Journal of Biomechanics 44 (2011) 561–566

Contents lists available at ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech
www.JBiomech.com

Short communication

Methods to temporally align gait cycle data

Nathaniel E. Helwig [a,b], Sungjin Hong [a,*], Elizabeth T. Hsiao-Wecksler [c], John D. Polk [d,e]

[a] Department of Psychology, University of Illinois at Urbana-Champaign, Champaign, IL 61820-6232, USA
[b] Department of Statistics, University of Illinois at Urbana-Champaign, Champaign, IL 61820-5710, USA
[c] Department of Mechanical Science and Engineering, University of Illinois at Urbana-Champaign, Urbana, IL 61801-2906, USA
[d] Department of Anthropology, University of Illinois at Urbana-Champaign, Urbana, IL 61801-3659, USA
[e] Department of Surgery, University of Illinois at Urbana-Champaign, Urbana, IL 61801-2500, USA

ARTICLE INFO

Article history:
Accepted 11 September 2010

Keywords:
Gait analysis
Temporal alignment
Time normalization
Time warping
Curve registration

ABSTRACT

The need for the temporal alignment of gait cycle data is well known; however, there is little consensus concerning which alignment method to use. In this paper, we discuss the pros and cons of some methods commonly applied to temporally align gait cycle data (normalization to percent gait cycle, dynamic time warping, derivative dynamic time warping, and piecewise alignment methods). In addition, we empirically evaluate these different methods' abilities to produce successful temporal alignment when mapping a test gait cycle trajectory to a target trajectory. We demonstrate that piecewise temporal alignment techniques outperform other commonly used alignment methods (normalization to percent gait cycle, dynamic time warping, and derivative dynamic time warping) in typical biomechanical and clinical alignment tasks. Lastly, we present an example of how these piecewise alignment techniques make it possible to separately examine intensity and temporal differences between gait cycle data throughout the entire gait cycle, which can provide greater insight into the complexities of movement patterns.

1. Introduction

Locomotor movement patterns are typically assumed to be periodic, so data are frequently segmented into gait cycles (GCs) for analysis. However, GC duration varies even under relatively steady state conditions (Chao et al., 1983; Cunningham et al., 1982; Murray et al., 1964), and within-GC events often vary in timing as well (Forner-Cordero et al., 2006; Sadeghi et al., 2000, 2003). These temporal differences between and within GCs cause gait data to slightly deviate from the assumed periodicity, which is referred to as quasi- or pseudo-periodicity (Forner-Cordero et al., 2006; Pecoraro et al., 2006). Thus, if point-by-point comparisons of GC trajectories are desired, some temporal alignment technique is needed to handle these between- and within-GC temporal differences.

Several methods are available to temporally align GC data, and different methods are preferred depending on the application. In biomechanical and clinical applications, GC trajectories are often aligned either by converting the data to percentages of the GC (e.g., Perry, 1992; Winter, 1991) or by segmenting trajectories into subphases and temporally aligning corresponding subphases with one another (e.g., Forner-Cordero et al., 2006; Sadeghi et al., 2000, 2003). In contrast, computer science identification/recognition applications often utilize variations of dynamic time warping to align GC data (e.g., Boulgouris et al., 2004; Kale et al., 2003).

While temporal alignment is almost always applied to GC data, there has been little comparison of the different methods used to temporally align GC trajectories. In this paper, we discuss the benefits and shortcomings of several temporal alignment techniques applicable to GC data. Also, we empirically evaluate these techniques' abilities to successfully align a test GC trajectory with a target trajectory. Lastly, given our empirical evaluation, we discuss and provide an example of how these techniques can be used to examine both intensity and temporal differences between GC trajectories throughout the entire GC, which can offer added insight into the movement patterns under study.

2. Methods

2.1. Temporal alignment techniques

An online supplement provides essential formulaic expressions for each alignment technique.

2.1.1. Linear length normalization

Most frequently, gait data are temporally aligned by expressing the data in percentages (0–100%) of the GC (e.g., Perry, 1992; Winter, 1991). Given that this approach linearly compresses/expands the time axis of each GC such that all GCs have the same

* Corresponding author. Tel.: +1 217 244 8296.
E-mail addresses: nhelwig2@illinois.edu (N.E. Helwig), hongsj@illinois.edu (S. Hong), ethw@illinois.edu (E.T. Hsiao-Wecksler), jdpolk@illinois.edu (J.D. Polk).

0021-9290/$ - see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.jbiomech.2010.09.015

length, we refer to this method as linear length normalization (LLN). LLN removes temporal differences between GCs due to differences in GC duration; however, even after GCs are aligned by LLN, temporal differences between events (e.g., peaks and valleys) within the GC still exist (Fig. 1). Such temporal misalignments will confound any point-by-point comparisons of intensity information between trajectories. Furthermore, if summary statistics are calculated for a set of GC trajectories, variation at any one time point will be inflated, and peaks/valleys in averaged GCs will be broader and flatter than for any individual cycle (Sadeghi et al., 2000, 2003).

