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Short communication

Automatic selection of a representative trial from multiple measurements using Principle Component Analysis

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ABSTRACT

Experimental data in human movement science commonly consist of repeated measurements under comparable conditions. One can face the question how to identify a single trial, a set of trials, or erroneous trials from the entire data set. This study presents and evaluates a Selection Method for a Representative Trial (SMaRT) based on the Principal Component Analysis. SMaRT was tested on 1841 data sets containing 11 joint angle curves of gait analysis. The automatically detected characteristic trials were compared with the choice of three independent experts. SMaRT required 1.4 s to analyse 100 data sets consisting of 8 ± 3 trials each. The robustness against outliers reached 98.8% (standard visual control). We conclude that SMaRT is a powerful tool to determine a representative, uncontaminated trial in movement analysis data sets with multiple parameters.

1. Introduction

Experimental data in human movement science commonly consist of repeated measurements under comparable conditions. A trial often comprises several parameters as function of time, such as joint angle curves. Here, the question arises how to identify a number of characteristic trials or how to exclude erroneous trials. For simplified interpretation the experimental data might be reduced to a single characteristic trial or to a mean of several trials to alleviate assimilation (Chau et al., 2005). Calculating the mean, however, can filter out peaks and time shifts (Kneip and Gasser, 1992). Regardless if one prefers to progress with one or with a mean of several trials, a defined number of uncontaminated trials from the entire data set has to be selected.

In the literature some alternative methods to identify representative trials were proposed (Brunner and Romkes, 2008; Carson et al., 2001; Duhamel et al., 2004; Schwartz et al., 2008). The most common approach is visual inspection (Brunner and Romkes, 2008). While outliers and contaminated data are easily identified, the constraints of this approach lie in time consumption and lack of objectivity. Random selection of trials is fast (Schwartz et al., 2008), but only meaningful for entirely uncontaminated data. Duhamel et al. (2004) published an algorithm to select the subset of four knee flexion/extension curves based on the intra-class correlation coefficient. Although this approach can be extended to several joint angles, it is unlikely that the same trial for each curve will be selected. The drawback of the proposal from Carson et al. (2001) to detect one representative trial across several inter-segment angles is the averaging, as waveform information is neglected. Therefore, it is desirable to reveal a method, which allows to (1) identify representative trials across several angles, (2) be automatic and fast, (3) be reliable and avoiding the subjectivity of visual inspection, and (4) to be robust against erroneous data, including labelling errors. The purpose of this work is to evaluate the Principle Component Analysis (PCA) (Jolliffe, 2002), as an approach for the automatic detection of representative trials.

2. Methods

2.1. Data acquisition and processing

To evaluate SMaRT, 1841 retrospective data sets, acquired from daily clinical practice between 1999 and 2010, were included. Data originated from patients

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with various gait disorders (1653 data) and healthy subjects (188 data). All participants signed written consent, as required by the responsible ethical committee.

A VICON motion capture system (Oxford, UK) with six cameras was used to track the trajectories of reflective markers which were attached to anatomical landmarks according to the Plug-in-Gait model (Kadaba et al., 1990). Eleven joint angles were calculated and normalised to one gait cycle by means of 51 discrete values: pelvic tilt/obliquity/rotation, hip flexion/abduction/rotation, knee flexion/abduction, ankle flexion/rotation, and foot progression.

2.2. SMaRT

SMaRT was implemented in MATLAB (MathWorks Inc., R2010a, Natick, USA) and was run separately for each body side. In the supplementary material we provide the SMaRT code.

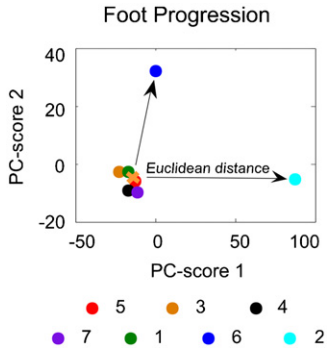

Fig. 1. PC-scores and median for all seven trials of a single subject. The scatter plot represents the first two PC-scores for the foot progression angle during walking for each trial (symbols) of a subject (compare to Fig. 3). The calculated median of the PC-scores is represented with a cross.

A data set for one subject consisted of a three-dimensional matrix X_{tif} containing a patient dependent number of trials t (3–18), data points $i=51$ and angles $f=11$.

Firstly, SMaRT applied a PCA (Jolliffe, 2002) on X_{ti}, i.e. on each trial and each angle of one individual subject, separately. The output delivered PC-scores Z_{tn}, where n is the number of PC-scores, i.e. number of trials minus one. Secondly, the median M_n of the PC-scores was determined across all trials of one individual subject for the 11 angles, separately. Thirdly, the Euclidean distances d_t (Bryant, 1996) of each trial of a subject to the median of the PC-score were computed (Fig. 1).

After applying the three steps for each angle individually, the distances of each trial across all angles were summed. In this specific evaluation of SMaRT, the trial with the smallest overall distance to the median (Fig. 2) was selected and defined as a representative trial.

