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A machine learning approach to estimate Minimum Toe Clearance using Inertial Measurement Units

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ABSTRACT

Falls are the primary cause of accidental injuries (52%) and one of the leading causes of death in individuals aged 65 and above. More than 50% of falls in healthy older adults are due to tripping while walking. Minimum toe clearance (i.e., minimum height of the toe above the ground during the mid-swing phase - MTC) has been investigated as an indicator of tripping risk. There is increasing demand for practicable gait monitoring using wearable sensors such as Inertial Measurement Units (IMU) comprising accelerometers and gyroscopes due to their wearability, compactness and low cost. A major limitation however, is intrinsic noise making acceleration integration unreliable and inaccurate for estimating MTC height from IMU data. A machine learning approach to MTC height estimation was investigated in this paper incorporating features from both raw and integrated inertial signals to train Generalized Regression Neural Networks (GRNN) models using a hill-climbing feature-selection method. The GRNN based MTC height predictions demonstrated root-mean-square-error (RMSE) of 6.6 mm with 9 optimum features for young adults and 7.1 mm RMSE with 5 features for the older adults during treadmill walking. The GRNN based MTC height estimation method devised in this project represents approximately 68% less RMSE than other estimation techniques. The research findings show a strong potential for gait monitoring outside the laboratory to provide real-time MTC height information during everyday locomotion.

1. Introduction

Tripping is one of the major causes of falls in the elderly (Blake et al., 1988) and a critical indicator of tripping risk is Minimum Toe Clearance (MTC), a biomechanical event during the mid-swing phase of the gait cycle. At MTC toe-ground clearance is small, typically 10–30 mm, the foot's horizontal velocity is at or near maximum and the body is supported by only one foot. Previous gait studies have investigated ageing (Barrett et al., 2010; Mills et al., 2008; Nagano et al., 2011; Taylor, 2012), walking speed (Chung and Wang, 2009), attention demands (Schulz et al., 2010; Sparrow et al., 2008) and tripping risk (Barrett et al., 2010; Begg et al., 2007) using MTC height distribution, characterized using the mean or median and standard deviation (SD) or inter quartile range. To date, accurate MTC height measurements have been possible only using 3D motion tracking systems in institutional gait laboratories (Guangyi et al., 2009; Zhou and Hu, 2008). Tirosh et al. (2013), for example, demonstrated that tripping risk could be reduced with a real-time display of toe-trajectory and MTC height from a 3D motion capture in both young and older adults by training them to target MTC height within a safer band above the baseline. Falls in older people and other gait impaired populations such as stroke patients, occur in everyday settings and there is an urgent need for an easily operated, portable, and inexpensive motion sensor based system capable of measuring MTC height during everyday locomotion (Hamacher et al., 2011; Lai et al., 2008b; Lau and Tong, 2008).

Inertial Measurement Units (IMUs or inertial sensors) are portable, light, inexpensive, low-power devices increasingly used in motion analysis (Dadashi et al., 2014; Ge and Shuwan, 2008; Lau et al., 2008; Mariani et al., 2012; Najafi et al., 2002; Zhou and Hu, 2008). IMUs directly measure linear acceleration and angular velocity but deriving positional data from IMU signals is a major challenge due

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to the "drift" over time issue, the essential limitation to IMU technology (Findlow et al., 2008; Guangyi et al., 2009; Lai et al., 2008b). Techniques such as strap down integration and regression have improved measurement accuracy for stride length (Peruzzi et al., 2011; Sabatini, 2005; Sabatini et al., 2005), walking speed (Li et al., 2010; Mannini and Sabatini, 2014), maximum toe-clearance (Mariani et al., 2010) and walking surface inclination (Sabatini, 2005). Using IMUs to measure MTC height, a narrower-range (10–30 mm) biomechanical parameter, remains a challenge because small errors in integration and regression considerably affect accuracy. Recently Mariani et al. (2012) used a de-drifted double-integration technique to estimate mean MTC height from inertial sensor data and reported the mean (−12.7 mm) and standard deviation (9.0 mm) of the difference between estimated and measured mean MTC height as accuracy and precision respectively. From these results, a root-mean-square-error (RMSE) of 21.7 mm can be estimated by summing absolute accuracy and precision. Using a quadratic regression modeling technique, McGrath et al. (2011) showed that foot mounted inertial sensors could estimate mean MTC height with upto 17.3 mm RMSE.