2.1.2. *Dynamic time warping*

Dynamic time warping (DTW) was developed for spoken-word recognition (Sakoe and Chiba, 1978) and has since been used to temporally align various types of biometric data (e.g., Boulgouris et al., 2004; Cho et al., 2003; Di Brina et al., 2008; Kovács-Vajna, 2000; Zifan et al., 2006). DTW non-linearly compresses/expands the time axis of a test trajectory to find the temporal alignment that minimizes the distance between the intensities of the test and target trajectories. There are two noteworthy consequences of DTW's minimization criterion: (1) when test and target trajectories differ in timing but not intensity, DTW produces successful temporal alignment; and (2) when subphases of test and target trajectories exhibit systematic intensity differences, DTW produces poor temporal alignment. Another important (yet rarely discussed) aspect of DTW is that solutions are highly dependent on user-specified constraints that can cause either distortion of trajectory features (lenient constraints) or insufficient warping to align the trajectories (strict constraints). For a thorough discussion of DTW and possible constraints, see Kruskal and Liberman (1983).

2.1.3. *Derivative dynamic time warping*

Derivative DTW (DDTW) is a modification of DTW that overcomes limitations of DTW's minimization criterion (Keogh and Pazzani, 2001). DDTW non-linearly compresses/expands the time axis of a test trajectory to find the temporal alignment that minimizes the distance between the (estimated) local derivatives of the test and target trajectories. This modification of the minimization criterion means that: (1) when test and target trajectories differ in timing but not shape pattern, DDTW produces successful temporal alignment; and (2) when subphases of test and target trajectories exhibit systematic shape pattern differences, DDTW produces poor temporal alignment. Like in DTW, DDTW solutions are highly dependent on user-specified constraints.

2.1.4. *Piecewise linear length normalization*

Another approach segments GC trajectories into subphases at points of interest (POI; user-determined points to align) and temporally aligns the POI in each test trajectory with the corresponding POI of a target trajectory (Sadeghi et al., 2000, 2003). Given that this approach utilizes LLN in a piecewise manner to align corresponding subphases of GC trajectories, we refer to this method as piecewise LLN (PLLN). POI can be characterizing-points of any within-GC features, so long as it is possible to identify these features across subjects and experimental conditions. The first and last POI in each trajectory should be the first and last time points of the GC to ensure that the cycles' endpoints are aligned. We recommend that within-GC POI be determined based on trajectory shape of the data (using an approach described in Hong, 2009) or be kinematically relevant points in the GC (e.g., heel-strike, toe-off, etc.).

2.1.5. *Piecewise dynamic time warping*

Once GC trajectories are segmented at POI, it is also possible to apply DTW in a piecewise fashion to align corresponding subphases of the trajectories. We recommend that each subphase of each trajectory be individually intensity normalized, since substantial intensity differences interfere with DTW alignment. After intensity normalization, the alignment of each subphase is treated as its own DTW problem, which we refer to as piecewise DTW (PDTW).

