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Trial- vs. cycle-level detrending in the analysis of cyclical biomechanical data

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Abstract

Biomechanical time series may contain low-frequency trends due to factors like electromechanical drift, attentional drift and fatigue. Existing detrending procedures are predominantly conducted at the trial level, removing trends that exist over finite, adjacent time windows, but this fails to consider what we term ‘cycle-level trends’: trends that occur in cyclical movements like gait and that vary across the movement cycle, for example: positive and negative drifts in early and late gait phases, respectively. The purposes of this study were to describe cycle-level detrending and to investigate the frequencies with which cycle-level trends (i) exist, and (ii) statistically affect results. Anteroposterior ground reaction forces (GRF) from the 41-subject, 8-speed, open treadmill walking dataset of Fukuchi (2018) were analyzed. Of a total of 574 analyzed trials, significant cycle-level trends were found approximately three times more frequently (21.1%) than significant trial-level trends (7.4%). In statistical comparisons of adjacent walking speeds (i.e., speed 1 vs. 2, 2 vs. 3, etc.) just 3.3% of trials exhibited cycle-level trends that changed the null hypothesis rejection decision. However 17.6% of trials exhibited cycle-level trends that qualitatively changed the stance phase regions identified as significant. Although these results are preliminary and derived from just one dataset, results suggest that cycle-level trends can contribute to analysis bias, and therefore that cycle-level trends should be considered and/or removed where possible. Software implementing the proposed cycle-level detrending is available at <https://github.com/0todd0000/detrend1d>.

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12 1. Introduction

13 Time series can contain drift, which may be generally defined as a low-frequency process that is
14 not considered to belong to the measured signal of interest. Drift may occur secondary to a variety
15 of hardware-related factors including changes in electronic and thermal environments (Wilmshurst,
16 1990). Reducing this type of drift can be done at hardware, firmware or software levels and remains
17 an ongoing area of research (e.g. Velásquez et al., 2019). In human experiments, fatigue and other
18 behavioral factors can also produce drift (Song et al., 2009) and this type of drift must be dealt
19 with at the software stage. This paper focuses on the influence of drift on statistical comparisons
20 of time series and offers software for the proposed drift corrections.

21 In the human biomechanics literature several movement tasks — especially treadmill gait —
22 involve measurements over several minutes or even seconds, and in these measurements drift is
23 generally reduced through high-pass filtering (Murphy and Robertson, 1993; Valentin and Zsoldos,
24 2016) or detrending (Fig.1). **Both high-pass filtering and detrending regard low-frequency content
25 as noise and are unconcerned with the electromechanical or physiological nature of that noise.**
26 Detrending is particularly important to detrended fluctuation analysis (DFA), which has become
27 an important analysis framework for investigating the structure of motor variability (Ducharme and
28 van Emmerik, 2018; Ravi et al., 2020); **detrending is useful for motor variability studies, for example
29 postural sway studies, to dissociate low- from higher-frequency content, which are associated with
30 very different (e.g. high- vs. low-level) neural control processes.** Unlike the simple long-term
31 detrending depicted in Fig.1, DFA instead uses local detrending to identify and remove multiple
32 trends that occur in adjacent movement segments. **While detrending is often employed in routine
33 analyses, we are unaware of explicit previous reports of trend prevalence, nor of the prevalence of
34 inferential errors which may occur if detrending is not employed.**

35 A key limitation to existing detrending approaches is that they do not consider cycle-level
36 drifts (Fig.2). In cyclical tasks like gait different parts of the cycle may drift differently and
37 even oppositely (Fig.2a-b). As a plausible biomechanical example, consider ground reaction force
38 (GRF) in treadmill walking which increases posteriorly in early stance over 100 cycles and also
39 increases anteriorly in late stance; these opposite changes must occur to maintain constant walking

40 speed. For example, maximal Floquet multipliers (representing the stability of the system at certain
41 instants of the gait cycle) have been found to vary within the gait cycle (Kang and Dingwell, 2009),
42 thus emphasizing the need to consider trends as non-constant within the cycle. Moreover, simple
43 simulation shows that trial- and cycle-level detrending can generally yield qualitatively different
44 results (Fig.2c-d). We are unaware of any previous study that has considered cycle-level drift.