Given that MTC height is typically only 25 mm, the RMSE values reported above would be impractical for further implementation of real-time MTC height monitoring of individual stride cycles. Lai et al. (2009) have, however, demonstrated that acceleration features from double differentiated camera-captured 3D displacement–time data could predict individual stride MTC height with an RMSE of 6.1 mm one gait cycle ahead. Lai et al. (2009) utilized Generalized Regression Neural Network (GRNN) machine learning to reveal the underlying relationship between toe trajectory control and accelerations derived from double differentiating motion captured position-time data. The GRNN is based on nonlinear regression theory for function estimation (Specht, 1991). The network architecture of GRNN is a one-pass learning algorithm which does not require an iterative training procedure as in the back-propagation method (Specht, 1991). Even with sparse data in a multi-dimensional measurement space, the algorithm provides smooth transitions from one observed value to another (Özgür, 2006). Unlike feedforward back-propagation method, GRNN simulations performance is less sensitive to randomly assigned initial weight value. Further, the local minima problem was not faced in GRNN simulations (Özgür, 2006). Despite these advantages no previous studies have applied GRNN machine learning to estimate MTC height from inertial sensor signals. The research question addressed in the present investigation was whether GRNN machine learning would estimate MTC heights from IMU signals with greater accuracy than previously reported for de-drifted integration and quadratic regression.

2. Methodology

2.1. GRNN for machine learning

The Generalized Regression Neural Network (GRNN) consisting of a radial basis layer and a special linear layer (Specht, 1991) was used to learn the underlying relationship between IMU sensor signals features and the target – MTC height. The estimated MTC height $\hat{y}$ is obtained using the following equation where σ is the width of the radial basis function:

$$G(Z) = \frac{1}{2\pi\left(\frac{k+1}{2}\right)} e^{-\frac{\|z\|^2}{2}}$$

$$\hat{y} = \frac{\sum_{i=1}^{n} y_i e^{\frac{-\|x-x_i\|^2}{2\sigma^2}}}{\sum_{i=1}^{n} e^{\frac{-\|x-x_i\|^2}{2\sigma^2}}}$$

The distance between the training sample and point of prediction measures how well each training sample represents the predicted position. If this distance is small, the exponential component becomes large such that a particular training sample best predicts the new value. The distance between the other training samples and the point of prediction is large, thus the exponential component is small and contributes less to the prediction. The GRNN was implemented in MATLAB v7.2 which required the user to select the model parameter. With a very small parameter the model over-fits the data and reduces generalizability. With larger parameters estimation becomes smoother (generalization increases) but may be less accurate.

A leave-one-subject-out (LOSO) cross validation method was used to obtain the optimum GRNN model for each group separately (Lai et al., 2008c). In this method, data from the 13 subjects were used to train the model and the remaining subject was tested. This was done for each subject sequentially and the group's mean accuracy was compared for different model parameters and combinations of feature. In all cases, each inertial sensor feature was scaled by calculating its z-score (i.e $(x-\mu)/\sigma$ where μ is the mean and σ is the SD for the training gait feature) before applying them to the regressor. Normalizing training data using z-scores minimized numerical computational error and improved convergence. Estimation accuracy was calculated as root-mean-square-error (RMSE) between measured MTC height (y_i) and estimated MTC height ($\hat{y}_i$) defined as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

where N is total number of gait cycles across all 14 subjects.

2.2. Hill-climbing feature-selection

A hill-climbing feature-selection method (Begg et al., 2005) was applied to eliminate redundant features and to choose the optimum feature set to estimate MTC height for both young and elderly separately. The feature-selection method began by computing the LOSO RMSE for an individual feature using the following values for model parameters: 0.0001, 0.01, 0.1, 1, 10, 50, 100, 500, and 1000. The feature with the lowest LOSO mean RMSE was retained and the algorithm executed to combine the remaining features sequentially, with the first feature having a fixed model parameter. The second best feature which further reduced RMSE in combination with the first was retained. The algorithm then proceeded in the same fashion until the RMSE value began to increase again. The optimum feature set was the combination which produced the lowest LOSO mean RMSE. Once the optimum feature set was obtained, the model parameter was narrowed to a 0.5–1.5 window and tested in 0.1 increments to obtain the optimum value which produced the least RMSE for each group. The lowest LOSO mean RMSE across 14 subjects for both groups separately was used to select the most effective GRNN model.

2.3. Sensor integration

A wireless foot-worn sensor module was employed utilizing a Sparkfun IMU digital combo board with 6 degrees of freedom (DOF) consisting of an accelerometer - ADXL345 and a gyroscope-ITG3200 to measure the distal foot linear accelerations and angular velocities (Fig. 1). The completely assembled sensor system weighed 78.7 g including a battery. The ultra low-powered tri-axis accelerometer had a ±16g (g represents gravitational acceleration, 1g = 9.8 m/s^2) capacity in full-scale and a maximum 3200 Hz bandwidth. The digital accelerometer's sensitivity was 31.2 LSB/g, measured by the number of least significant bits required to represent a change of 1g. The ITG3200 16 bit digital