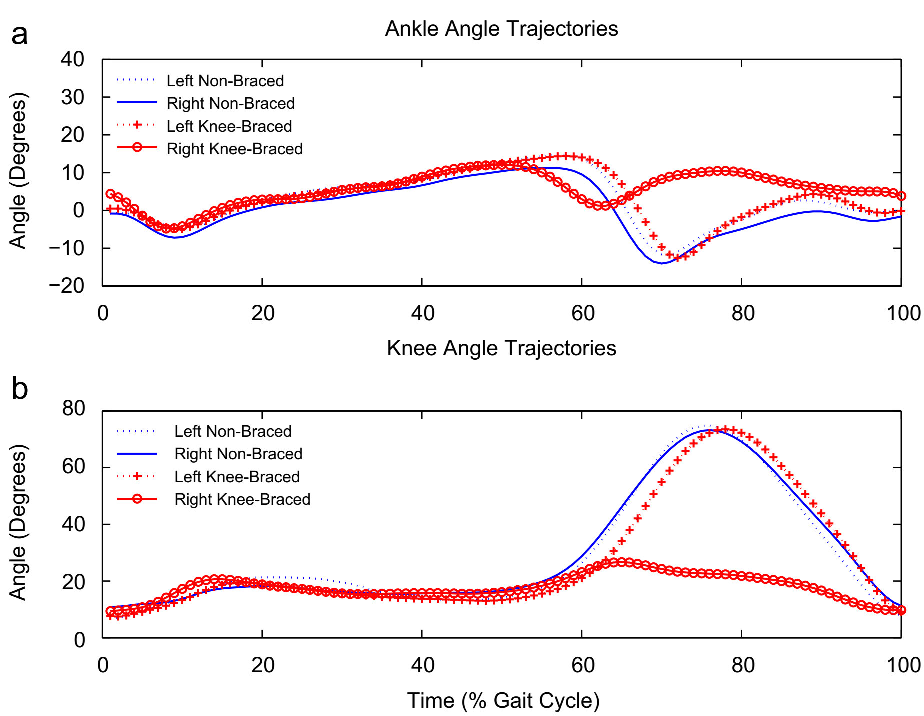

Fig. 1. A sample subject's linear length normalized ankle (a) and knee (b) angular displacement trajectories for a single GC depicting intensity and temporal differences between normal walking (non-braced) and walking with a knee brace on the right knee (knee-braced).

2.2. Data

To illustrate these techniques, we use walking data from Shorter et al. (2008). In these experiments, 10 healthy male subjects (21 ± 2 yrs) walked on a treadmill under two conditions: (1) normal (non-braced) walking; and (2) knee-braced walking. The brace prevented right knee flexion, simulating an injury or other abnormal gait pattern. Bilateral ankle and knee sagittal-plane angles were determined from the motion-capture data (Vicon, Oxford, UK), and 10 consecutive GCs per condition were used per subject.

Before temporal alignment, continuous data were divided into GCs (from heel-strike to heel-strike), and LLN was used to make each GC 100 time points in length. LLN is not a necessary preprocessing step for any of the alignment techniques in this paper. However, LLN makes the data easier to manipulate and facilitates interpretation. Also, the equal length constraint is often applied in any temporal alignment technique mapping a test trajectory to a target, so applying LLN as a preprocessing step will not influence conclusions drawn from the alignment procedures.

2.3. Analyses

Temporal alignment methods (DTW, DDTW, PLLN, and PDTW) were applied to align non-braced and braced trajectories with the appropriate (ankle or knee) target trajectory. The target trajectory is defined as the average trajectory (averaged over legs, subjects, and GC replications) during the non-braced condition. This average was chosen as the target to quantify intensity and temporal differences from normative behavior within and between subjects in both conditions.

For the dynamic warping algorithms, several constraints were imposed. *Boundary* constraints required alignment of the test and target trajectory endpoints. *Monotonicity* constraints preserved the order of the test trajectory time indices. *Continuity* constraints ensured mapping of all test trajectory time indices onto some time index/indices of the target (and vice-versa). *Window* constraints required that the alignment did not stray too far from the LLN mapping. Lastly, *slope* constraints prevented excessive compression and expansion of test trajectory points. Window and slope constraints were empirically determined to find a balance between trajectory shape preservation and effective temporal alignment. For the piecewise techniques, we selected POI to be the prominent maxima and minima in the data trajectories by taking the time indices nearest to local maxima and minima within predetermined ranges of interest (Figs. 2a and 3a).

To evaluate the effectiveness of the temporal alignment techniques at matching the shape patterns of the test and target trajectories, we calculated the Euclidean distance between the (estimated) local derivatives of the test and target trajectories after alignment, referred to as the derivative distance. A smaller derivative distance represents a better alignment of the shape patterns in the trajectories, regardless of intensity differences. The average derivative distance (averaged over subjects and GC replications) was used for evaluating the temporal alignment techniques.

3. Results

For the non-braced data, temporal and intensity deviations from the target trajectories were minimal after only LLN was applied (Figs. 2a, 3a, and 4a LLN). DTW resulted in poor alignment of the POI, and both DTW and DDTW produced distorted aligned cycles (Figs. 2b,c and 3b,c). Furthermore, relative to the LLN baseline, both DTW and DDTW increased shape dissimilarity (i.e., derivative distance) between the test and target trajectories (Fig. 4a DTW, DDTW). In contrast, PDTW and PLLN provided more