2.3. Evaluation of SMaRT

Two evaluation procedures were accomplished. Firstly, the robustness of SMaRT against outliers was determined by counting the false positives. The first author estimated the error rate via visual inspection of 1841 data sets.

Secondly, three experts in clinical gait analysis visually selected representative trials to be compared with the SMaRT choice. From the experimental data, 30 sets with 219 trials were randomly selected using a MATLAB routine. The experts independently worked through these data, where each data set was plotted into consistency graphs containing all recorded trials for a subject. The experts assessed each trial and angle, and decided whether the trial was representative or not while multiple selections were allowed.

The number of representative trials on which one, two, or all three experts agreed on was expressed in percentage of the total number of trials. Additionally, the percentage of conformity between the selections of SMaRT and experts was evaluated.

3. Results and discussion

SMaRT, since based on PCA, is sensitive to waveforms (Deluzio and Astephen, 2007). Whereas trials with large waveform deviation (e.g. mirrored curves due to labelling errors) will have a large

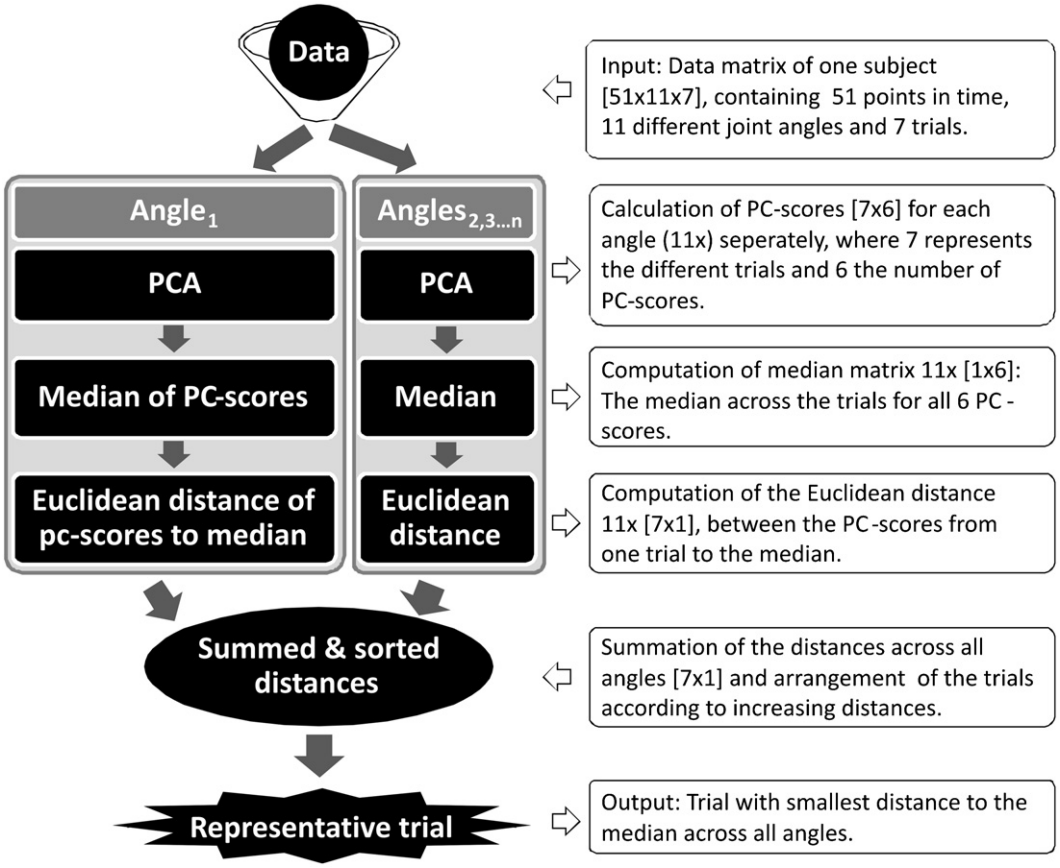

Fig. 2. Flowchart of SMaRT, showing the single steps to select the representative trial. The black fields represent each step of the algorithm. The text boxes on the right give an accurate description of the input and output data of the single steps. As an example, we here used 11 joint angles normalised to 51 data points for 7 trials.

Euclidean distance to the median, trials with similar waveforms but with an offset from the median have a small distance. This is beneficial, as we usually consider larger waveform deviations more likely to result from measurement errors than offset curves with characteristic waveforms. Note that SMaRT does not evaluate the variability of the data. The consistency of the data could be determined by one of the methods proposed by Chau et al. (2005) before running SMaRT.

3.1. Performance of SMaRT

SMaRT ran 1.4 s to analyse 100 data sets consisting of 8 ± 3 trials each on a 64 bit computer (HP Compaq 8100 Elite). The three experts needed 15, 28, and 43 min to assess the 30 data sets. Hence, SMaRT evaluates the data, without subjective, bias more than three orders of magnitude faster than the experts. While visual and random selection can produce different results in multiple assessments, SMaRT provides full repeatability.