45 The purposes of this study were: (1) to describe a generic cycle-level detrending procedure, (2)
46 to estimate the prevalence with which significant cycle-level trends exist in an open treadmill GRF
47 dataset, and (3) to estimate the frequency with which these cycle-level trends can qualitatively
48 affect hypothesis testing results. Software implementing all subsequently described detrending
49 procedures is available at <https://github.com/0todd0000/detrend1d> along with notebooks and
50 data files that replicate this paper's main results.

51 **2. Methods**

52 *2.1. Dataset*

53 A subset of an open gait dataset was analyzed (Fukuchi et al., 2018). The dataset contains
54 a barrage of biomechanical measurements made during overground and treadmill walking in 42
55 individuals (24 young adults: 27.6 ± 4.4 years, 171.1 ± 10.5 cm, 68.4 ± 12.2 kg; 18 older adults:
56 62.7 ± 8.0 years, 161.8 ± 9.5 cm, 66.9 ± 10.1 kg).; data for 41 individuals are available in the
57 open dataset. Here analyses are limited to anteroposterior and vertical GRF during treadmill
58 walking (Fig.3), for which 30 s trials were recorded at eight different walking speeds for each
59 subject. Data recording started after steady-state walking was achieved. GRF data were originally
60 recorded at 300 Hz and were smoothed here with a fifth-order lowpass Butterworth filter with a
61 cutoff frequency of 20 Hz. Cycles were segmented (i.e. stance phase identified) with a preliminary
62 threshold of 30 N on vertical GRF followed by a walk-back (from the first point) or walk-forward
63 (from the last point) to the time points where vertical GRF reached zero, equalized or increased.
64 To avoid overpowering analyses only the first 10 recorded steps of each trial were analyzed here;
65 one-dimensional numerical power analyses (Pataky, 2017) suggest that 10 steps yielded power in
66 the range of 0.7-0.9 for a moderate effect size of 0.5.

67 *2.2. Detrending*

68 Trial-level detrending (common detrending) was conducted by fitting the following model to
69 each GRF time series:

$$y(t) = at + b \tag{1}$$

70 where $y(t)$ is the GRF value at time t , a is the slope and b is the intercept. Detrended data were
71 then calculated as the difference between the observed data and the fitted model. This type of
72 detrending is available in several software packages including Scipy (Virtanen et al., 2020) and
73 MATLAB (MATLAB, 2023).

74 Cycle-level detrending was conducted separately at each cycle point as depicted in Fig.2. First
75 the data were linearly registered (Ramsay and Li, 1998; Sadeghi et al., 2000)(i.e., time-normalized)
76 by linearly interpolating to 101 points. **The following linear model was then fitted to the registered**
77 **data, separately for each cycle time point t_c :**

$$y(t_c) = a_c t_c + b_c \ ; \ c \in [1, 101] \tag{2}$$

78 where t_c represents the time for cycle point c and $y(t_c)$ contains only y values for that cycle point.
79 Thus $y(t_c)$ contained n values where n is the number of cycles recorded in a single trial. Since
80 the model was fitted separately for each of the 101 cycle points, the fitted parameters a_c and b_c
81 generally vary over the course of the cycle (Fig.2b). Following model fitting the detrended results
82 were obtained, as above, by calculating the difference between the observed data and the fitted
83 model.

84 *2.3. Trend prevalence*

85 Since the aforementioned statistical tests pertained to a small subset of the Fukuchi et al.
86 (2018) dataset, and since we manually selected that subset to highlight specific effects regarding
87 detrending, it is possible that those tests are not representative of the larger dataset. We therefore
88 aimed to summarize trends across the larger dataset using two approaches. First, the prevalence of
89 statistically significant (at $\alpha = 0.05$) trial- and cycle-level trends was assessed separately for each

90 trial using Eqns.1 and 2, respectively. For the latter, random field theory (Pataky, 2016) was used
91 to correct for multiple comparisons across the 101 data points (Eqn.2) and thus retain a Type I
92 error rate of $\alpha = 0.05$.