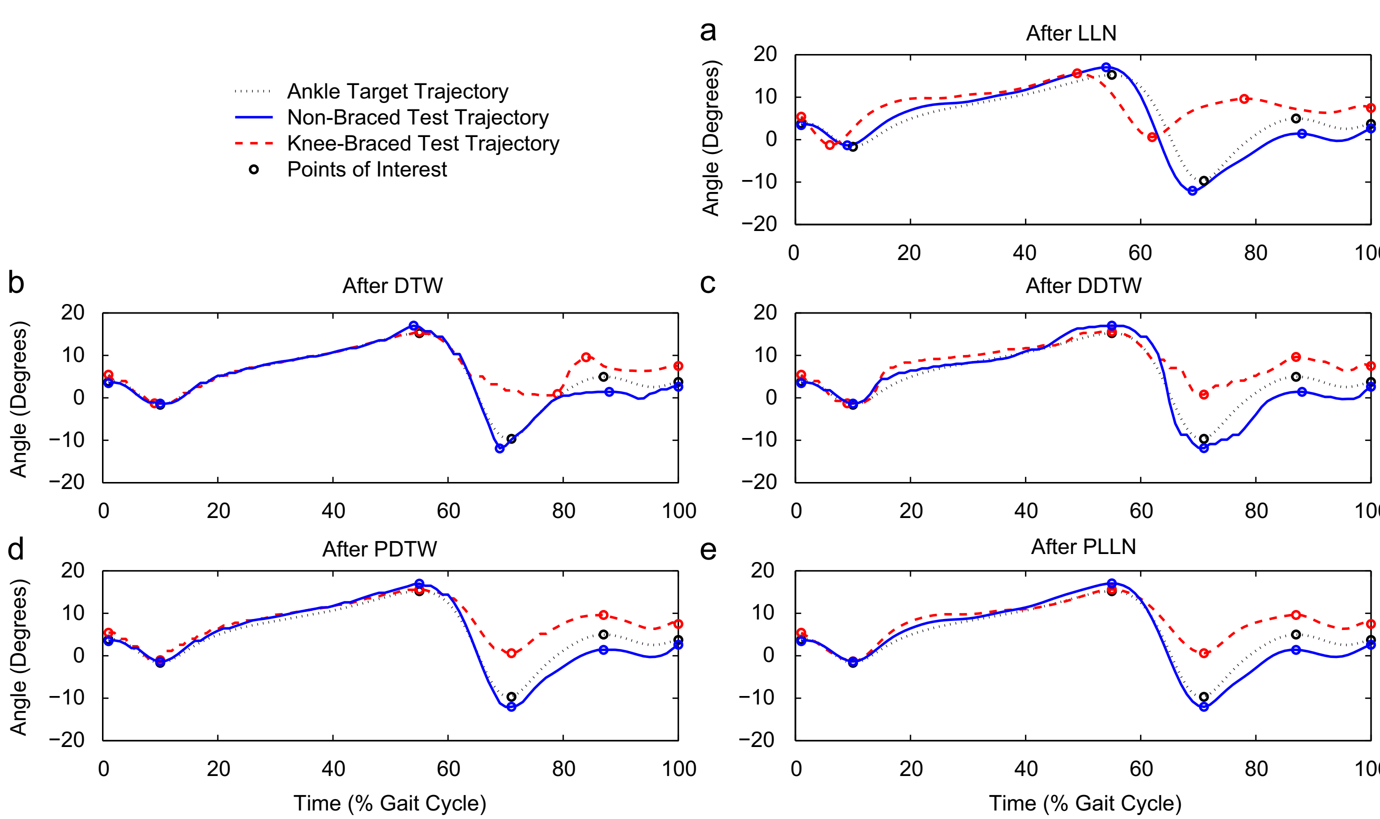

Fig. 2. The target ankle angle trajectory and a typical subject's right ankle angle trajectory in both conditions after each temporal alignment method.