3.2. Evaluation of SMaRT

In data sets with contaminated trials, SMaRT selected a trial without visible sign of contamination (Fig. 3). The first author revealed an error rate of SMaRT of 1.2%. SMaRT filters adequately erroneous data because the median, which is robust against outliers, is calculated. Hence, SMaRT operates as quality assurance where visual control is impossible due to large amounts of data. The procedure is limited to data with less than half of the trials contaminated.

The SMaRT selection agreed with those of at least one expert to 96.7% (29/30), with those of at least two experts to 80.0% (24/30), and with those of all three experts to 56.7% (17/30). SMaRT once selected a trial not chosen by the experts. This trial, not a distinct outlier, showed a small irregularity in one angle. Although selection of multiple representative trials was allowed, the inter-rater reliability between the three experts was low. The three experts agreed on 25.1% (55/219) of representative trials only, and at least two experts agreed on 44.3% (97/219). This affects the agreement between SMaRT and the choice of two, or even three experts. Nonetheless, the agreement between two experts and SMaRT is still regarded as high.

In conclusion, SMaRT meets our requirements for an objective, fast, reliable, and automatic selection tool of a characteristic trial from multiple trials containing numerous angles. Hence, the selected trial is the same trial for all curves. Additionally, the method can be used as a filter for contaminated data or quality assurance procedure, as it is robust against a limited number of outliers. The algorithm can either be extended to an arbitrary choice of trials or to an individually required number of parameters (e.g. kinetic parameters) or both. The successful application of SMaRT may be profitably applicable to any kind of time series derived by movement analysis.

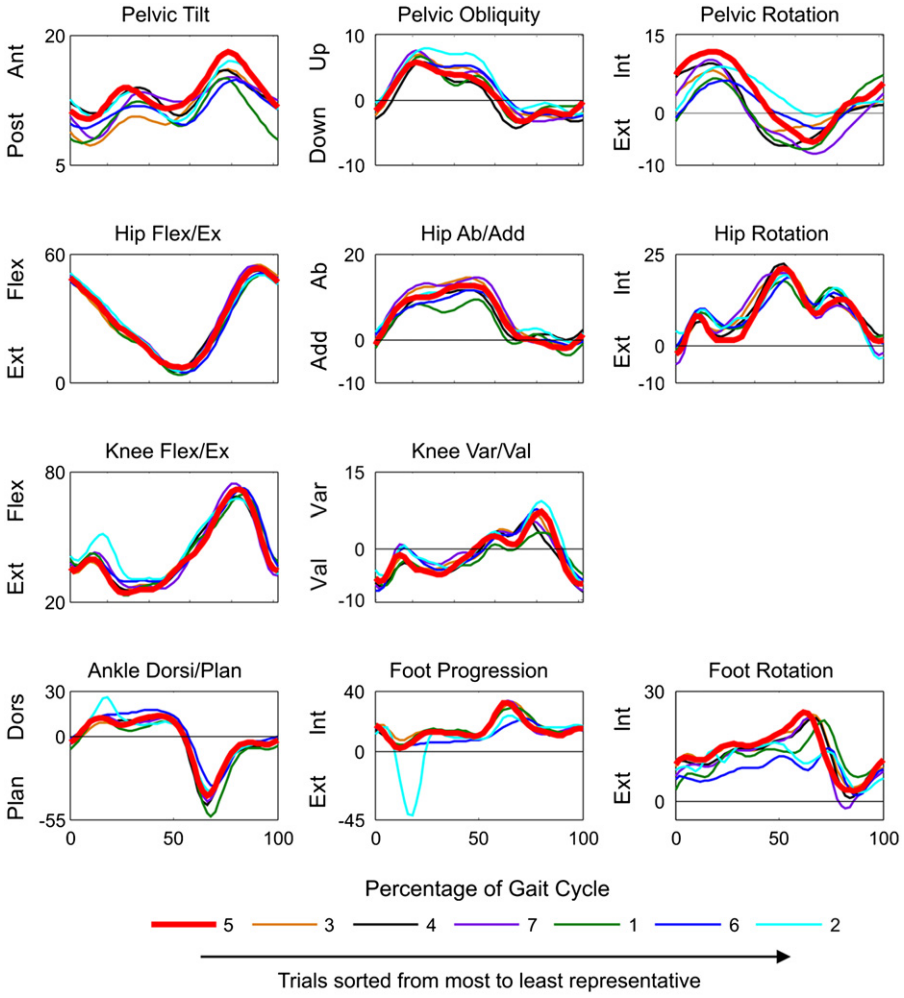

Fig. 3. Consistency plot of all seven trials for one subject. The joint angle curves are plotted for all seven trials of one data set, representing a single subject. The representative trial (bold line) is the trial selected by the algorithm.

Conflicts of interest statement

All authors disclose any financial and personal relationships with other people or organisations that could inappropriately influence or bias their work.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jbiomech.2012.06.012.

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