COMPREHENSIVE NON-DIMENSIONAL NORMALIZATION OF GAIT DATA

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ABSTRACT

Normalising clinical gait analysis data is required to remove variability due to that in physical characteristics such as leg length and weight. This is particularly important for children where both are associated with age. In most clinical centres conventional normalisation (by mass only) is used whereas there is a stronger biomechanical for non-dimensional normalisation. This study used data from 82 typically developing children to compare how the two schemes performed over a wide range of temporal-spatial and kinetic parameters by calculating the coefficients of determination with leg length, weight and height. 81% of the conventionally normalised parameters had a coefficient of determination above the threshold for a statistical association ($p<0.05$) compared to 23% of those normalised non-dimensionally. All the conventionally normalised parameters exceeding this threshold showed a reduced association with non-dimensional normalisation. In conclusion, non-dimensional normalisation is more effective that conventional normalisation in reducing the effects of height, weight and age in a comprehensive range of temporal-spatial and kinetic parameters.

INTRODUCTION

It is often desirable to normalise clinical gait analysis data to make a more clinically meaningful comparison of data from individuals with different dimensions and body mass. The variance of temporal-distance parameters such as stride length and cadence, for example, includes differences due to height as well as the natural variability of the population. The effect of differences in mass and segmental moments of inertia may similarly affect force, moment and power data [1]. The variation in such body parameters is particularly pronounced in children. Use of appropriate normalisation techniques may be particularly important when monitoring progress or outcomes from surgery of other interventions over periods during which the child may have grown.

A range of different normalization techniques were proposed by O'Malley in 1996 [2]. In this paper, normalization was treated as a two-step process: first a model for the data was developed and then data were normalized with respect to the model. The main problems with this approach are that it needs to be applied separately to every variable and dataset under investigation, gives no insight into the underlying mechanisms through which size variation affects walking and rigorous validation requires testing on a dataset separate to that used to develop the normalisation scheme.

Hof [3] suggested non-dimensional normalisation (NDN) in which measurements are rendered dimensionless by dividing each parameter by combinations of body mass, leg lengths and gravitational acceleration. The resulting variables are often referred to as non-dimensional variables. This provides a general conceptual basis for normalising all gait analysis variables but is essentially a hypothesis about how they vary with body size that requires experimental validation.

Hof and Zijlstra [4] provided the first such validation illustrating that non-dimensional cadence and stride length remain constant after the age of 3 until adulthood. Pierrynowski and Galea [5], demonstrated (in sample of 10), that inter-subject variability was reduced by non-dimensional normalisation in a group of patients with significant variation of their body parameters (heights and weights). Stansfield et al. [6], tested how different normalization techniques affect correlations between a range of temporal-spatial parameters and factors, such as speed and age and concluded, through this rather oblique analysis, that non-dimensional normalisation was preferable to semi-dimensional normalisation. Moisio et al. [7] showed that appropriate normalization of joint moment data reduced the dependence on height, weight and speed and gender substantially in adults. Schwartz et al. [8] have also demonstrated that non-dimensional normalisation techniques can be applied effectively to Oxygen consumption and cost data. There has, however, been no previous study to test non-dimensional normalisation comprehensively across the range of clinically important gait variables in children and this is the aim of this paper.

MATERIALS and METHODS

Data from typically developing children over an age range of 4 to 17 were analysed. This dataset was previously captured and analysed as described in Schwartz et al. in 2008 [9]. In summary, participants were given general instructions to walk at very slow, slow, self-selected comfortable (free), and fast walking speeds during a single testing session. The order of the speeds was not prescribed, other than collecting the free speed data first. Only data from free walking speed was included in this analysis. All data had been collected with a Vicon kinematic measuring system (Oxford, UK) and AMTI force plates (Watertown, MA, USA). Trajectories had been filtered with a Woltring spline filter [10] and then processed using Plug-in Gait [11] software (Vicon, Oxford, UK). A subset of the data related to barefoot walking at self-selected walking speed has been used as a basis for this analysis. Weight, leg length (ASIS to medial malleolus) and age data were also recorded.

