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Short communication

Determinants of gait stability while walking on a treadmill: A machine learning approach

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A B S T R A C T

Dynamic balance in human locomotion can be assessed through the local dynamic stability (LDS) method. Whereas gait LDS has been used successfully in many settings and applications, little is known about its sensitivity to individual characteristics of healthy adults. Therefore, we reanalyzed a large dataset of accelerometric data measured for 100 healthy adults from 20 to 70 years of age performing 10 min treadmill walking. We sought to assess the extent to which the variations of age, body mass and height, sex, and preferred walking speed (PWS) could influence gait LDS. The random forest (RF) and multiple adaptive regression splines (MARS) algorithms were selected for their good bias-variance tradeoff and their capabilities to handle nonlinear associations. First, through variable importance measure (VIM), we used RF to evaluate which individual characteristics had the highest influence on gait LDS. Second, we used MARS to detect potential interactions among individual characteristics that may influence LDS. The VIM and MARS results indicated that PWS and age correlated with LDS, whereas no associations were found for sex, body height, and body mass. Further, the MARS model detected an age by PWS interaction: on one hand, at high PWS, gait stability is constant across age while, on the other hand, at low PWS, gait instability increases substantially with age. We conclude that it is advisable to consider the participants' age as well as their PWS to avoid potential biases in evaluating dynamic balance through LDS.

1. Introduction

Dynamic balance in human locomotion can be assessed through the local dynamic stability (LDS) method. Inspired by the maximal Lyapunov exponent that can detect deterministic chaos in nonlinear dynamic systems, LDS is a nonlinear method designed specifically to detect gait instabilities (Dingwell, 2006; Kurz et al., 2010; Terrier and Dériaz, 2013). Using LDS to characterize dynamic balance has recently become increasingly widespread. Besides several studies that highlighted the association between gait LDS and falls in elderly (Lockhart and Liu, 2008; Toebes et al., 2012), most recent examples of LDS use include: the effect of active arm swing while walking (Wu et al., 2016); the characterization of ataxic gait (Chini et al., 2017); the effect of physical exhaustion (Hamacher et al., 2016); or the influence of inclined surfaces (Vieira et al., 2017).

Potential confounders that might influence LDS have not yet been investigated thoroughly (Bizovska et al., 2015). Several studies have focused on how walking at different speeds modifies LDS (Bruijn et al., 2009; Kang and Dingwell, 2008). However, further studies are needed to characterize the association between LDS and preferred walking speed (PWS). Several have established that LDS diminishes in older adults (Bruijn et al., 2014; Kang and Dingwell, 2008). We also highlighted an age effect among young and middle-aged adults (Terrier and Reynard, 2015). However, the effects of anthropometric characteristics (mass, height) and sex are largely unknown. Furthermore, information is lacking about how those different individual characteristics may interact to modify LDS.

Therefore, the aim of this short communication was to give further insight into the factors that may influence the dynamic balance – assessed through LDS—in a population of healthy adults. The variables of interest were: age, sex, body height and mass, and PWS. We used two complementary machine learning algorithms to evaluate the variables' ability to predict gait LDS: random forest (RF) and multivariate adaptive regression splines (MARS).

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2. Methods

We retrospectively analyzed a dataset that was described in previous publications (Reynard and Terrier, 2014, 2015; Terrier and Reynard, 2015), which include details on the experimental procedure, the ethical considerations, the material, and the analytical methods. We briefly summarize hereafter the essential information.

2.1. Subjects and experimental procedure

One hundred healthy adults participated in the study; they were recruited across five classes of age with an equal number of males and females. The means and the standard deviations (SD) of individual characteristics across the age classes were reported in Table 1 of Terrier and Reynard (2015), which also shows that body mass and height, as well as PWS, did not depend on age. The participants walked 2×5 min on a treadmill at PWS with a nine-day interval. PWS was measured in two steps by (1) progressively increasing the treadmill speed from a low speed and (2) progressively decreasing the treadmill speed from a high speed, until the subject reported a comfortable speed. The PWS was defined as the average speed of both tests. An inertial sensor measured trunk accelerations. Following insight gained from our previous studies (Reynard and Terrier, 2014; Reynard et al., 2014), we only analyzed the mediolateral acceleration.

2.2. Data analysis

The five-minute acceleration signals were truncated at 210 gait cycles (420 steps) and then resampled to a uniform length of 14,000 samples. We used Rosenstein's algorithm to assess the divergence in the state space that was reconstructed using the embedding principles; see Terrier and Dériaz (2013) for a presentation of the theoretical background. We used an average mutual information (AMI) algorithm to determine the average time delay (six samples). We used a global false nearest neighbors (GFNN) method to assess the dimension (six). We computed the divergence exponent over a number of samples corresponding to one step (i.e., 34). Both sessions' results were averaged. Note that a higher divergence rate indicates lower stability.