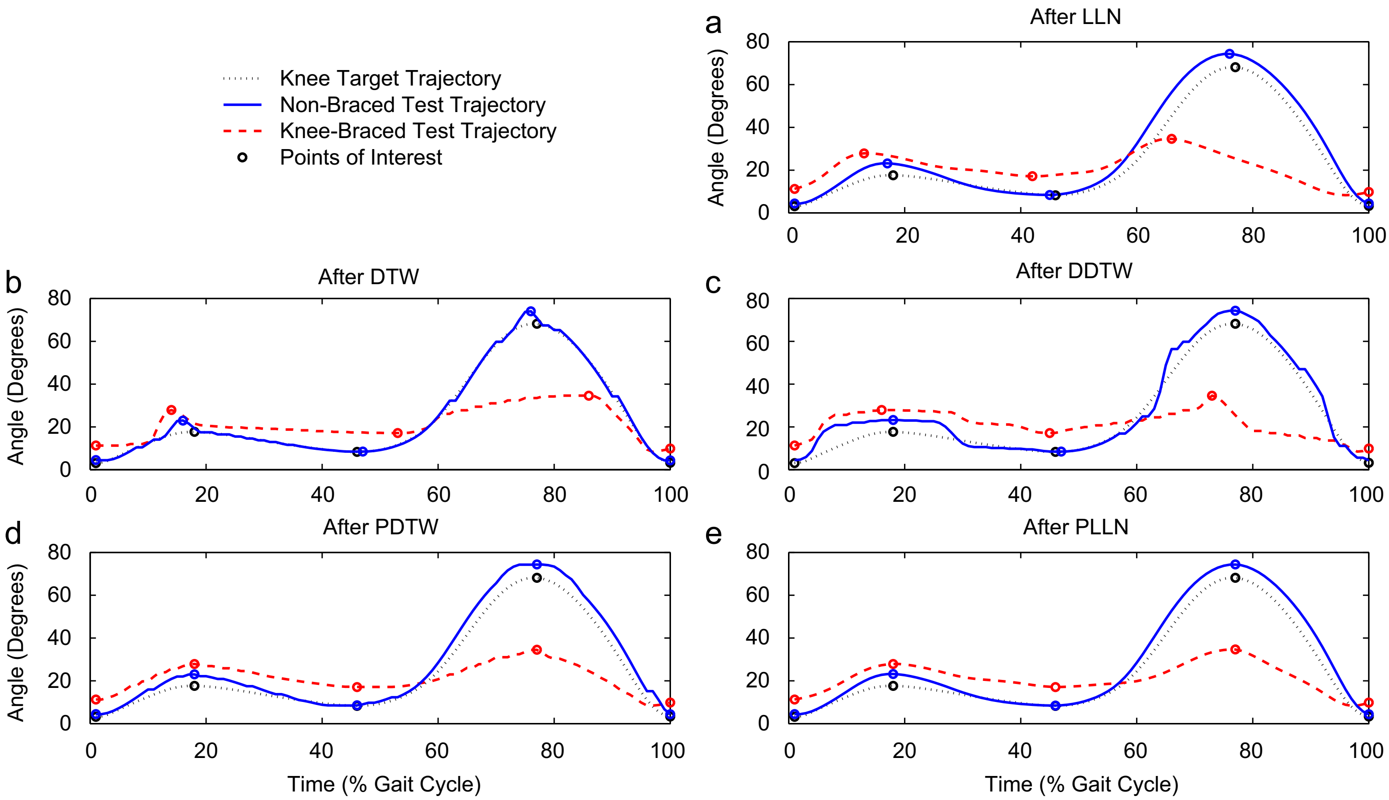

Fig. 3. The target knee angle trajectory and a typical subject's right knee angle trajectory in both conditions after each temporal alignment method.

desirable alignment results (Figs. 2d,e and 3d,e) and produced less shape dissimilarity (Fig. 4a PDTW, PLLN).

The braced-walking results differed depending on the limb. For the left limb, the results were similar to the non-braced data (Fig. 4 Left Ankle, Left Knee). However, the right limb results illustrated the systematic differences caused by the right knee bracing. For the right ankle, all of the temporal alignment procedures removed some of the systematic temporal differences caused by the brace, with PDTW and PLLN providing the best alignment (Figs. 2 and 4b Right Ankle). For the Right Knee, DDTW actually increased the shape dissimilarity, whereas the other techniques reduced the dissimilarity, with PDTW and PLLN performing best (Figs. 3 and 4b Right Knee).

4. Discussion

4.1. Comparison of temporal alignment techniques

These results demonstrate that different techniques used to temporally align GC data can produce quite different alignment results, potentially leading to different interpretations of the data. Unlike LLN, DTW was able to reduce some of the temporal differences between events within GC trajectories; however, DTW misaligned GC events when systematic intensity differences existed between subphases of the test and target trajectories. DDTW, on the other hand, was better able to align GC events despite intensity differences and without requiring any *a priori* information on where to search for the events. However, DDTW sometimes introduced distortion to the aligned trajectories and did not produce ideal alignment for the right knee-braced data (due to systematic shape pattern differences induced by the bracing). Like DDTW, PDTW and PLLN were able to effectively align shape patterns in GC trajectories regardless of intensity differences. Furthermore, PDTW and PLLN produced more desirable alignment results than DDTW when trajectory shape differences existed between the test and target trajectories.

The question of which temporal alignment technique should be used depends on the application. In recognition/identification applications, a researcher desires an alignment technique that only provides successful alignment when the test and target trajectories "match" (i.e., when they differ in timing but not intensity or shape pattern). In these applications, DTW or DDTW should be preferred, given that the piecewise approaches constrain the alignment such that POI are aligned regardless of whether the test and target match. However, in biomechanical and clinical applications, a researcher often desires to temporally align GC trajectories for the purpose of aligning subphases in the trajectories. For these applications, PDTW or PLLN is the more logical choice, given that these piecewise approaches directly accomplish the alignment goals. Given the straightforwardness of the algorithm, we recommend PLLN to align POI in GC trajectories.

When using PLLN, the choice between trajectory shape versus kinematic POI depends on the research goals. Kinematic POI preserve temporal synchronization between joints and often provide more meaningful biomechanical and clinical interpretations. In contrast, trajectory shape POI make it possible to separately analyze each joint trajectory's distinct temporal deviation from its corresponding target. Thus, kinematic POI should be used when it is important for data to be analyzed holistically, whereas trajectory shape POI are more appropriate when data are to be analyzed atomistically.