93 Second, the prevalence of trial- and cycle-level trends that affected a statistical comparison of
94 two adjacent walking speeds (i.e., speed 1 vs. 2, 2 vs. 3, . . . 7 vs. speed 8) was assessed as depicted
95 in Fig.4. After fitting equations 1-2 to the data (Fig.4a-d) the detrended, registered data (Fig.4e-
96 h) were compared using statistical parametric mapping (Friston et al., 1995) as implemented in
97 the two-sample t test in spm1d version 0.4 (Pataky, 2012). If the statistical results qualitatively
98 changed with the detrending approach then that test was deemed to have had a substantial effect
99 on the statistical results. Here ‘qualitative change’ was determined subjectively, based on whether
100 supracluster thresholds emerged in qualitatively different parts of the gait cycle. For example,
101 the suprathreshold clusters depicted in Figs.4e and 4f were deemed to be qualitatively different
102 because the significant effect at approximate time=60% in Fig.4f did not reach significance in
103 Fig.4e. We felt that this qualitative approach was necessary because a purely objective approach
104 overstated prevalence, for example by suggesting that results changed even for minor time shifts in
105 suprathreshold signal. As we are unaware of any robust, objective statistical method for comparing
106 these types of statistical outcomes we chose this qualitative approach, which we feel most accurately
107 and conservatively conveys true prevalence. These qualitative checks were conducted independently
108 by two raters (the co-authors), for all subjects, all adjacent speed pairs, and for both anterioposterior
109 and vertical GRF components. From the potential total of 574 combinations (41 subjects, 7 speed
110 pairs, 2 force components) 22 combinations were discarded due to missing or noisy data, so a total
111 of 552 tests were conducted. Inter-rater agreement was near perfect across the 552 tests, with just
112 7 disagreements that were resolved with discussion.

113 3. Results

114 Significant trial- and cycle-level trends were observed in 7.4% and 21.1% of all trials, respectively.
115 Figs.4a-b depict an example trial that had a non-significant trial-level trend but a significant cycle-
116 level trend, respectively.

117 An example statistical comparison of a single speed pair for a single subject showed that trial-
 118 and cycle-level detrending could produce results whose interpretations were substantially different,
 119 with some temporal regions' statistical regions suppressed and others amplified, depending on the
 120 detrending technique employed (Figs.4i-j).

121 Relative to no detrending, trial-level detrending affected the null hypothesis (H0) rejection
 122 decision in just 2.4% of the 41 subjects and just 0.2% of the 552 trials. In contrast, cycle-level
 123 detrending affected the H0 rejection decision approximately ten times more frequently: in 24.4%
 124 of subjects and 3.4% of trials (Table 1). Similarly, trial- and cycle-level detrending affected the
 125 'regional interpretation' (i.e., whether or not a cycle region reached statistical significance) in 5.1%
 126 and 18.3% of trials, respectively. In total, 92.7% of the 41 subjects had at least one trial where the
 127 regional interpretation changed upon cycle-level detrending.

Table 1: Summary of detrending-affected results. For each trial a result was considered affected by detrending if results were qualitatively different from the no-detrending case. For subject- and trial-level analyses percentages are relative to the total number of subjects (41) and total number of trials (552), respectively. H0 = null hypothesis.

Across all...	Affected result	Trial-level detrending	Cycle-level detrending
... Subjects	H0 rejection	2.4%	24.4%
	Regional interpretation	46.3%	92.7%
... Trials	H0 rejection	0.2%	3.4%
	Regional interpretation	5.1%	18.3%

128 4. Discussion

129 The results of this study indicate that statistically significant cycle-trends were approximately
 130 three-times more common than trial-level trends in the considered treadmill GRF dataset. They
 131 also indicate that cycle-level detrending affects statistical conclusions substantially more than trial-
 132 level detrending (Table 1). Collectively these results suggest that cycle-level trends may be a
 133 more important source of analysis bias than trial-level trends, and thus that cycle-level trends
 134 should be considered in analyses where detrending is deemed to be a suitable data processing
 135 step. The proposed cycle-level detrending supports experimental protocol involving cycle-level
 136 independent variable control like tripping initiated at a specific gait cycle instant. Additionally,

