Shimmer Gait Algorithm Updates

April 8, 2017

The purpose of this report is to highlight development of the Shimmer gait algorithm and describe what changes could potentially become part of the algorithm that is deployed to customers. Shimmer has obtained two powerful data-sets (UCD-INSIGHT 2015 / 2016) that give us the ability to test out different processing methods and determine which is most appropriate to include as part of the Shimmer gait algorithm.

Specifically this report will assess the ability to implement toe-off (TO) detection algorithms. During normal walking one foot is placed on the ground while the contra-lateral foot is still in contact with the ground. Shortly after initial contact (IC) the contra-lateral foot leaves the ground, this gait event is known as toe-off (TO). It has been shown to be more difficult to detect TO from a lumbar mounted inertial sensor than IC due to the fact that TO is not associated with sharp changes in acceleration like IC is. However, it is still important to assess how well accurate TO detection (and subsequent stance time) is on the large data-sets that have been collected as part o the UCD-INSIGHT collaboration in 2015 / 2016.

Contents

1. Highlights

- Original method of TO detection
  - In the current Shimmer Gait Algorithm gait event detection is based on the Zjlistra et al, 2003 method of IC detection and Kose et al, 2012 method of TO detection.
- CWT gait event detection
  - McCamley et al, 2012 proposed using a continuous wavelet function to obtain a sinusoidal signal from the vertical acceleration channel to zero in on IC and TO locations
- Filter step frequency method (better because we can avoid the use of MATLAB Toolboxes)
  - Primary frequency of stepping is already calculated in the Shimmer Gait Algorithm
  - Use this to create a filter on the vertical acceleration signal to show the main frequency of walking
  - Use this curve in place of the wavelet to zero in on IC and TO locations

1.1. Results – 2015 Data-Set

	Zjlistra et al, 2013	McCamley et al, 2012	New filter
2015 data-set (correlation / CI width %)	0.9921 5.27%	0.9900 5.87%	0.9945 4.41%
2016 data-set (correlation / CI width %)	0.9874 7.20%	0.9800 8.54%	0.9858 7.07%

1.2. Results – 2016 Data-Set

	Kose et al, 2012	McCamley et al, 2012	New filter (IC-Zjlistra)	New filter (IC-new)
2015 data-set (correlation / CI width %)	0.8591 26.22%	0.8676 26.37%	0.9201 18.70%	0.9463 17.17%
2016 data-set (correlation / CI width %)	0.8758 21.70%	0.6163 35.83%	0.7212 28.68%	0.8433 23.38%

1.3. Conclusion

- New filter method of IC detection results in slightly more accurate detections than the current algorithm. These improvements are marginal, and do not warrant changing the algorithm at this point, but is relevant to keep in mind for future development, as an option to improve slightly.
- Stance time measures are not accurate enough to include in the Shimmer Gait Algorithm. Error rates were 17% on the healthy data-set and 21% on the pathological data-set. These errors are high enough that it would not be appropriate for Shimmer to provide to customers.
- If there are customers that want stance time specifically we could either look at providing algorithms based on sensors that are worn lower down on the body, or else providing the described algorithms with the caveat that they are solely based of the academic literature description of the algorithms and they have not been validated specifically by Shimmer.

2. Algorithm Summaries

2.1. Original Shimmer Algorithm: IC - Zijlstra & Hof, 2003, TO – Kose et al, 2012

IC finding in the current Shimmer Gait Algorithm is based on method proposed by Zijlistra & Hof, 2003 and are shown in Figure 1.

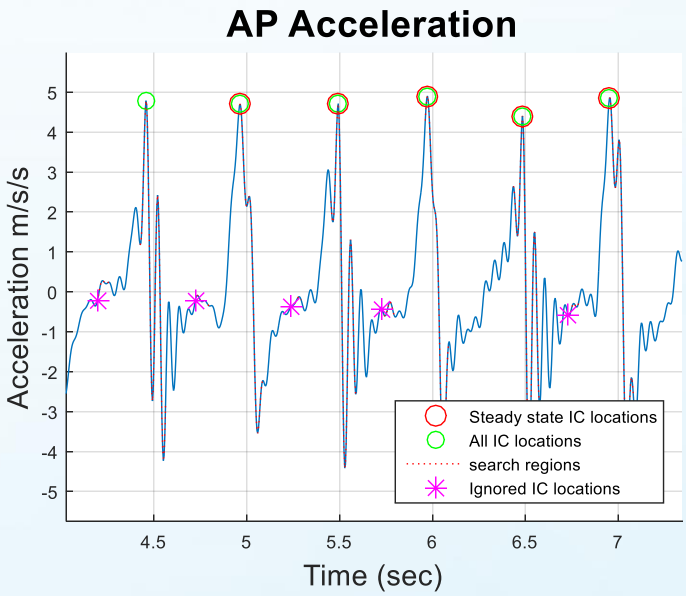


Figure 1 - IC detection in Shimmer Gait Algorithm is based on methods proposed by Zijlistra and Hof, 2003.

In the current Shimmer Gait Algorithm, TO is detected, however, no TO based metrics are provided by the algorithm as the TO functionality was not formally validated. The TO detection method that is implemented is based on a paper by Kose et al, 2012 which proposes to find TO at a minimum on the vertical acceleration channel following the large spike associated with mid-step (Figure 2).