Parameters

From these data 26 parameters were calculated. Three were the basic temporal and spatial parameters: walking speed, cadence and step length defined as the longitudinal distance between the contact of one foot and the contact of the other foot. 23 key features were chosen from hip, knee and ankle moment (14 features) and power (9 features) traces (see Figure 1).

It is widespread clinical practice (e.g. output of PlugInGait, VICON, UK) to normalise kinetic variables with respect to mass only and this is referred to here as conventional normalisation (CN). This was compared with non-dimensional normalization [3, NDN] as described in Table 1. It should be noted that angle is inherently non-dimensional being the ratio of one length (arc) to another (radius) and joint kinematics have thus not been included in this analysis.

Data analysis

The goal of normalization is to remove systematic dependences of a parameter on relevant factors such as mass, leg length and age. Following the approach first suggested by Schwartz et al. for O_2 cost normalisation [8] the quality of normalisation is therefore assessed by plotting the gait parameter under investigation against these size parameters. A linear least-squares regression of each parameter against mass, leg length and age separately was performed to calculate the coefficient of determination (r^2) for both normalisation schemes. The lower the value of the coefficient of determination the better the normalisation scheme. [8]. Normalisation should reduce the between subject standard deviation by removing variability associated with size. To allow comparison given the different units of measurement the coefficient of variation (CV, standard deviation divided by mean) was also calculated.

RESULTS

Data from 81 participants were included. These ranged in age from 4.5 to 18 years (mean = 10.6) , in height from 1.05 to 1.85m (mean = 1.44m, mean leg length = 0.75m) and in weight from 16 to 82 kg (mean = 40kg). 42% were female. Non dimensional walking speed varied between 0.36 and 0.50 (mean = 0.42).

Figure 2 plots the coefficient of determination for each of the parameters with leg length, mass and age separately allowing a comparison of the two normalisation schemes. The error bars represent the 95% confidence intervals. The dotted line represents that r^2 coefficient of determination that indicates that the correlation coefficient (r) is different from zero with a statistical significance of 0.05 [12].

81% of the coefficients of determination (r^2) were above the threshold for statistical significance under conventional normalisation compared to 23% under non-dimensional normalisation. All parameters with a r^2 value of greater than this threshold for conventional normalisation had a smaller value with non-dimensional normalisation. The differences may also be clinically important. 38% of the conventionally normalised variables had a coefficient of determination of greater than 0.2 indicating that more than 20% of the variance can be attributed to differences in leg length, mass or age. By contrast none of the non-dimensionally normalised variables exceeded this (admittedly arbitrary) threshold. In summary non-dimensional normalisation reduces the dependence with leg length, mass and age for all parameters studied.

The temporal and spatial parameters show the highest r^2 values with conventional normalisation and this dependence is almost entirely removed by non-dimensional normalisation. Within the kinetic parameters there is a tendency for the conventionally normalised moments to show a greater dependency on leg length, mass and age than the powers but there is considerable variation between the individual parameters.

Figure 3 depicts the coefficient of variation for the different variables under the two normalisation schemes. It can be seen the non-dimensional normalisation consistently results in smaller coefficients of variation but the differences are always small with an average reduction of just 3%. Many of the coefficients of variation were large with 12 out of 26 parameters having a coefficient of variation of greater than 40% even after non-dimensional normalisation.

DISCUSSION

The results have confirmed previous studies [5-7] that all the investigated parameters are improved with non-dimensional normalisation with 81% of the correlation coefficients being below the threshold for statistical significant differences from zero at p = 0.05. This strongly supports Hof's proposal [3] that the principle of dynamic equivalence provides a rational basis for such non-dimensional normalisation. The study has extended this to a greater number of participants (81), across a wider age range (4-17) and a wider range of temporal spatial and kinetic parameters (26 in total) than previous studies.

