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Activity classification in persons with stroke based on frequency features

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ABSTRACT

Recent advances in the use of inertial measurement units (IMUs) for motion analysis suggest the possibility of using this technology for the monitoring of daily activities of individuals during rehabilitation post-stroke. Previous studies have utilized features extracted from accelerometer and gyroscope signals to develop classification models capable of identifying activities performed within large datasets. In this study, nine k-nearest neighbor cross-validated classifiers were developed using frequency-features derived from shank-mounted IMUs on the less-affected and affected limbs of subjects with stroke. These classifiers were evaluated for two separate datasets of post-stroke gait; the first a classification of three separate gait activities (overground walking, stair ascent, and stair descent), and the second a classification of five gait activities, overground walking, stair ascent, and descent with a distinction between stepping pattern used while negotiating stairs (step-over-step (SOS) and step-by-step (SBS)). The comparison showed the highest classification accuracy, 100% for the three-activities and 94% for the five-activities, was obtained using a classifier composed of features derived from accelerometer and gyroscope measurements from both IMUs on less-affected and affected limbs.

1. Introduction

Currently, healthcare professionals gain insight into individuals' daily activity levels mostly through self reported measures and questionnaires, yet these methods have been proven to overestimate physical ability and are thus considered unreliable as a substitute to physical examination [11,12]. Systems capable of monitoring individuals' activities and rehabilitation progress outside on a day-to-day basis are therefore gaining popularity within the fields of rehabilitation [3]. Inertial measurement units (IMUs) present a low-cost and minimally intrusive way of measuring gait parameters in both healthy and disabled individuals [7,15]. These sensors provide rehabilitation professionals the possibilities to quantitatively measure changes in gait, in aging populations as well as in those aiming to return to a level of physical activity after rehabilitation. However, in order to use this technology for monitoring daily activities, effective algorithms are required to classify specific activities.

Activity classification using inertial sensors has recently been the subject of many studies [1,4,9] and studies have shown that machine learning approaches have proven effective in the identification of different activities from acceleration data [9,13]. The majority of these approaches involve a two-stage process [9]. In the first stage, classification features are derived from a series of smaller, sequential time windows of sensor signals. A classification algorithm is then used on the extracted features to associate each window with a specific activity. In order to generate the features from accelerometer data for the classification algorithm, different approaches have been suggested in previous studies, including directly deriving time-domain features from the acceleration signal [4], the use of Fourier transforms to derive features from a frequency analysis [8], or the use of wavelet analysis for the derivation of time-frequency features [10,13].

Time-domain features can be obtained through the calculation of statistical measures such as mean or median, taken directly from a window of accelerometer data [9]. These features can also be obtained by using high and low pass filters to separate accelerometer signals into their AC and DC signal components. Classifiers can then be identified based on these features for each condition [4]. A second method to get classification features from accelerometer data is through the derivation of frequency-domain features through the use of fast Fourier transform (FFT). The applied FFT to a specific window of accelerometer data typically yields a set of basis coefficients which represent the amplitudes of the signal's frequency components as well as the distribution of the signal's energy [5]. Various methods of using the derived frequency components for activity classification based on accelerometer data have been presented in previous studies [1,4,8,9]. Preece et al. proposed a unique feature set in addition to those previously suggested, composed of the magnitudes of the first five components of the FFT power spectrum [8].

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Although each of these studies employed a different approach in using frequency-domain features for gait activity classification, each FFT derived feature set was reported to effectively predict gait activities in its respective classifier. Wavelet analysis has also been used for activity classification [9]. A main advantage of using wavelet analysis to extract features from accelerometer signals is that no time or frequency information is lost from the original signal. Various sets of wavelet features have been used in previous studies for the classification of activities recorded using accelerometers [10,12]. In both of these studies, clear distinction in wavelet features between activities was shown. Therefore, this method offers promise for the detection of dynamic changes in gait.

Although all three methods of generating features capable of classifying activities from accelerometer data have proven valid, Preece et al. performed a comparative study of 14 methods of extracting classification features using wavelet, time-domain, and frequency-domain analysis to determine which method would best serve for the classification of different gait activities [8]. Preece et al. found that the use of an FFT feature set composed of the magnitude of the first five or more components of the FFT analysis was optimal for activity classification in healthy individuals. Preece et al. therefore suggested the use of FFT feature set for classification of activities including level walking, stair ascent, stair descent, jogging, running, hopping, and jumping from accelerometer data collected using ankle-mounted sensors. However, little effort has attempted to classify gait activities with kinematic data collected from non-healthy subjects, therefore it is our goal to apply these classification methods to gait post-stroke.

The main objective of this study was to develop and compare an activity recognition algorithm for mobility in level ground, stair ascent, and stair descent activities in individuals presenting with post-stroke hemiparesis. Our first aim was therefore to develop an activity classification algorithm using multiple sets of FFT features derived from shank-mounted IMU sensors capable of identifying overground walking, stair ascent, and stair descent by individuals presenting with post stroke hemiparesis. As a second aim, we sought to extend activity classification to include varying stepping patterns adopted by stroke survivors during stair negotiation. This distinction could serve to provide additional information to rehabilitation professionals as to the stair stepping strategies employed by individuals day-to-day while rehabilitating.