4.2. Examining intensity and temporal differences

In biomechanical and clinical applications, intensity and temporal differences between GC trajectories are often discussed only at select points within the GC (e.g., Shorter et al., 2008; Wojcik et al., 2001). In contrast, the techniques discussed here make it

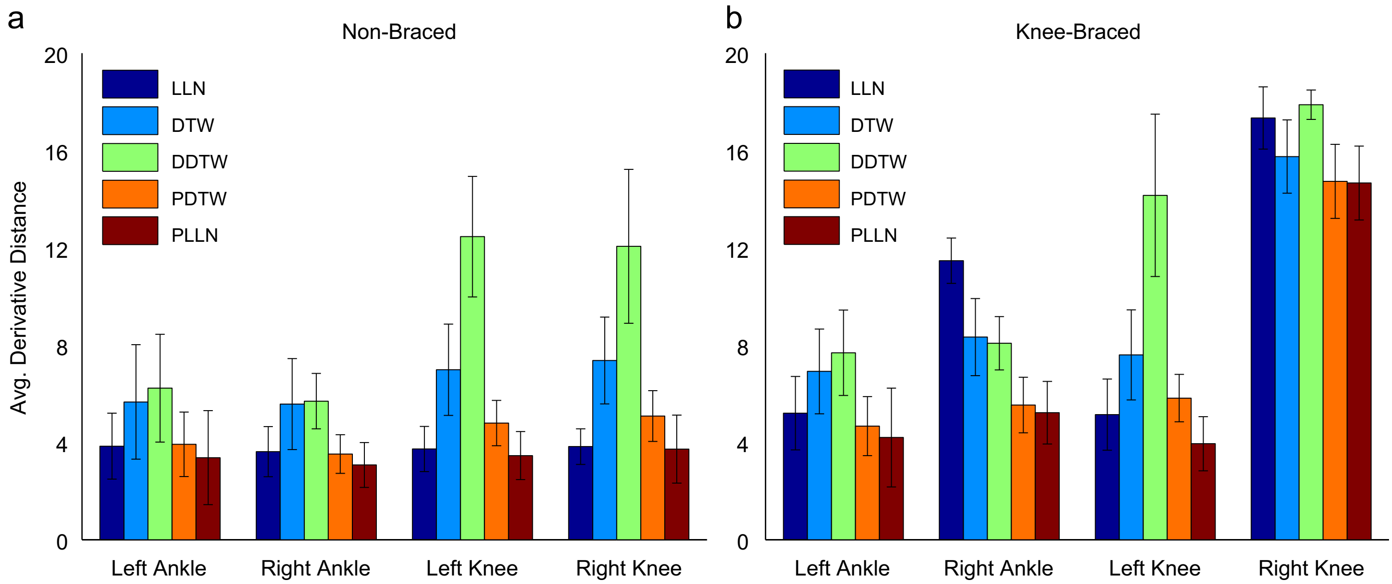

Fig. 4. The average (with standard deviation bars) derivative distance between the test and target trajectories for each joint angle after each temporal alignment method. The averages are across 100 GCs (10 GC replications from 10 subjects). Smaller values indicate better shape alignment of the joint angle trajectories.