2.3. Descriptive statistics

A boxplot (median, quartiles and data extent) was used to show the LDS distribution among participants (Fig. 1). Four scatterplots with separated marks for males and females show bivariate distributions of LDS against other variables (Fig. 2).

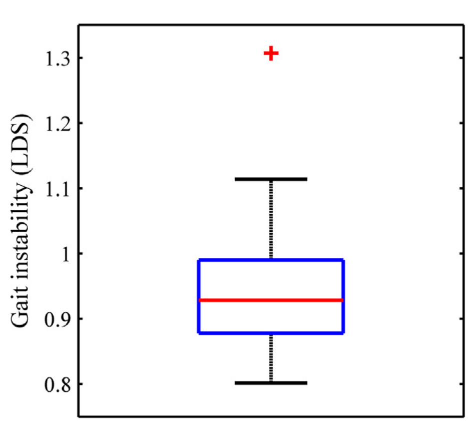

Fig. 1. Distribution of gait stability results measured for the 100 participants. LDS: local dynamic stability.

2.4. Machine learning

As the first machine learning approach, we built an RF model with individual characteristics as predictors of LDS. In short, RF aggregates many decision trees that are built through recursive partitioning across predictors (Breiman, 2001). As the main advantage, the RF algorithm offers a variable importance measure (VIM), which can differentiate among crucial and negligible predictors (Strobl et al., 2007). In addition, RF is a robust nonparametric method that detects nonlinear associations and while considering interactions among predictors. RF is not subjected to overfitting because of its built-in resampling algorithm. Specifically, we sought (1) to assess the strength of the association between LDS and individual characteristics through RF's cross-validation capability, and (2) to classify the predictors through VIM. We used the RF implementation provided in the *R* (v. 3.3.3) package *Party* (v. 1.2-2) (Strobl et al., 2009a), which is based on conditional inference trees (Hothorn et al., 2006) and is robust to biases that may affect other RF implementations (Strobl et al., 2007). For VIM computation, we used the conditional variable importance method (Strobl et al., 2008), which does not overstate correlated predictors' importance and, hence, can be interpreted similarly to the coefficients of parametric regression models (Boulesteix et al., 2014; Strobl et al., 2009b). The procedure was as follows: (1) we declared PWS, age, body mass, and body height as continuous predictors whereas sex was encoded as a two-level categorical variable; we defined the outcome (LDS) as a continuous variable. (2) We set up the *cforest* function to grow 2000 regression trees ('*ntree* = 2000'), each using a subset of two randomly-selected predictors for splitting ('*mtry* = 2'). We set the other tuning parameters to their default values. (3) As cross-validation based on out-of-bag (OOB) data, we used R^2 to assess how well the model prediction fit with the measured outcome. (4) We used the *varimp* function to evaluate the variable importance of the five predictors through the conditional importance method ('*conditional* = TRUE') (Strobl et al., 2008). Fig. 2 shows the 'mean decrease in accuracy' importance scores of the predictors.

As the second machine learning approach, we selected the MARS algorithm (Friedman, 1991) because of its appropriateness to handle nonlinear relationships, its ability to detect interactions among predictors, and its good bias-variance tradeoff. In short, the MARS algorithm combines the logic of stepwise multiple regression models and regression trees. MARS fits a model with the help of piecewise linear splines as basis functions, which split predictors around knots. As in recursive partitioning trees, the MARS model is built through forward and backward phases. The forward pass recursively adds basis functions that reduce the residual error. The backward phase prunes the model to lower overfitting by penalizing model complexity.

MARS was implemented through the MATLAB (R2015a) package known as ARESLab (v. 1.13.0) (Jekabsons, 2016). We used the *aresbuild* function for piecewise-linear modelling ('cubic', false). A preliminary cross-validation analysis (command *arescvc*) had indicated that a high penalty ('*c*', 5) of generalized cross-validation (GCV) per knot decreased overall error. We also tuned the model to include potential pairwise interactions ('*maxInteraction*', 2). Finally, we set a minimal span of 15 near edges ('*useEndSpan*', 15) to lower the risk of spurious fitting at the end of data intervals. We set the other tuning parameters to their default values. The detailed equation of the MARS model is reported in Fig. 2. Along with the equation, we placed fitting curves onto the scatter plots (Fig. 2), one for each continuous predictor retained by the MARS model. More precisely, the model was fed with each predictor with

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