2. Methodology

2.1. Data collection protocol

Ten chronic, hemiparetic stroke survivors (67.0 ± 10.9 years), self-reporting to be in good health and capable of independent ambulation and stair negotiation after a minimum of six months post-stroke, were recruited for this study. All subjects provided informed consent to participate in the protocol, which was approved by Queen's University's research ethics board. Seven subjects were left-side affected and three were right-side affected. Subjects were instrumented with seven IMUs (Xsens Technology B.V., Netherlands) and only those measurements obtained from the accelerometer and gyroscope z-axes from the shanks mounted IMUs were used in this study. Sensor configuration can be seen in Fig. 1. Subjects completed up to three self-paced walking trials along a straight hallway over a 10 m distance. In addition to the overground walking trials, subjects ascended and descended a sixteen-step staircase in a step-over-step (SOS) manner, placing one foot on each stair, and a step-by-step (SBS) manner, placing both feet on the same stair, always leading with their less-affected side, with handrail use as needed. Subjects were instructed to rest prior to beginning each trial, and when they felt ready, maneuvered the steps at a self-selected pace. In this way, five different activities

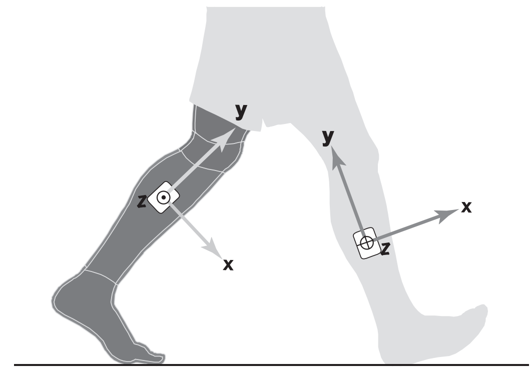

Fig. 1. Sensor configuration. An IMU is attached to the lateral aspect of both the less-affected (light grey) and affected (dark grey) shanks in the sagittal plane. The z-axes of both the accelerometer and gyroscope signals lay orthogonal to the sagittal plane defined by the x and y directions. The arrows indicate positive direction of each axis.

(overground walking, stair ascent SOS, stair descent SOS, stair ascent SBS, and stair descent SBS) were recorded for each subject outside of a traditional laboratory setting. Data were collected using MVN Studio (Xsens Technology B.V., Netherlands) at a sampling frequency of 120 Hz.

2.2. Signal conditioning

Offline signal processing was performed using MATLAB (The MathWorks, Natick, MA, USA). For each of the overground walking trials and the stair ascent and descent trials, analysis was conducted on a series of 2-s (240-sample) consecutive windows, with an overlap of 1 s between each. The decision to use a 2-s window was motived by previous work by Wang et al. [13] (2.56 s) and by Preece et al. [8] (2 s) that demonstrated this window length as appropriate for the frequency analysis of similar activities to those used in this paper. Due to the slow speed of post-stroke mobility, we chose a 2-s window, which would sufficiently capture a minimum of one gait cycle in all activities while not being so long as to limit the number of windows that could be extracted from each trial. The 50% overlap between consecutive windows has also been proven to be effective in previous activity classification studies [1,8].

2.3. Frequency-domain feature derivation

The frequency-domain features for each 2-s window were derived using FFTs. The FFT is a faster version of the Discrete Fourier Transform (DFT), which transforms a discrete signal in the time domain into its discrete frequency domain representation [5]. From each of the shank-mounted IMUs, the accelerometer and gyroscope signals were converted into the frequency domain using the Matlab *fft* function seen in Eq. (1), to calculate the N-point DFT.

$$X(k) = \sum_{t=0}^{N-1} x(t)\omega_N^{tk}$$
$$\omega_N = e^{(-2\pi i)/N} \qquad (1)$$

where ω_N is an Nth root of unity, t is the time range for the data set $x(t)$ such that $t = [0,1,\ldots,(\text{length of signal } x\text{-}1)] \times$ sampling time, k is a discrete (integer) variable such that $k = 0, 1, \ldots, (N\text{-}1)$, and N is the transform length which will optimize the FFT algorithm, defined as 2^N such that $2^N \geq |length\,(x)|$ ($length\,(x) = 240,\ N = 8$) [5].

As the frequency spectrum, $X(k)$, calculated in Eq. (1) is symmetric, only the first $(1 + 2^{N\text{-}1})$ points of the spectrum will be unique, and the rest are symmetrically redundant. $X(1)$ is the DC component of the original signal $x(t)$ and $X(1 + 2^{N\text{-}1})$ is the Nyquist frequency component of $x(t)$. In order to truncate the frequency data, it must first be