The overall conclusion is that non-dimensional normalisation is a much better technique for normalising data than is used conventionally in clinical gait analysis and should be implemented for this purpose. In several other fields, including measurement of knee moments in research relating to osteoarthritis, normalising moments by both height and weight, an example of a non-dimensional approach, has been assumed appropriate for many years [see for example, 13] and it is not at all clear why this practice has not been adopted more widely.

Non-dimensional normalisation only reduces the dependence of variables on age to the extent that changes are primarily dependent on increases in weight and leg length with growth. The success of non-dimensional normalisation suggests that these are the predominant effects of age within this cohort. Age may have other effects, most obviously through motor development and learning in children and deterioration of motor capacity in the older adults. These may affect both how people walk and how they respond to any interventions. Use of non-dimensional normalisation is still important to allow differentiation of the direct effects of growth (which should be removed by normalisation) and other effects (which will be unaffected by normalisation).

Non-dimensional normalisation has only had a small effect on the coefficient of variation (Figure 3). Consideration of sample data from just three of the parameter's studied as plotted in Figure 4 allows an explanation of this. The data shows that whilst the conventionally normalised data (upper row of graphs) shows a dependence on body size (leg length in this example) there is considerable variability in the data coming from other sources. This is, of course, reflected in the generally quite low r^2 values for many of the variables suggesting that only a small proportion of the total variance can be attributed to systematic variability with size. Whilst the non-dimensional normalisation reduces the gradient of the least squares regression line, it has little effect in the variability about this line and thus little effect on the coefficient of variation.

If the analysis is performed rigorously controlling for multiple comparisons then none of the non-dimensional parameters show a statistically significant correlation with age, height or weight. Lack of evidence that a correlation does exist, is not, of course evidence that it doesn't. Whilst accepting that non-dimensional normalisation reduces dependence on size and age it is important to acknowledge that it does not remove it completely and investigating dependence of data on these factors may still be important in applying such techniques more broadly.

It should be noted that the coefficients of variation are large (12 out of 26 exceed 40% even after the generally successful non-dimensional normalisation). This is also reflected in the broad standard deviation ranges depicted in Figure 1 and the sample data presented in Figure 4. Such high levels of variability in kinetic parameters was observed first by Winter [14] and more recently by Simonsen and Alkjaer [15]. It is in agreement with high levels of variability in Oxygen cost data [8]. In general the high coefficients of variation for kinetic parameters reported in this and other studies brings into question the generally held view that walking at self-selected speed within a gait laboratory is a stereotypical and well defined activity.

Being the ratio of the standard deviation to the mean, the coefficient of variation will be influenced by both. It can give misleadingly high values if the mean value is low (mean values can be compared from the data presented in Figure 1). By definition, however, all the kinetic parameters represent extreme values of the underlying variables (local maxima or minima) and the corresponding coefficients of variation will thus tend to give a conservative indication of the underlying variability.

The source of this variability is not clear. Two possibilities that this dataset allows exploration of are variability associated with walking speed and body mass index (BMI). Correlation of the non-dimensional parameters with non-dimensional speed identifies that 19 of the 25 have an r^2 value higher than the threshold for statistical significance of less than 0.05. Closer inspection shows that the parameters that vary most with speed are those that also show the most variability with speed in the analysis by Schwartz et al. [9]. Given that the current data is a sub-set of data from that source this is unsurprising. It does make it clear that variability within the relatively small range of self-selected speeds shows similar effects to variability over the much range of walking speeds included in that study and may be large enough to influence clinical interpretation of results (particularly, perhaps, in patients walking with lower self-selected walking speeds). From the coefficients of variability derived in this analysis, however, it is possible to calculate the coefficients of variability that would have been derived if dependence on walking speed had been accounted for and these are displayed as the shaded areas in Figure 3. It can be seen that whilst the unexplained variance is smaller, it is still high.