137 our results showed qualitative influences of cycle-level trends in (92.7%) of the 41 participants, thus
138 emphasizing the need for subject-specific methodology (Harry et al., 2020). **Although not reported**
139 **in the Methods and Results above due to space constraints, sensitivity analyses showed that the**
140 **results reported above were robust to processing parameter tweaks including: filter frequency, stance**
141 **phase identification threshold, etc. Also not reported above was a consideration of the ‘Young’ vs.**
142 **‘Older’ age groups in the Fukuchi et al. (2018) dataset. We found that separately considering the**
143 **age groups did not qualitatively affect the prevalence results reported above in Table 1 so these**
144 **results were excluded due to space constraints.**

145 Common detrending procedures, including both simple trial-level detrending (Fig.1) and piece-
146 wise detrending as implemented in the widely-employed detrended fluctuation analysis (DFA)
147 (Ducharme and van Emmerik, 2018; Ravi et al., 2020), consider trends only over a finite number of
148 adjacent time segments. This type of detrending is fundamentally different from the proposed cycle-
149 level detrending, which instead considers a trend profile that varies across the cycle (Figs.2b,4d).
150 The proposed cycle-level detrending is coherent with bias reduction, in that an experiment con-
151 trols the influence of an independent variable like walking speed but does not directly control drift
152 through the time-series.

153 This study has several limitations. The most serious limitation is that just one dataset and
154 one data modality were considered. Examinations of other data modalities, populations, and trend
155 types are needed before general conclusions can be made regarding both the prevalence of cycle-level
156 trends and their results-affecting implications. **Nevertheless, this paper’s main findings are simply**
157 **that cycle-level results generally exist and that they can substantially affect data interpretation;**
158 **we expect this main finding would be consistent across a broad range of datasets just as trends**
159 **themselves also exist a range of datasets (Song et al., 2009; Ravi et al., 2020).**

160 A second, minor limitation is that this paper considered only linear models (Eqns.1-2). While
161 linear drift is also commonly used in alternative detrending procedures including DFA (Ducharme
162 and van Emmerik, 2018; Ravi et al., 2020), it is unclear whether a linear approximation is a
163 suitable model for cycle-level trends. While the software we have developed ([https://github.com/
164 Otodd0000/detrend1d](https://github.com/Otodd0000/detrend1d)) supports several models including: polynomial, exponential, and linear

165 (with or without intercept), further research is needed to consider the appropriateness of these
166 drift models.

167 A final limitation is that we did not consider sample size directly. On one hand, detrending
168 is like filtering in that it is applied to single observations, so sample size is not directly related to
169 detrending. On the other hand, when planning experiments one must consider sample size to ensure
170 that the experiment is both adequately powered but not over-powered. For such power analysis, it
171 would be necessary to understand how detrended results may be affected by factors like recording
172 length. As this study focusses on detrending itself as a data processing procedure, we leave the
173 connection between sample size and detrending for future work.

174 In summary, this study has found that cycle-level trends can generally be present in cyclical
175 biomechanical data, and that these trends can nontrivially bias statistical analyses — and ultimately
176 biomechanical interpretations — with a moderately high frequencies of 24.4% of the 552 trials and
177 92.7% of the 41 participants in the analyzed dataset. It appears advisable to consider cycle-level
178 trends and possibly also to detrend at the cycle level when possible.