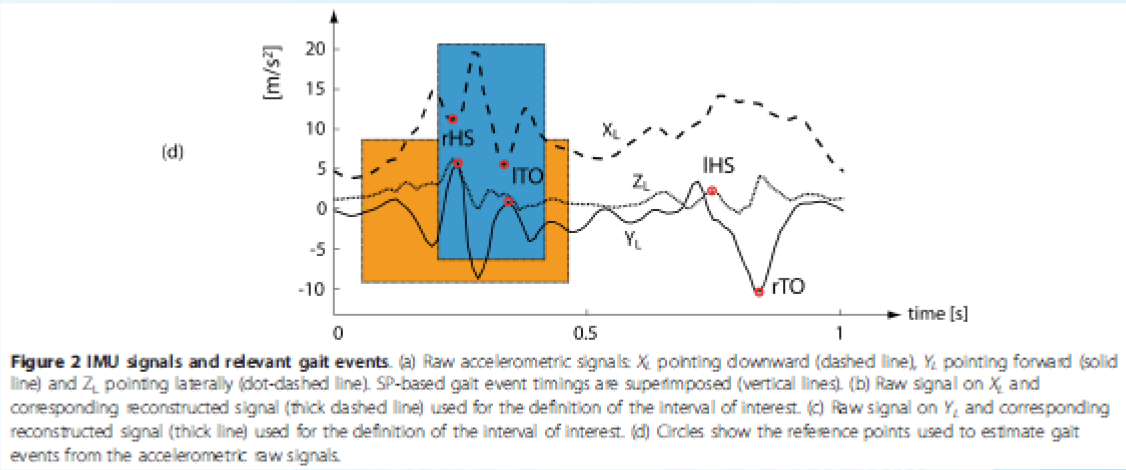


Figure 2 - A figure from Kose et al, 2012 describing where TO can be found on the vertical acceleration channel.

2.2. CWT Method of Gait Event Detection

An alternate method of gait event detection was investigated. This method is based on the McCamley et al 2012 paper and is based on first integrating the vertical acceleration and then differentiating it using a continuous wavelet transform and finding initial contact (IC) and toe-off (TO) events at minimums and upwards zero crossings on the resulting sinusoidal curve (Figure 1).

J. McCamley et al. / Gait & Posture 36 (2012) 316–318 317

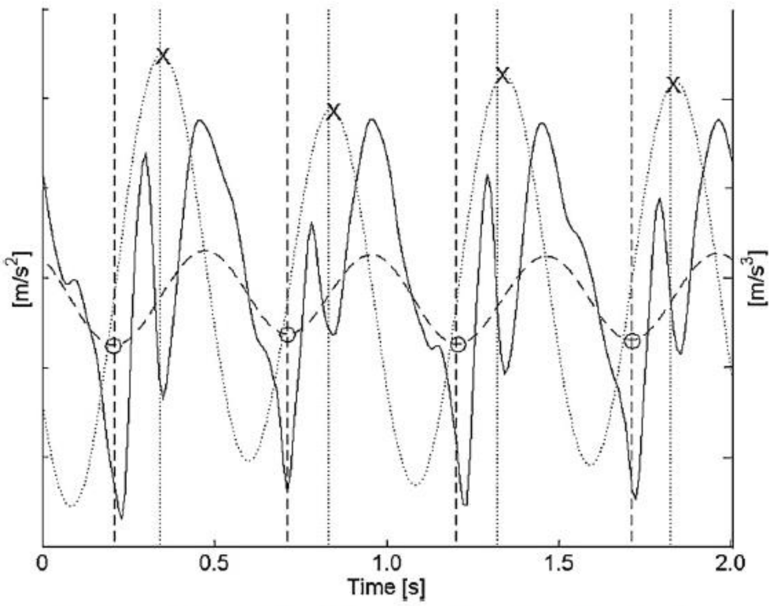


Fig. 1. Proposed method (M1) for determining gait event times. Vertical acceleration (solid line) is integrated and then differentiated using CWT (dashed line). Minima from this signal correspond to the ICs (○). Further differentiation (dotted line) provides jerk maxima which correspond to the FCs (×). Vertical dashed and dotted lines indicate the ICs and FCs measured from the mat, respectively.

Figure 3 - Visual explanation of McCamley et al, 2012 method of gait event detection.

Figure 3 shows the typical performance of the McCamley continuous waveform method of gait event detection. The implementation in the algorithm was to detect IC and TO events with the current Shimmer gait algorithm (based on Zjlistra and Kose methods) and then zero in on IC and TO points on the wavelet recommended from McCamley. Note that McCamley recommends differentiating the wavelet signal and then zeroing in on TO locations at the peak on the differentiated curve. For the current implementation, the differentiation step was ignored and TO's were zeroed in on at positive going zero crossings on the wavelet signal, which is the same location at the peak on the differentiated signal.