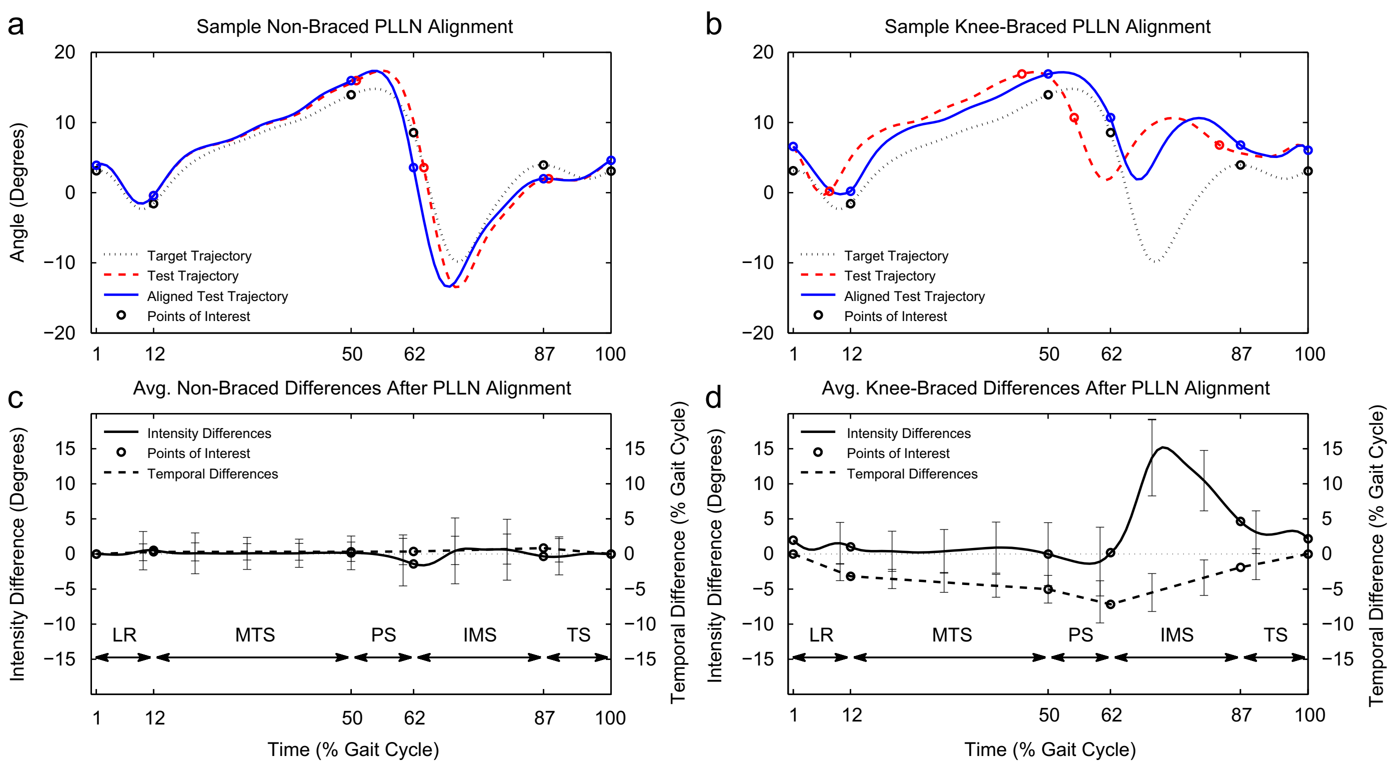

Fig. 5. PLLN alignment of a typical subject's non-braced (a) and knee-braced (b) right ankle angle trajectory using four within-GC kinematic POI that segment the GC into five biomechanical subphases: (1) loading response (LR); (2) mid- and terminal-stance (MTS); (3) pre-swing (PS); (4) initial- and mid-swing (IMS); and (5) terminal-swing (TS). The average (with standard deviation bars) intensity and temporal differences (i.e., test minus target values) for the non-braced (c) and knee-braced (d) data are plotted over the course of the GC. The averages are across 100 GCs (10 GC replications from 10 subjects). Larger absolute values indicate greater deviations from normative behavior.

possible to separately examine intensity and temporal differences between GC trajectories throughout the entire GC. After temporal alignment, intensity differences between trajectories can be meaningfully calculated at each point throughout the GC. In addition, by recording the directions and magnitudes of the temporal shifts necessary for alignment, it is possible to quantify temporal differences between trajectories at each point throughout the GC. When examined together, these intensity and temporal differences may be used to characterize and better understand the movement patterns of subjects or subject populations.

As an example, we show how PLLN can be used to examine intensity and temporal differences between biomechanical subphases of GC trajectories (as defined by Perry, 1992). We segment non-braced and knee-braced right ankle angle trajectories at four within-GC kinematic POI (Fig. 5a,b) to examine five biomechanical subphases of the GC: (1) loading response (LR); (2) mid- and terminal-stance (MTS); (3) pre-swing (PS); (4) initial- and mid-swing (IMS); and (5) terminal-swing (TS). In the non-braced data, intensity and temporal differences (i.e., test minus target values) are minimal throughout the GC (Fig. 5c). In contrast, the knee-braced data show average intensity differences as large as 15° during IMS (Fig. 5d). Also, the knee-braced data display substantial negative temporal differences throughout the GC, indicating that the POI in the braced data lead the POI in the target (Fig. 5d). By examining temporal differences at the pairs of POI defining the stance subphases, we see that the brace causes the average durations of LR, MTS, and PS to decrease by about 3%, 2%, and 2% GC, respectively, causing IMS to begin about 7% GC earlier (Fig. 5d). Thus, taken together, these differences suggest that the knee-braced walkers spend a longer-than-normal percentage of the GC in the swing subphases, i.e., IMS (5% GC longer) and TS (2% GC longer), during which they exhibit substantially reduced motion at the right ankle.

4.3. Concluding remarks

Temporal alignment of gait data is a necessary step to make point-by-point comparisons of GC trajectories meaningful and accurate. This work demonstrates that piecewise temporal alignment methods outperform several commonly applied alignment techniques at mapping a test GC trajectory to a target. In addition, we demonstrate how these piecewise methods facilitate the examination of both intensity and temporal differences between GC trajectories at all points throughout the GC, which permits a more detailed quantification and characterization of the behaviors under study.