179 **Acknowledgments**

180 (None)

181 **Conflict of Interest Statement**

182 The authors report no conflict of interest, financial or otherwise.

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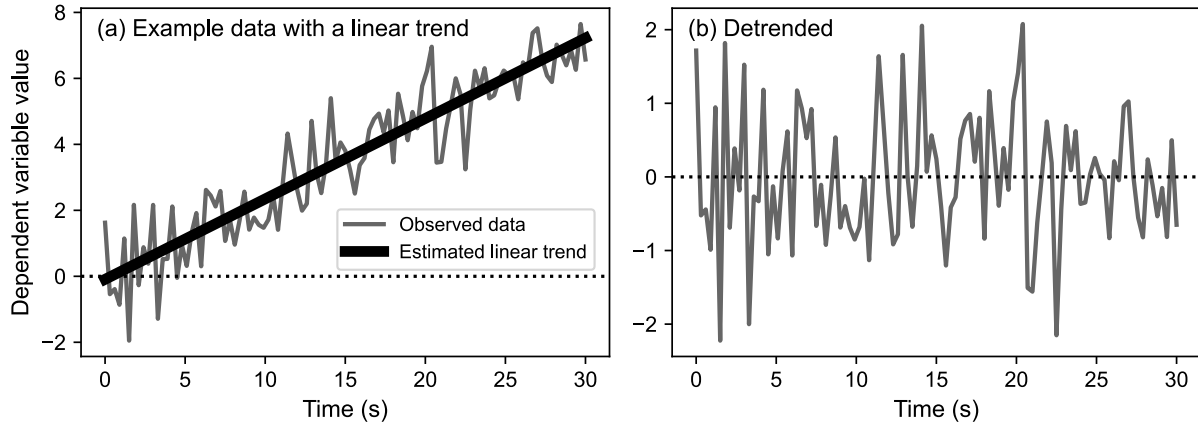


Figure 1: Common trial-level detrending example. (a) Example noisy data with a linear trend. (b) Detrended data: observed data minus estimated trend.