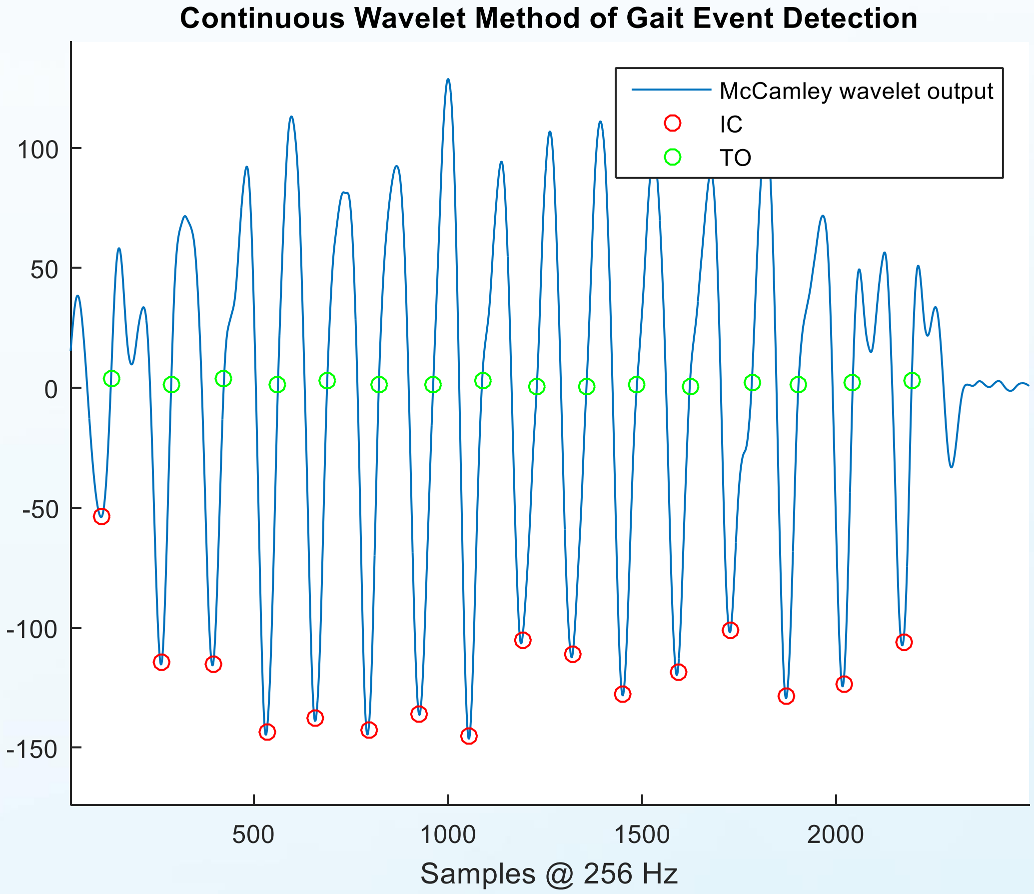


Figure 4 - Typical output from the McCamley et al, 2012 method of IC/TO detection.

2.3. New band pass filter on vertical acceleration

The resulting wavelet that McCamley et al 2012 proposes gait event detection on is representative of the frequency of stepping, as it is a sinusoidal curve that shows clearly each step during the walking trial. In the current Shimmer Gait Algorithm, the primary frequency of stepping is obtained in order to create a filtered version of the anterior-posterior acceleration which is then used for feature finding. The primary frequency was used to determine the low pass filter level to create a sinusoidal curve based around the frequency of stepping on the vertical acceleration channel. A small training set revealed that 1.5 times the primary frequency was an appropriate threshold. The result is that essentially the same curve is obtained as the McCamley method without having to use the Continuous Wavelet function from MATLAB, which only exists in the MATLAB Signal Processing Toolbox. This means that implementation into production code would be much cheaper and more simple. Figure 5 shows an example of the new filter on one participant.

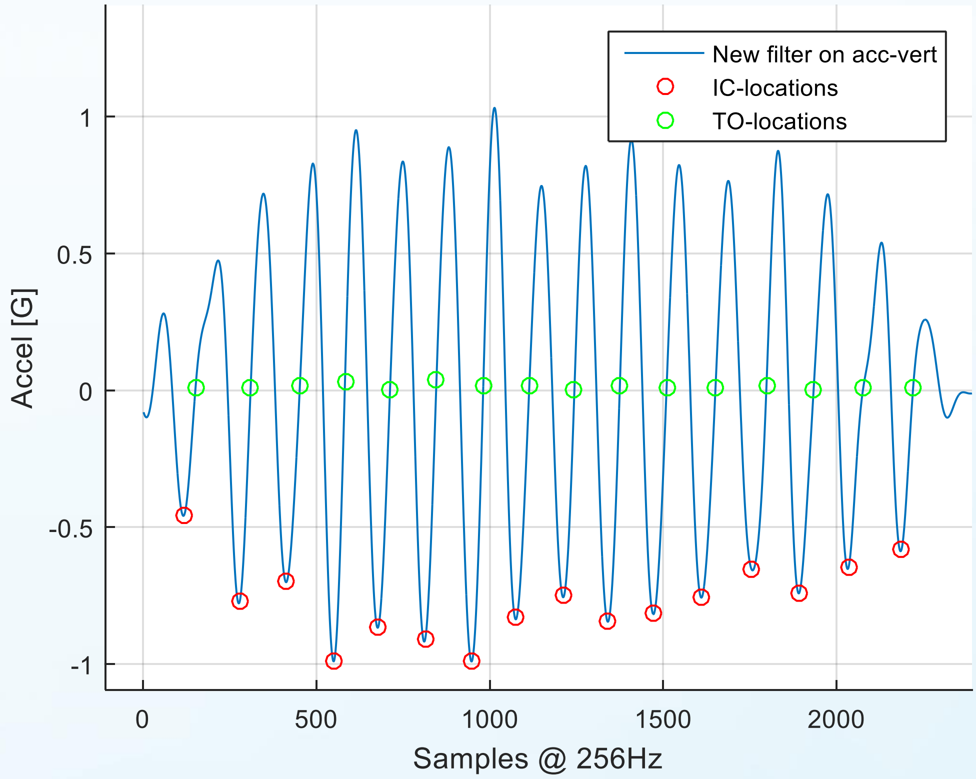


Figure 5 - New filter that has been used to detect gait events. Sinusoidal curve results in similar curve to McCamley et al, 2012 output to zero in on IC and TO locations.

