

# TIME-NORMALIZATION TECHNIQUES FOR GAIT DATA

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## INTRODUCTION

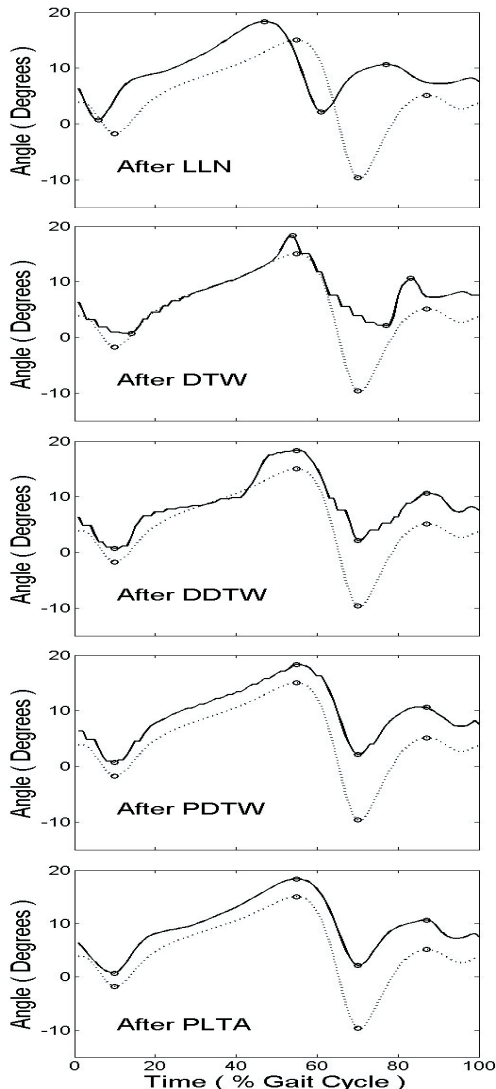
Given natural variation in walking behavior, segmenting data into gait cycles almost always results in gait cycle data of differing lengths. To compare data (e.g., ankle angle trajectories) within or between individuals, it is necessary to use some time-normalization technique so that a point-by-point comparison of intensity information between the data trajectories is possible.

A method commonly used to “time-normalize” gait data (here referred to as linear length normalization [LLN]) is to linearly convert the trajectory’s time axis from the experimentally-recorded time units to an axis representing percentage of the gait cycle. However, other time-normalization techniques are also possible, such as dynamic time warping [DTW]<sup>1</sup> and derivative dynamic time warping [DDTW]<sup>2</sup>. DTW shifts the time index of each data point in a test trajectory to minimize the distance between the test and consensus trajectories. DDTW is a modification of DTW that minimizes the difference in the first derivatives of the trajectories.

In this paper, we compare the performance of LLN, DTW, and DDTW for aligning gait data trajectories and present the benefits of two new methods (piecewise linear temporal alignment [PLTA] and piecewise dynamic time warping [PDTW]). PLTA segments trajectories at points of interest (i.e., prominent maxima and minima) and applies LLN to align corresponding segments in the test and consensus trajectories. PDTW is a modification of DTW where trajectories are segmented at points of interest and classical DTW is used to align corresponding intensity-normalized segments.

## METHODS

For our analysis, we focused on joint angle trajectories collected from the right and left legs of



**Figure 1:** Ankle angle trajectory for consensus non-braced data (dotted) and a right ankle angle trajectory during knee-braced condition after the given time-normalization technique is applied (solid).

10 young ( $21 \pm 2$  years) male subjects. (Note: these techniques can be used to temporally align other 1D gait data trajectories as well). Subjects ambulated on a treadmill under two conditions: 1) non-braced (normal) walking, and 2) knee-braced walking such that right knee motion was completely restricted by a brace (DonJoy, Vista, CA). Kinematic data were

collected using a six camera motion analysis system at 120 Hz (Vicon, Oxford, UK; Model 460).