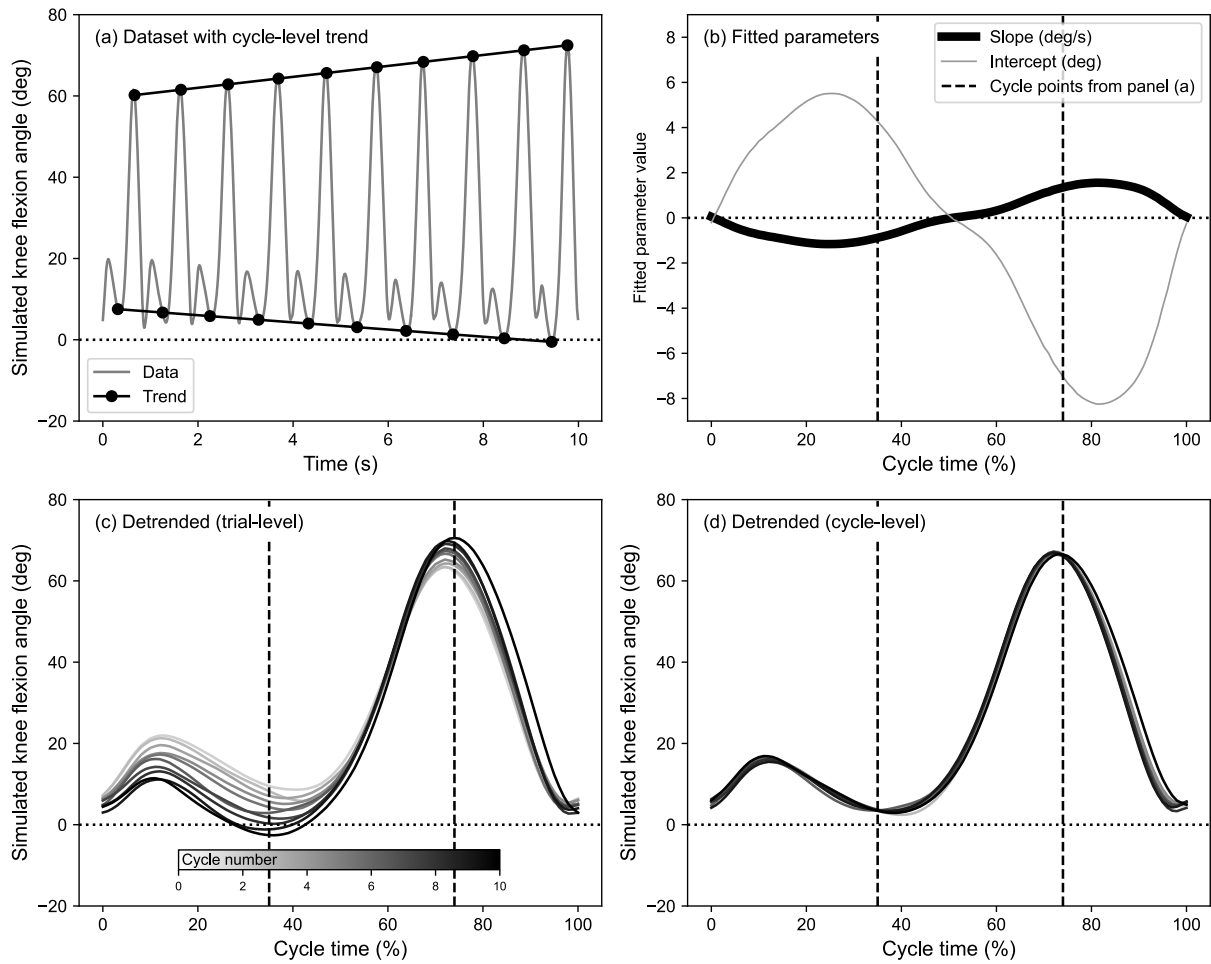


Figure 2: Example cycle-level detrending. (a) Synthetic knee flexion data based on averages from Schwartz et al. (2008), but with a cycle-level trend (i.e., a trend that varies across the cycle). (b) Fitted trend parameters. (c) Trial-level detrended data; curve color encodes cycle number. (d) Cycle-level detrended data.

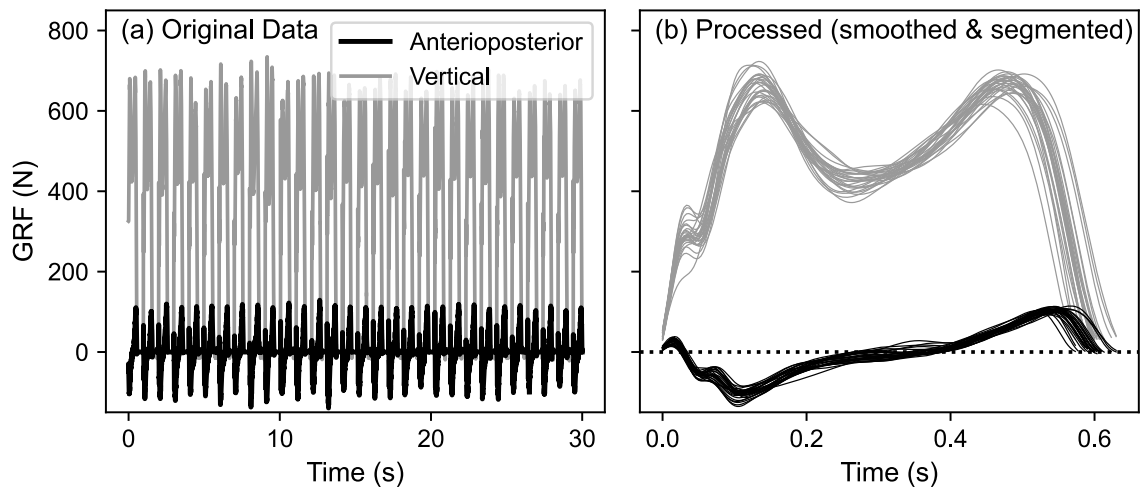


Figure 3: Example trial from the Fukuchi et al. (2018) dataset. (a) Raw ground reaction force (GRF) data recorded during treadmill walking. (b) Same data as (a) but smoothed and segmented into separate cycles.