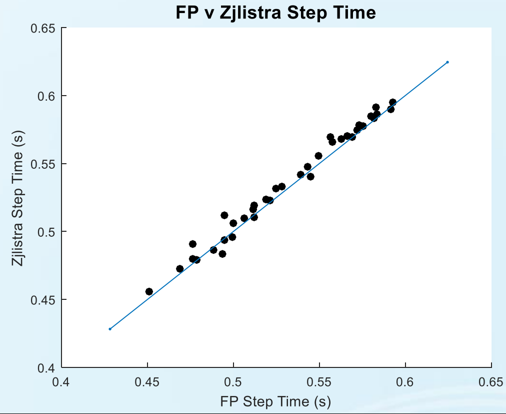
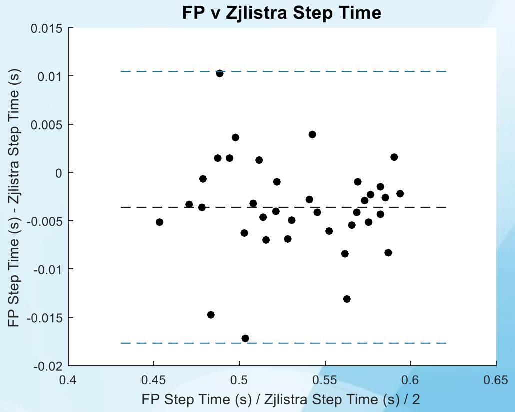
3. 2015 Data-set step time comparison

A test was carried out to determine if step time derived from the McCamley et al, 2012 method was more accurate than the current Shimmer gait algorithm which is based on the Zjlistra et al, 2003 method, which is based around finding the sharp decreases in forward acceleration as the patients foot first hits the ground at IC. The McCamley method is more based around extracting the main frequency of stepping and assuming that gait events occur in consistent relationship to points on that curve. The new filter performs better than the Zjlistra method, which was somewhat suprising.

	Zjlistra et al, 2003	McCamley et al, 2012	New filter
Mean difference	-0.0036	-0.0046	-0.0033
SD difference corrected	0.0072	0.0080	0.0060
Correlation	0.9921	0.9900	0.9945
p-value	<0.000	<0.000	<0.000
Upper 95% CI	0.0104	0.0110	0.0085
Lower 95% CI	-0.0177	-0.0203	-0.0150
CI width	0.0281	0.0314	0.0235
CI width %	5.27	5.87	4.41

Table 1 – Validation statistics of the Zjilstra method, the McCamley method and the new filter compared to the gold standard force plate on the UCD-INSIGHT 2015 training data set.

3.1. Bland-Altman Plots: Stance Time Comparison (2015 data-set)

<table>
<tr><td>Processing method</td><td>Bland-Altman Plot 1: Step times from the lumbar IMU + processing method are plotted against step times from the force plate. Solid line in figure has a slope of 1 and represents where the points would fall if both systems agreed perfectly</td><td>Bland-Altman Plot 2: The difference between force plate and lumbar IMU + processing method step time plotted against the mean of both measures. Blue horizontal lines represent the 95% confidence interval and the black horizontal line represents the mean difference</td></tr>
<tr><td>Zjilstra et al, 2013</td><td>
</td><td>
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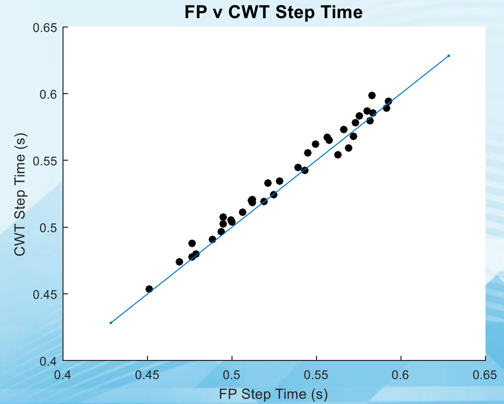
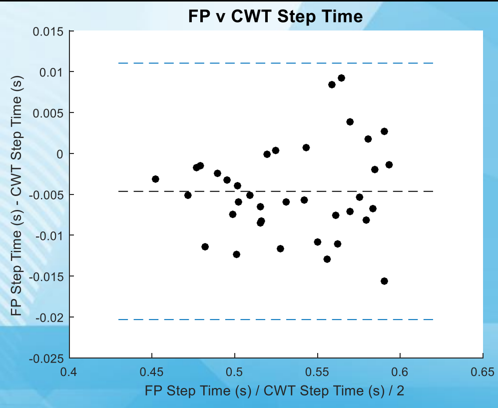
<tr><td>McCamley et al, 2012</td><td>
</td><td>
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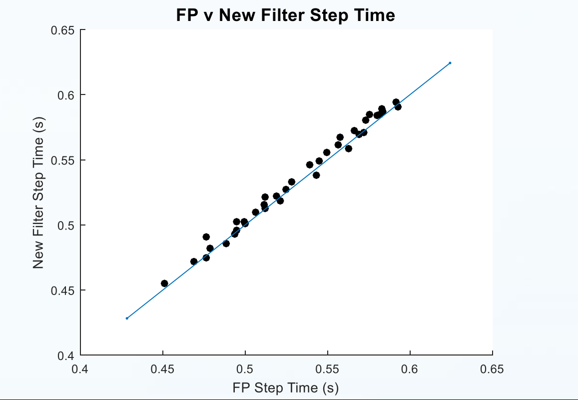
<td>
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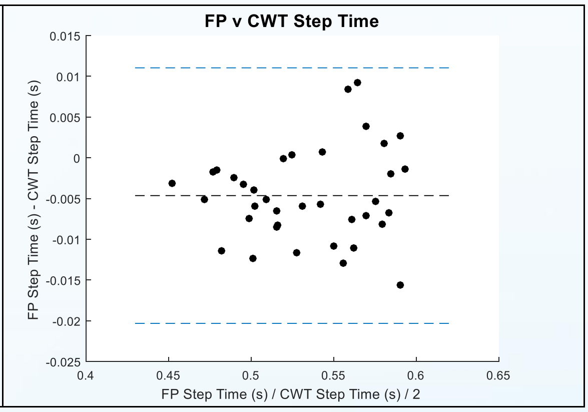
<td>
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3.2. Discussion