Conflict of interest statement

The authors have no conflicting interests.

Acknowledgements

This work was supported by the NSF (#0727083) and Mary Jane Neer Disability Research Fund at the University of Illinois. Thanks to Louis DiBerardino, K. Alex Shorter, Prof. Karl Rosengren, and anonymous reviewers for their assistance and comments.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jbiomech.2010.09.015.

References

Boulgouris, N.V., Plataniotis, K.N., Hatzinakos, D., 2004. Gait recognition using dynamic time warping. In: IEEE 6th Workshop on Multimedia Signal Processing, pp. 263–266.

Chao, E., Laughman, R., Schneider, E., Stauffer, R.N., 1983. Normative data of knee joint motion and ground reaction forces in level walking. Journal of Biomechanics 16, 213–233.

Cho, H., Ojemann, G.A., Corina, D., Shapiro, L., 2003. Detection of neural activity in event related fMRI using wavelets and dynamic time warping. Proceedings of SPIE—The International Society for Optical Engineering 5203, 638–647.

Cunningham, D., Rechnitzer, P., Pearce, M.A., Donner, A.P., 1982. Determinants of self selected walking pace across ages 19 to 66. Journal of Gerontology 37, 560–564.

Di Brina, C., Niels, R., Overvelde, A., Levi, G., Hulstijn, W., 2008. Dynamic time warping: a new method in the study of poor handwriting. Human Movement Science 27, 242–255.

Forner-Cordero, A., Koopman, H.J.F.M., van der Helm, F.C., 2006. Describing gait as a sequence of states. Journal of Biomechanics 39, 948–957.

Hong, S., 2009. Warped factor analysis. Journal of Chemometrics 23, 371–384.

Kale, A., Cuntoor, N., Yegnanarayana, B., Rajagopalan, A.N., Chellappa, R., 2003. Gait analysis for human identification. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 2688, pp. 706–714.

Keogh, E., Pazzani, M., 2001. Derivative dynamic time warping. In: First SIAM International Conference on Data Mining, Chicago, Illinois.

Kovács-Vajna, Z.M., 2000. A fingerprint verification system based on triangular matching and dynamic time warping. IEEE Transactions on Pattern Analysis and Machine Intelligence 22, 1266–1276.

Kruskal, J., Liberman, M., 1983. The symmetric time-warping problem: from continuous to discrete. In: Sankoff, D., Kruskal, J. (Eds.), Time Warps, String Edits, and Macromolecules: The Theory and Practice of Sequence Comparison. Addison-Wesley, Reading, MA, pp. 125–161.

Murray, M.P., Drought, A.B., Kory, R.C., 1964. Walking patterns of normal men. Journal of Bone and Joint Surgery 46, 335–360.

Pecoraro, F., Mazzà, C., Zok, M., Cappozzo, A., 2006. Assessment of level-walking aperiodicity. Journal of NeuroEngineering and Rehabilitation 3, 28. doi:10.1186/1743-0003-3-28.

Perry, J., 1992. Gait Analysis: Normal and Pathological Function. SLACK Incorporated, Thorofare, NJ.

Sadeghi, H., Allard, P., Shafie, K., Mathieu, P.A., Sadeghi, S., Prince, F., Ramsay, J., 2000. Reduction of gait data variability using curve registration. Gait and Posture 12, 257–264.

Sadeghi, H., Mathieu, P.A., Sadeghi, S., Labelle, H., 2003. Continuous curve registration as an intertrial gait variability reduction technique. IEEE Transactions on Neural Systems and Rehabilitation Engineering 11, 24–30.

Sakoe, H., Chiba, S., 1978. Dynamic programming algorithm optimization for spoken word recognition. IEEE Transactions on Acoustics, Speech, and Signal Processing 26, 43–49.

Shorter, K.A., Polk, J.D., Rosengren, K.S., Hsiao-Wecksler, E.T., 2008. A new approach to detecting asymmetries in gait. Clinical Biomechanics 23, 459–467.

Winter, D.A., 1991. The Biomechanics and Motor Control of Human Gait: Normal, Elderly, and Pathological. University of Waterloo Press, Waterloo, Ontario.

Wojcik, L.A., Thelen, D.G., Schultz, A.B., Ashton-Miller, J.A., Alexander, N.B., 2001. Age and gender differences in peak lower extremity joint torques and ranges of motion used during single-step balance recovery from a forward fall. Journal of Biomechanics 34, 67–73.

Zifan, A., Saberi, S., Moradi, M.H., Towhidkhah, F., 2006. Automated ECG segmentation using piecewise derivative dynamic time warping. International Journal of Biomedical Sciences 1, 181–185.