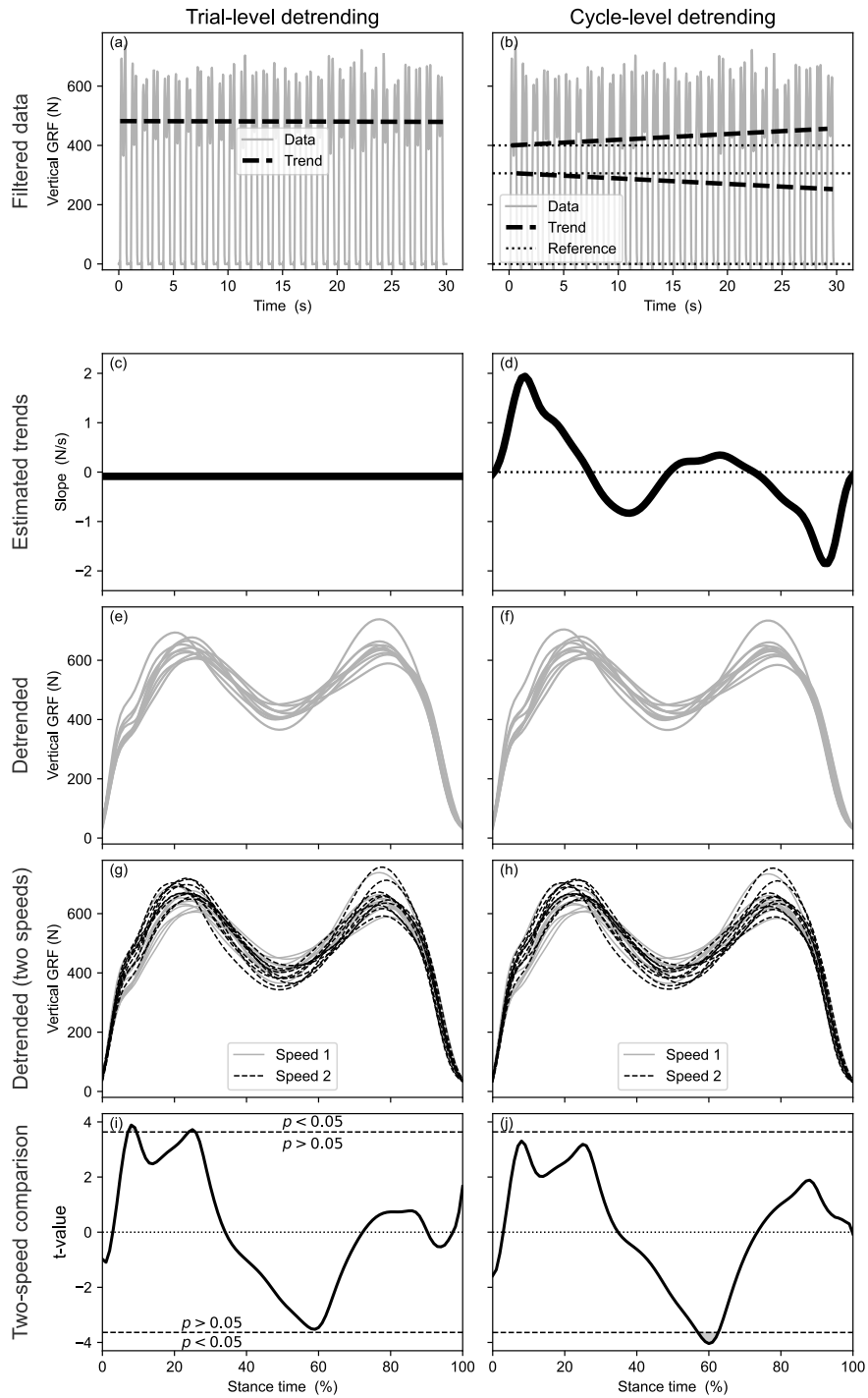


Figure 4: Overview of methods for evaluating whether statistical results differed following trial- vs. cycle-level detrending. (a-b) Raw data depicting estimated trends. (c-d) Trends' slope as a function of cycle time; **while trial-level detrending estimates just a single slope (Eqn.1), cycle-level detrending estimates slope separately for each cycle time point (Eqn.2)**. (e-f) Detrended and temporally registered (time-normalized) data. (g-h) Same as panels e-f but with an additional speed depicted; these two speeds are statistically compared in the last panel row. (i-j) Two-sample t-test results; if the regions identified as significant differed qualitatively — as in this case — detrending was deemed to have had a substantial effect on the statistical analysis.