The Zjilstra method is more accurate than the McCamley method of gait event detection on the 2015 UCD-INSIGHT data-set. This data-set consists of 36 healthy participants walking in a biomechanics laboratory with simultaneous recordings from the gold standard force plate and a waist worn Shimmer 3 sensor. The two method of gait event detection were applied to the waist worn inertial sensor data. The McCamley method is not that much worse than the Zjilstra method. Confidence interval width percentage (CI width %) was 5.92% for the McCamley method and was 5.27% for the Zjilstra method. The pearson product correlation was 0.9920 for the Zjilstra method and 0.9898 for the McCamley method, showing that the Zjlistra method has a slightly more accurate step time as compared to the gold standard force plate. It should be noted that these differences are not that large and an argument could be made to include the option for the CWT detection method in any algorithms that Shimmer were to offer to the health research community. It will also be important to test the two gait event detection algorithm types on the 2016 UCD-INSIGHT data-set to determine how they perform against each other on a clinically oriented data-set.

The new filter resulted in the most accurate results in step time on the 2015 data-set. This is not a massive improvement over the current algorithm, but should be kept in mind for future development and possibly implemented into the algorithms if other additions are being made.

4. 2015 Data-set Stance Time Comparison

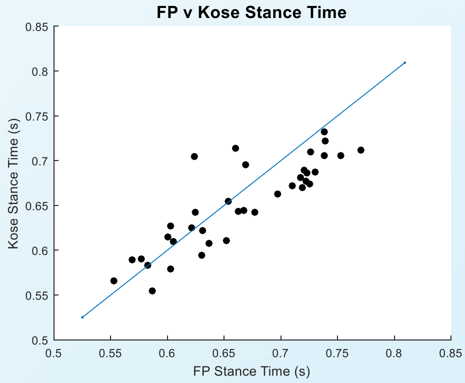
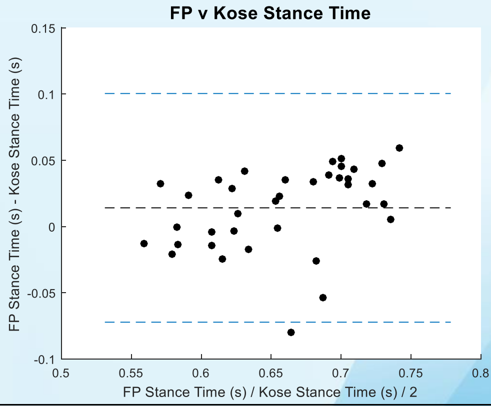
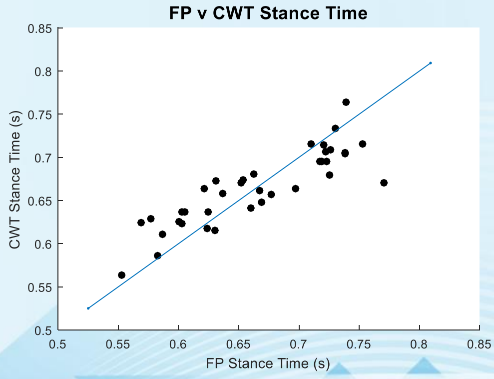
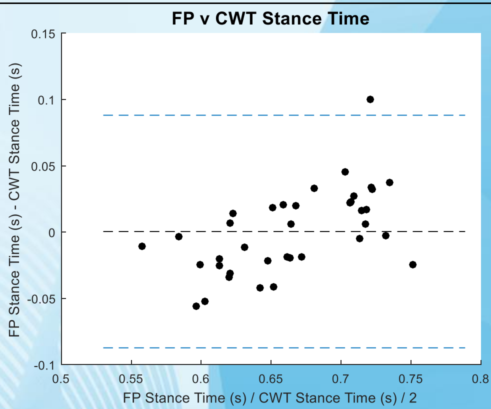
Toe-off detection is more difficult from a sensor on the waist than IC detection due to the fact that TO is not associated with large, sharp changes in acceleration, like IC is. TO is a soft feature that occurs while the contra-lateral foot is already on the ground. Stance time is the time between IC on one foot to TO on the same foot, thus is longer than step time as during walking double stance occurs and TO will occur after the contra-lateral leg IC event.

