Abstract

Differences in gait performance can be explained by variations in walking speed, which is a major analytical problem. Some investigators have standardised speed during testing, but this can result in an unnatural control of gait characteristics. Other investigators have developed test procedures where participants walking at their self-selected slow, preferred and fast speeds, with computation of gait characteristics at a standardised speed. However, this analysis is dependent upon an overlap in the ranges of gait speed observed within and between participants, and this is difficult to achieve under self-selected conditions. In this report a statistical analysis procedure is introduced that utilises multilevel modelling to analyse data from walking tests at self-selected speeds, without requiring an overlap in the range of speeds observed or the routine use of data transformations.

Keywords

Multilevel modelling, speed, velocity, gait analysis

1. Introduction

A major methodological challenge in gait analysis is delineating if changes in temporo-spatial characteristics are due to changes to the condition or variance in walking speed.[1, 2] Differences observed in speed-dependent gait variables under different conditions (repeated measures or between individuals or different interventions) can therefore be explained by differences in gait velocity. As a result, gait velocity needs to be accounted for in experimental design and analysis, however there is not a universally accepted approach.[3]

Approaches to normalising gait speed involve either experimentally standardising walking speed or using statistical procedures. Experimental options include participants walking at a range of speeds, with the walk nearest a pre-selected speed being used in the analysis, or cadence pacing can be attempted using a metronome.[3] Both of these approaches rely on all participants to walk at a common speed in all experimental conditions, which may not be practical or possible as self-selected speed varies markedly between people – some people naturally walk slowly and others do not. Statistical methods to normalising gait velocity using adjustments can also violate the assumptions of the models used.[3]

A technique has been developed that combines experimental and statistical approaches.[4] The technique requires participants to walk twice at their self-selected slow, preferred and fast speeds. The purpose of 2 walks at each speed is to reduce random error. Velocity normalised estimates for speed-dependent gait variables, such as step width, are obtained using the data from the 6 walks, to construct a linear regression plot across all conditions. A curvilinear regression plot is used instead if adding a quadratic term improves the fit of the model (see Figure 1 for a detailed illustration and explanation of this technique).[4]

As shown in Figure 1, the reference walking velocity is taken at a selected point somewhere within the range of observed velocities common to all test conditions. The advantage of this method is the normalisation of velocity using an estimate from the regression plots within the range observed across the experimental conditions. However, to utilise this technique, all participants require an overlap in the range of walking velocities. If an intervention is being studied there needs to be an overlap between the ranges of gait velocities within and between participants for all interventions. We found this can be problematic in clinical populations, or when assessing the effect of different interventions, as large differences in walking capacity can make this requirement impractical.

In this report we present an analytical procedure to deal with these issues using multilevel modelling (MLM), without the use of data standardisation. The repeated-measures from gait analysis are clustered within subject and are correlated observations, therefore the use of multilevel modelling is appropriate.[5, 6] MLM is an extension of linear regression modelling, the main difference being that the models account for hierarchy in the data. In the context of repeated measures in gait analysis, the measures are level 1 data and these observations are clustered by participant, the level 2 data, consistent with other applications of multilevel modelling for longitudinal data.[5, 6]

van Iersel et al.,[7] proposed use of MLM to normalise walking velocity, recommending modelling of log transformed data. Although log transformation can address skewness of predictor variables, its use is compromised by limitations in interpreting log transformed outcomes in the real world.[8] We suggest MLM should be applied to the data first, prior to considering the need for transformation. To ensure MLM is an appropriate fit of the data, the normal distribution of the residuals, not the predictor variables, is of primary importance.[6] We illustrate our approach with an example.

2. Procedure

The stages for MLM we suggest are:

1) random intercept model unadjusted for velocity

2) random intercept model adjusted for velocity

3) random slope model adjusted for velocity

4) random curve model adjusted for velocity

Multilevel modelling deals with the clustering of observations from repeated measures by accounting for the variance of the intercepts i.e. a variance parameter is estimated for the random intercept (stages 1 and 2).[5, 6] One assumption of the random intercept model is that the effect of the explanatory variable(s) is the same in every participant. In these circumstances, exploring the use of a random slope model is recommended (stage 3).[5, 6] Finally, if the random slope improves the fit of the model a random curve can be explored using a quadratic term for the walking velocity (stage 4). Explanatory variables can be added to these models to control for differences in the conditions for each participant (e.g. intervention used).