Consensus angle trajectories were created for both the ankle and knee by averaging LLN-adjusted non-braced data over cycles, legs, and subjects. Each trajectory (non-braced or knee-braced) was then aligned with the appropriate non-braced consensus by all of the time-normalization methods (Figure 1). To evaluate the effectiveness of the temporal alignment techniques, we calculated the difference in the first derivatives (i.e., rate-of-change) between the test and consensus trajectories after alignment.

## RESULTS AND DISCUSSION

As expected, when aligning the non-braced data, temporal and shape pattern differences from the consensus were minimal after LLN was applied. Compared to LLN, DTW and DDTW increased the average shape dissimilarity (i.e., squared difference in the first derivatives) between the test trajectories and the consensus (Figure 2). In contrast, both PDTW and PLTA reduced the shape dissimilarity (compared to LLN) for the ankle data, and PLTA reduced the dissimilarity for the knee data.

Results from the braced condition illustrate the systematic temporal and shape pattern differences caused by the knee brace (Figure 2). For the right ankle, all time-normalization techniques were able to remove (compared to LLN) some of the systematic temporal differences caused by the brace (with PDTW and PLTA performing best). For the right knee, DDTW increased (compared to LLN) the shape dissimilarity between the aligned

trajectories and the consensus, whereas the other techniques reduced the dissimilarity (with PDTW and PLTA providing the best alignment).

## CONCLUSIONS

Our results demonstrate that different methods used to temporally align gait data can produce rather different alignment results (Figure 1).

LLN makes gait data trajectories length-comparable but does nothing to address localized temporal differences within the trajectories. DTW is able to address localized temporal differences but is inappropriate when natural intensity differences exist in localized segments of the data trajectories (which is true of most gait data).

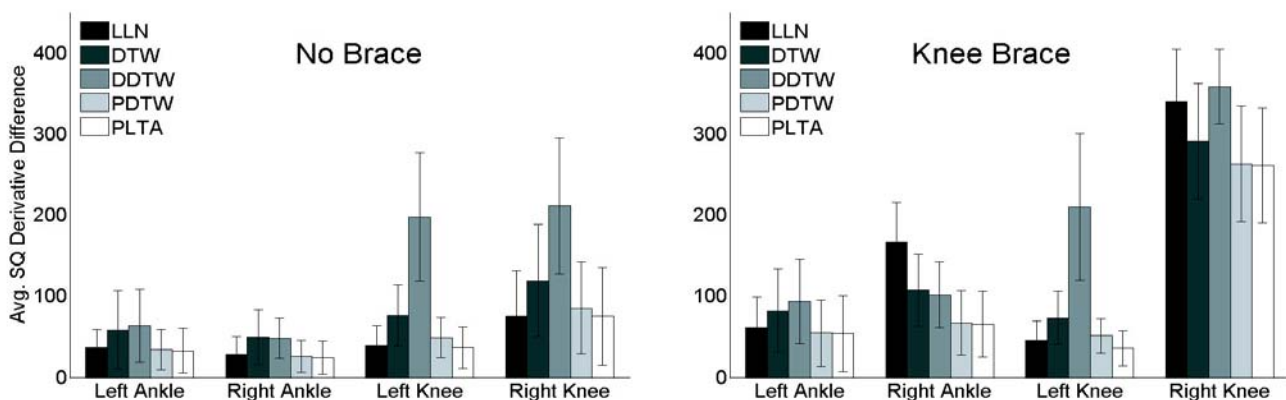
In contrast, DDTW, PDTW, and PLTA are able to effectively align points of interest in gait data trajectories, regardless of intensity differences. We have found that PLTA and PDTW produce smoother, more natural looking curves than DDTW. Thus, we recommend the use of PLTA or PDTW to temporally align (and to quantify temporal differences within) gait data trajectories.

## REFERENCES

1. Sakoe H & Chiba S. *IEEE Trans. on Acoustics, Speech, and Signal Processing*, **26**, 43–49, 1978.
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## ACKNOWLEDGEMENTS

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**Figure 2:** Average squared difference in the first derivatives of the consensus angle trajectory and the aligned trajectory after each time-normalization method.