Only two of the non-dimensional parameters (HM1, $p = 0.001$ and AM2, $p < 0.001$) show a p-value of less than 0.05 for correlations with BMI. Although the p-values are very low, the coefficients of determination are also modest leading to the same conclusion as with the walking speed analysis, that there is considerable unexplained variability in the data. In principle it would be possible to search through the 26 parameters separately to identify correlations with a range of other parameters not so far considered (e.g, foot length) to explain the variability. This would require a much more sophisticated analysis to protect against the probability of false positive results from multiple testing and is beyond the scope of the current study.

Given that they are measured in different units it is difficult to make a direct comparison but it appears that the variability in kinetic variables is larger than that in kinematic variables. Consideration of the coefficients of variation reported by Winter [16] corroborates this. It should perhaps be remembered, however, that kinetic data, in combining both position and force data, may well be more susceptible to measurement error than kinematic data.

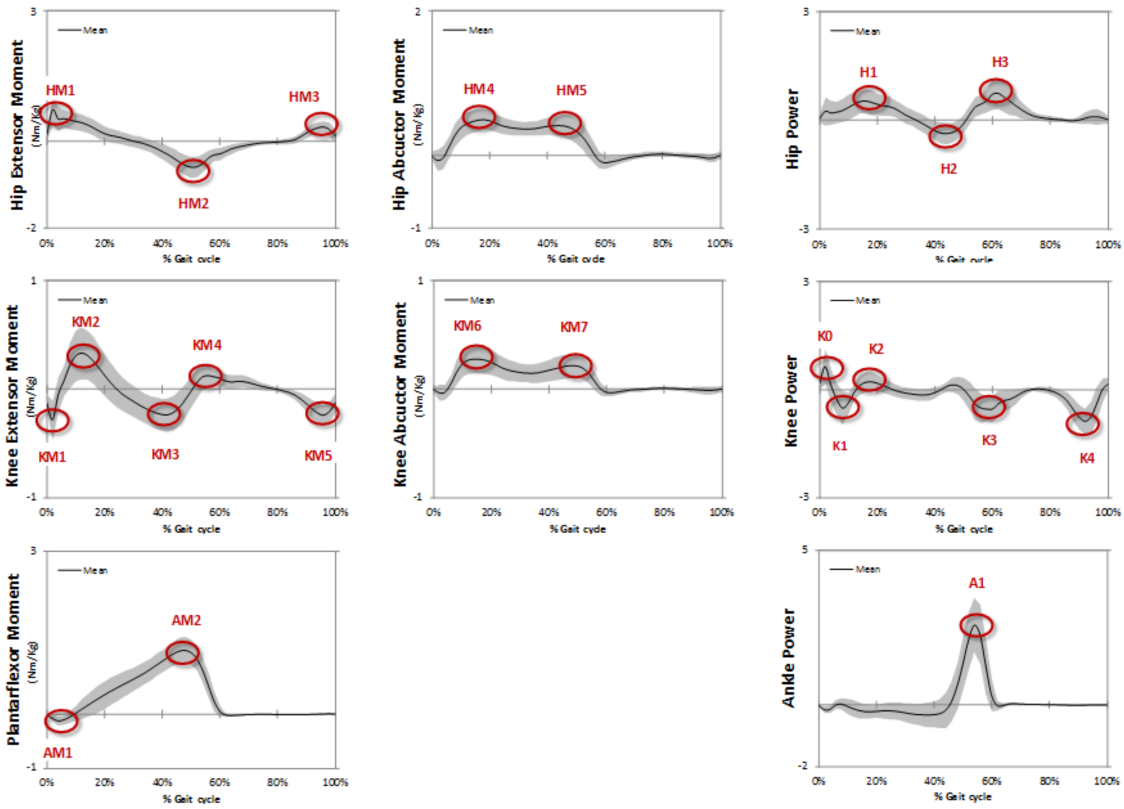

Figure 1. Kinetic parameters selected for analysis in this study (mean – solid line and +/- one standard deviations – shaded area). All are defined as maximum values over a particular interval of the gait cycle. *HM1/3*, maximum hip extensor moment in first half of stance/second half of swing; *HM2*, maximum hip flexor moment in second half of stance; *HM4/HM5*, maximum hip abductor moment in first/second half of stance; *KM1/3/4*, maximum knee flexor moment in first double support/single support/second half of swing, *KM2/4* maximum knee extensor moment in first/second half of stance; *KM6/7* maximum knee abductor moment in first/second half of stance; *AM1/2* maximum dorsiflexor/plantarflexor moment in stance; *H1*, maximum total hip power generation in between opposite foot off (OFO) and mid-stance; *H2* maximum total power absorption in second half of stance; *H3*, maximum hip power generation between mid-stance and mid-swing; *K0/2*, maximum total knee power generation in first double support/between OFO and mid-stance, *K1/3/4*. Maximum total knee power absorption in first half of stance/second half of stance/second half of swing; *A1*, maximum total ankle power generation in second half of stance.

