiating gait or walking in PD, with a triaxial linear waist-mounted accelerometer. The offline video-analysis (gold standard) is applied to identify FOG episodes that provides the ground truth for classification. This research shows promising results of FOG detection. However, the requirement of vision-based analysis limits the experiment in a clinical environment. A lightweight and portable system that can