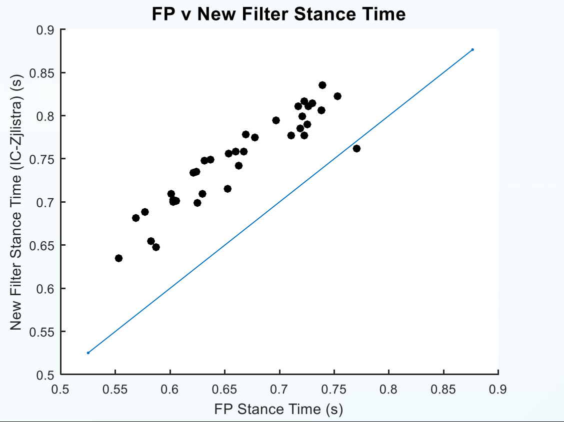
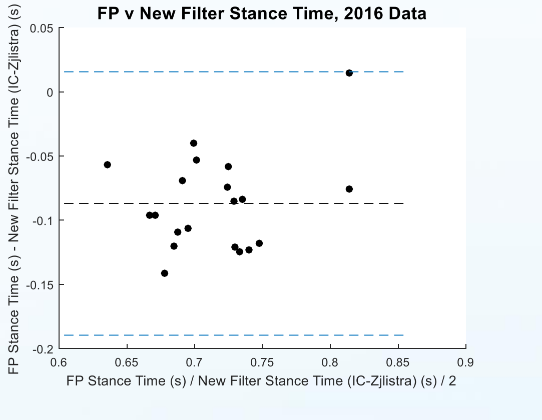
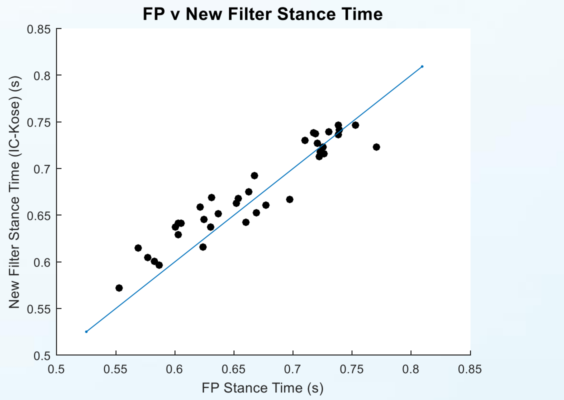
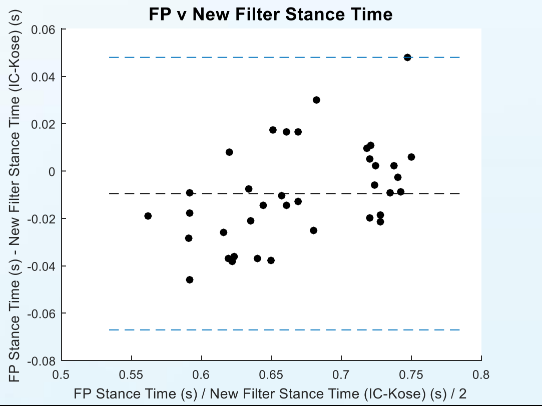
The McCamley et al, 2012 method was based off detecting TO on a wavelet, that seemed to be filtering the main frequency of stepping from the vertical acceleration channel. As the table below shows, the validation of stance time from the Kose et al, 2012 and McCamley et al, 2012 method were very similar, the McCamley method did not improve stance time estimation by much and both methods had error values that are too high to deploy in a product for users. Error percentages for each were 26.3%. Upon inspection it was found that there was difficulty detecting the correct wavelet to use for analysis. Since, the idea behind generating the correct wavelet to search on seemed to be based on pulling out the main stepping frequency, an alternative filter was created on the vertical acceleration channel that was low pass filtered at 1.5 x the primary walking frequency. Upon visual inspection of several subjects data, this seemed to result in a sinusoidal curve. This curve was then used in place of the curve in the McCamley et al, 2012 method to zero in on TO locations. As Table 2 shows, the new filtering method results in more accurate data than the other methods. The correlation level is quite good (0.9459), however, the CI width % is at 17%, so this would require some consideration before being confident it is appropriate to include in a user solution. More work should be completed to investigate edge cases to determine if the algorithm can be improved for the calculation of stance time.

	Kose et al, 2012	McCamley et al, 2012	New filter (Zjilstra IC method)	New filter (Kose IC method)
Mean difference	0.0144	4.228e-04	-0.0854	-0.0095
SD difference corrected	0.0440	0.0448	0.0239	0.0294
Correlation	0.8591	0.8676	0.9201	0.9463
p-value	< 0.000	< 0.000	< 0.000	< 0.000
Upper 95% CI	0.1004	0.0881	-0.0192	0.0480
Lower 95% CI	-0.0722	-0.0873	-0.1516	-0.0671
CI width	0.1726	0.1754	0.1324	0.1151
CI width %	26.22	26.37	18.70	17.17

Table 1 – Validation statistics of the various methods of stance time detection as compared to the gold standard force plate on the UCD-INSIGHT 2015 training data set.

4.1. Bland-Altman Plots: Stance Time Comparison (2015 data-set)

Processing method	Bland-Altman Plot 1: Stance times from the lumbar IMU + processing method are plotted against stance times from the force plate. Solid line in figure has a slope of 1 and represents where the points would fall if both systems agreed perfectly	Bland-Altman Plot 2: The difference between force plate and lumbar IMU + processing method stance time plotted against the mean of both measures. Blue horizontal lines represent the 95% confidence interval and the black dashed line represents the mean difference
Kose et al, 2012		
McCamley et al, 2012		

New filter (IC-Zjlistra)		
New filter (IC-new)		