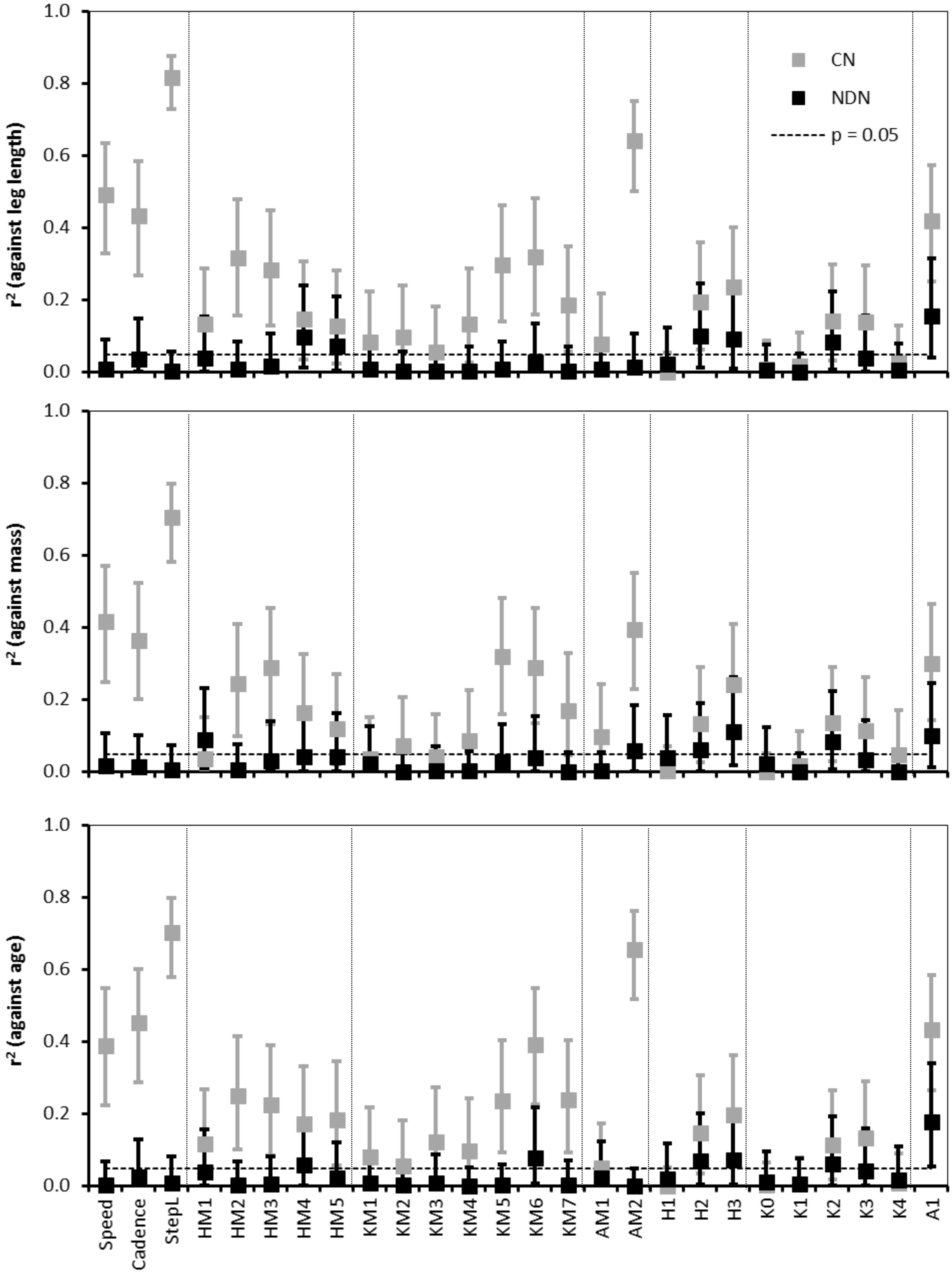

Figure 2. r^2 values for correlation of each of gait variables with age, mass and height for conventional (CN) and non-dimensional normalisation (NDN). Error bars represent 95% confidence limits. Dotted line represents p = 0.05.

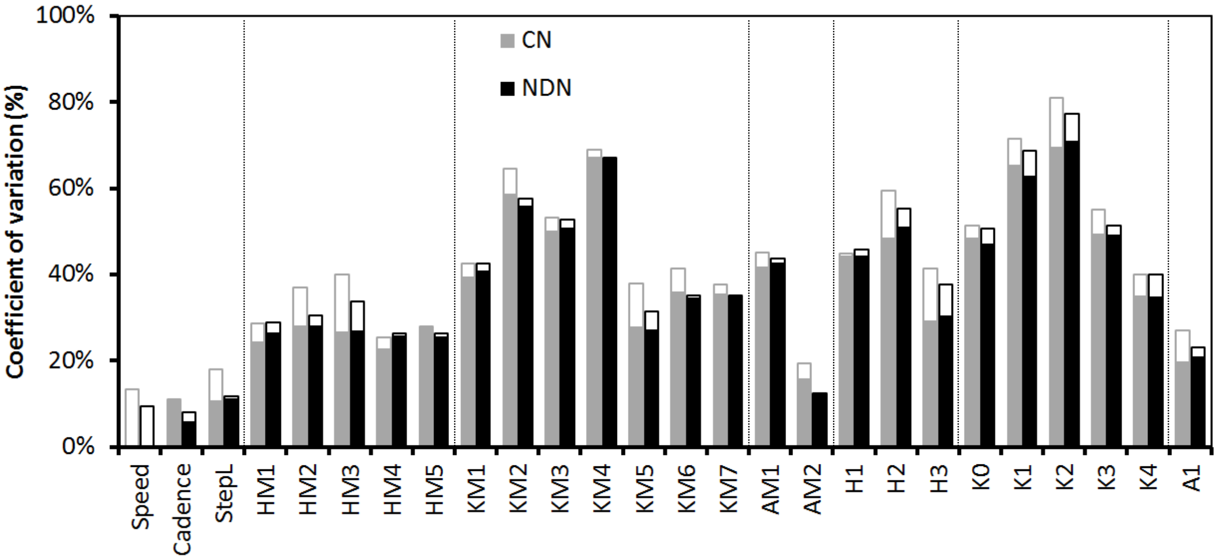

Figure 3. Coefficient of variation for the variables scaled by the two normalisation schemes (conventional, CN and non-dimensional, NDN). Full bars (inculding white areas) represent values calculated directly from data, coloured areas represent values that would be obtained if systematic variability with walking speed had been accounted for in the analysis.