At each stage of modelling, a chi-square likelihood-ratio test is used to assess if the extra terms improve the model. The LR test compares log-likelihood (measure of error or unexplained variation) of two models and determines if there is a statistically significant difference.[9] If it is not statistically significant ($P<0.05$), the previous model is the final model used for the estimates. For the final model, post-regression diagnostics of residuals are conducted to check key assumptions before accepting and reporting the results.[6]

Example

Eighteen participants performed 2 walks at slow, preferred and fast speeds. Two interventions (ankle braces) were compared to a control intervention (no ankle brace). The outcome variable in this example was the step width (cm). Data from the GAITRite electronic walkway (CIR Systems, Peekskill, NY, USA) were analysed in STATA 12 (StataCorp, College Station, TX, USA). Stages and output of the modelling are shown in Table 1. A fixed effect was added to the models to estimate the effects of the ankle braces compared to the control condition (reference category set at zero). As the stages of modelling advanced, the first step of adjusting for gait velocity had an effect on the coefficients, and precision was further enhanced as a random slope then random curve model were fitted. To illustrate further, by the end of the stages of modelling the coefficients for ankle brace B were reduced by 0.35 and 95% confidence intervals also narrowed. In the final stage of modelling, the effects of the interventions on the speed-dependent variable, step width, were adjusted for velocity in a non-linear model to optimise the estimate. The result from the final model for the experimental ankle brace A and B compared to the control of no ankle brace is the best overall estimate of the difference in the step width independent of walking velocity. This approach does not require a point-estimate at a specific walking velocity to estimate the difference in step width between the interventions. When compared with the control, step width was 0.9cm (95% CI 0.5 to 1.3, P<0.001) wider with ankle brace A and 4.1cm (95% CI 3.7 to 4.5, P <0.001) wider with ankle brace B. Figure 2 shows that residuals at level 1 were normally distributed (plot of quantiles of standardised residuals against quantiles of normal distribution [Q-Q plot]).

Discussion

Humans have the capacity to adjust their gait speed without necessarily sacrificing their 'natural' gait pattern, for instance when walking uphill or downhill, when walking together in a group, when in a hurry and so on. It is well documented that the relation between step length and step frequency (cadence), called walk ratio,[10] is fairly constant through different walking speeds, suggesting that the basic kinematics of walking are robust and allows walking in a variety of speeds beyond what is ‘normal’ for the individual. We suggest this supports the rationale for the proposed test procedures and statistical methodology based upon different walking speeds within the capacity of the individual, and that such approaches may add insight beyond what is captured when a person is walking at ‘normal’ or ‘natural’ walking velocity.

Multilevel models may be limited in their use due to the relative complexity of the analysis when compared with other approaches.[6] Many of the specialised software packages also require statistical programming to optimise analysis.[5] However, when analysing speed-dependent gait variables, commonly used regression techniques overlook the issue of correlated observations from repeated measurements [5] and simpler summary statistics ignore the influence of walking speed and so complicate interpretation. MLM has several advantages over other statistical methods, it reduces the confounding effect of walking velocity, offers a closer model of the true treatment effect on a speed-dependent gait outcome, does not violate the assumptions of the model, utilises the information on repeated gait measurements at a range of walking velocities, allows adjustment for participant level variability in gait performance over different walking speeds (intercepts and slope variance for each participant), does not require overlap of walking speeds, can be applied without routine use of log transformations, which can aid interpretation, and are robust in situations where missing data could present, as is often an issue in clinical research.[5] When attempting to detect clinically worthwhile but subtle changes in speed-dependent gait variables, it is particularly desirable to apply a more complex analysis that increases precision and accounts for walking speed variability under different experimental conditions. The MLM approaches suggested here and by van Iersal et al.[7] require further development to refine their use in a range of settings. It is anticipated that the technique could have broader application to other speed-dependent gait and motion analysis variables.

Word count: 1519

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