5. 2016 Data Step Time Comparison

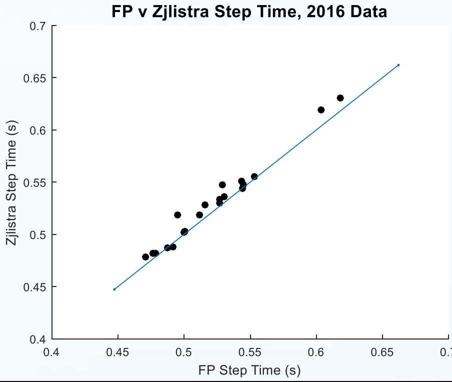
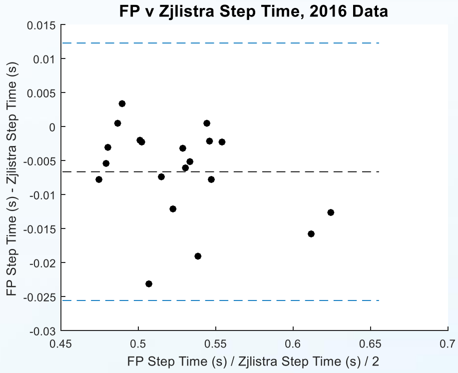
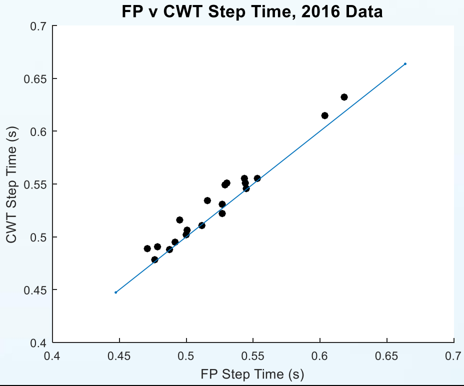
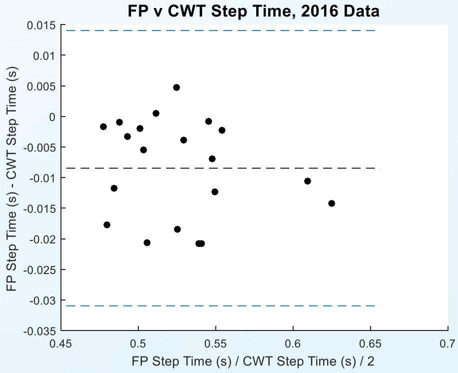
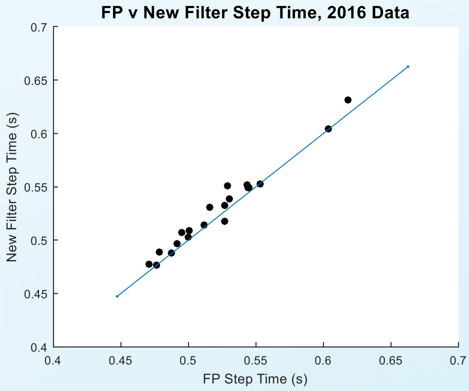
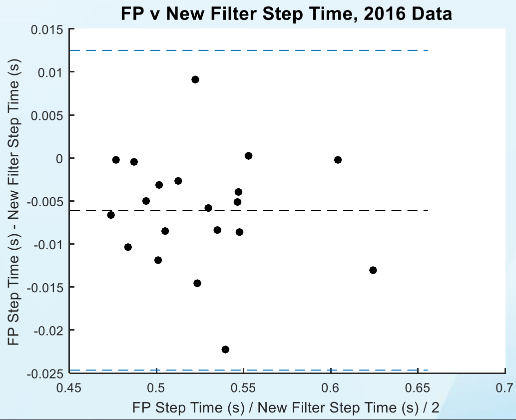
Step time using the new filter was assessed on the UCD-INSIGHT 2016 pathological data-set to determine how it compared to the gold standard force plate on a more clinically oriented data-set. Not that the CWT / McCamley et al, 2012 method was not applied since it proved to be inaccurate and computationally expensive on the 2015 training data-set. Table 3 show the main validation metrics of the original algorithm and the new filter method.

	Zjlistra et al, 2003	McCamely et al, 2012	New filter
Mean difference	-0.0066	-0.0085	-0.061
SD difference corrected	0.0097	0.0115	0.0095
Correlation	0.9874	0.9800	0.9858
p-value	< 0.000	< 0.000	< 0.000
Upper 95% CI	0.0123	0.0140	0.0125
Lower 95% CI	-0.0256	-0.0310	-0.0247
CI width	0.0379	0.0450	0.0372
CI width %	7.20	8.54	7.07

Table 3 – Validation statistics of the Zjilstra method, the McCamley method and the new filter compared to the gold standard force plate on the UCD-INSIGHT 2016 pathological testing data set. Note that the CWT / McCamley method was not tested on this data as it was proven to be inaccurate on the 2015 data-set.

5.1. Bland-Altman Plots: Step Time Comparison (2016 data-set)

Processing method	Bland-Altman Plot 1: Step times from the lumbar IMU + processing method are plotted against step times from the force plate. Solid line in figure has a slope of 1 and represents where the	Bland-Altman Plot 2: The difference between force plate and lumbar IMU + processing method step time plotted against the mean of both measures. Blue horizontal lines represent the 95% confidence

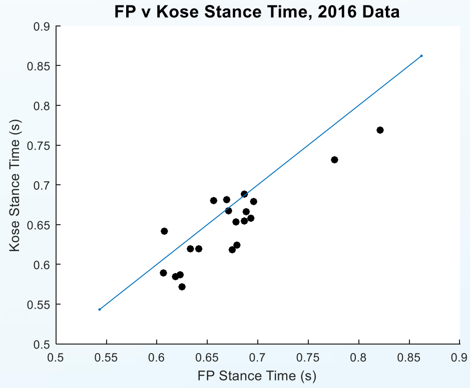
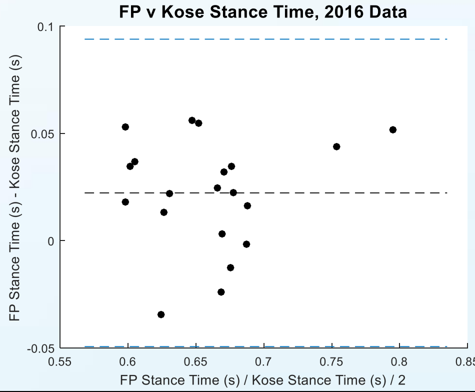
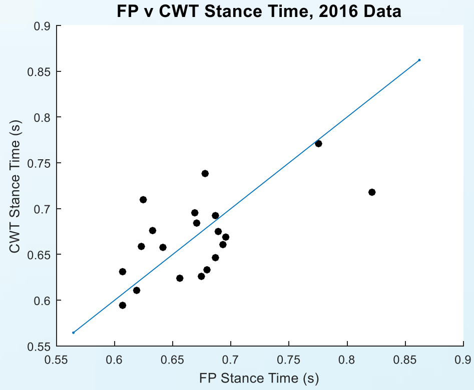
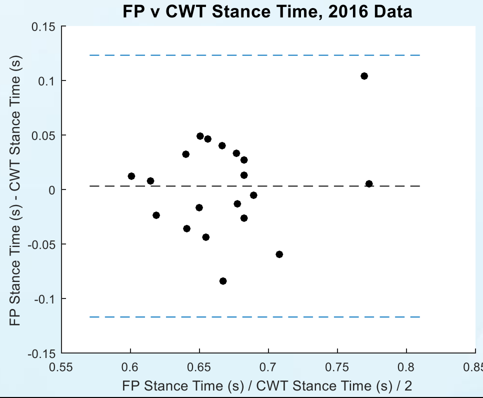
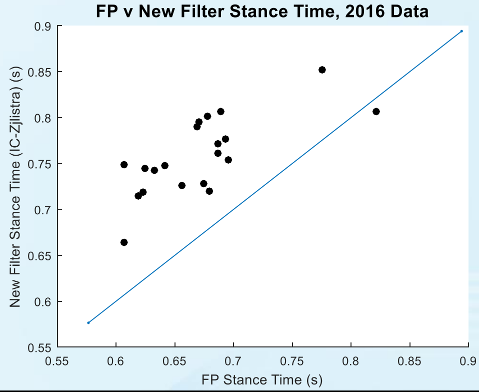
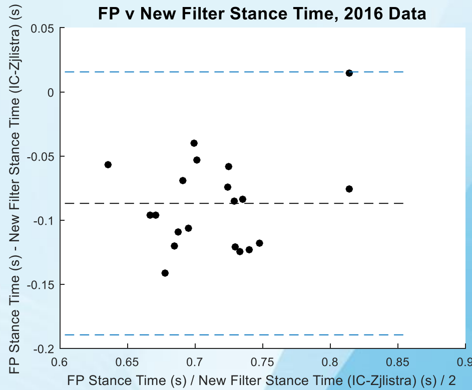
	points would fall if both systems agreed perfectly	interval and the black horizontal line represents the mean difference
Zjlistra et al, 2013		
McCamley et al, 2012		
New filter		