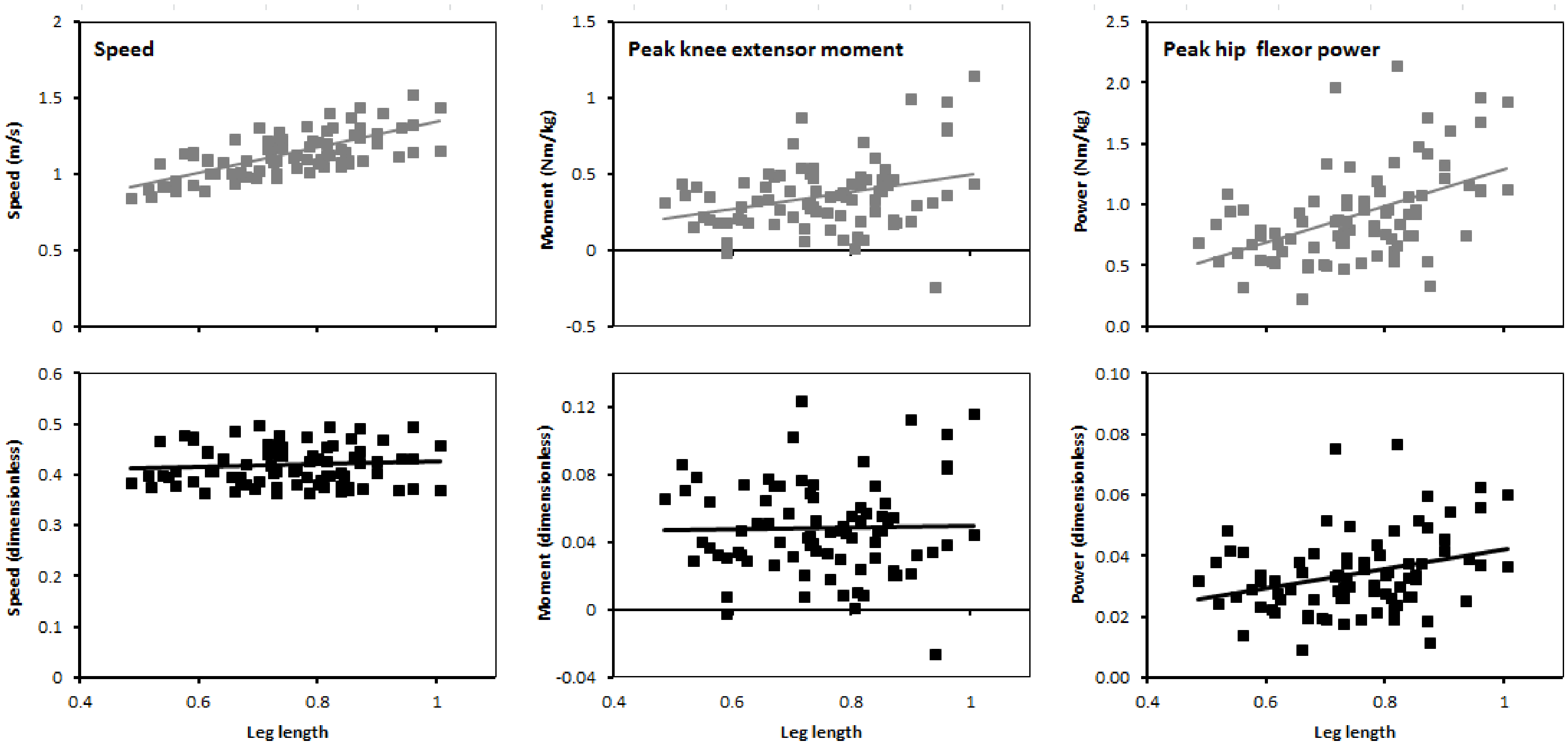

Figure 4. Sample data for speed, peak knee extensor moment (early stance) and peak hip flexor power showing relationship with leg length under conventional (CN) and non-dimensional normalisation (NDN)

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