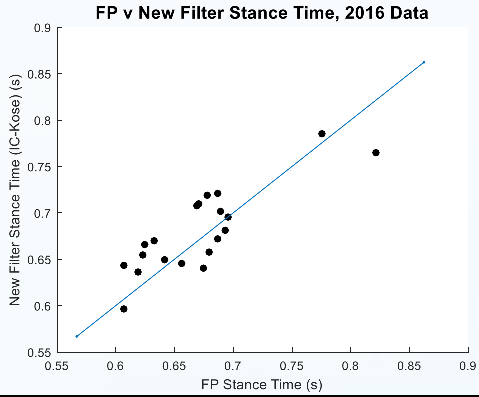
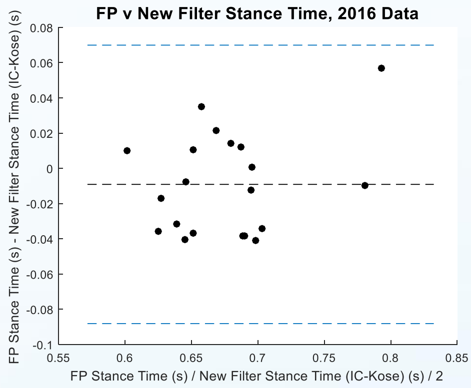
6. 2016 Data Stance Time Comparison

	Kose et al, 2012	McCamley et al, 2012	New filter (Zjilstra IC method)	New filter (Kose IC method)
Mean difference	0.0223	0.0031	-0.0870	-0.0091
SD difference corrected	0.0366	0.0612	0.0523	0.0403
Correlation	0.8758	0.6163	0.7212	0.8433
p-value	< 0.000	< 0.000	< 0.000	< 0.000
Upper 95% CI	0.0939	0.1232	0.0156	0.0699
Lower 95% CI	-0.0494	-0.1169	-0.1895	-0.0881
CI width	0.1433	0.2401	0.2051	0.1581
CI width %	21.70	35.83	28.68	23.38

Table 4 – Validation statistics of the various methods of stance time detection as compared to the gold standard force plate on the UCD-INSIGHT 2016 pathological testing data set.

6.1. Bland-Altman Plots: Stance Time Comparison (2016 data-set)

Processing method	Bland-Altman Plot 1: Stance times from the lumbar IMU + processing method are plotted against stance times from the force plate. Solid line in figure has a slope of 1 and represents where the points would fall if both systems agreed perfectly	Bland-Altman Plot 2: The difference between force plate and lumbar IMU + processing method stance time plotted against the mean of both measures. Blue horizontal lines represent the 95% confidence interval and the black horizontal line represents the mean difference
Kose et al, 2012		
McCamley et al, 2012		
New filter (IC-Zjlistra)		

New filter (IC-new)		

Stance time estimation on the 2016 pathological data-set was not very accurate using any of the proposed processing methods. The Kose et al, 2012 method was most accurate at 21.7% followed closely by the new filter method at 23%. This was a decrement of performance from the 2015 data-set and indicates that the new filter method TO detection breaks down with more pathological types of gait patterns. Error rates were quite high for the new filter with Zijlistra IC detection (28%) and with the McCamley et al, 2012 method (35%).

7. Conclusion

- New filter method of IC detection results in slightly more accurate detections than the current algorithm. These improvements are marginal, and do not warrant changing the algorithm at this point, but is relevant to keep in mind for future development, as an option to improve slightly.
- Stance time measures are not accurate enough to include in the Shimmer Gait Algorithm. Error rates were 17% on the healthy data-set and 21% on the pathological data-set. These errors are high enough that it would not be appropriate for Shimmer to provide to customers.
- If there are customers that want stance time specifically we could either look at providing algorithms based on sensors that are worn lower down on the body, or else providing the described algorithms with the caveat that they are solely based of the academic literature description of the algorithms and they have not been validated specifically by Shimmer.

8. References

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