Effect of sensor location around the belt on the estimation of gait speed

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Abstract — **Gait speed is a powerful clinical marker in predicting the functional decline of a person's condition or determining the stage of a mobility-related disease. Existing gait speed assessment methods often require the sensor to be attached to a specific location which is not always possible. Indeed, when acquiring data at home, patients and especially the elderly, who often suffer from postural issues, could place the sensor at a slightly different site. This is a real limitation as individuals have demonstrated different behavior in real life comparing to clinical settings. The objective of this study was to propose a gait speed estimation method based on inertial measurement units (IMU) sensors placed around the belt in four locations: sternum, hip, L5 and an arbitrary position on waist belt. It is challenging as the trunk cannot always be considered rigid. To propose a location-independent solution, the strategy adopted here is to extract several features from the vertical acceleration signal in global frame and map them into gait speed using a machine learning regression process. The algorithm has been validated in 15 young healthy patients who performed daily-life activities. It achieved a bias that is negligible (smaller that 0.05m/s for every sensor) and the precision is around 0.18 m/s in average among all sensors.**

Index Terms — **real-word gait speed, machine learning algorithm, Gaussian process regression, inertial sensors**

1 Introduction

Since several years now, gait speed is recognized as an important marker of a patient's health [1]. It is highly associated with physiological and functional capacity [2]. Gait speed is a reliable factor not only in defining the current situation of a patient but also in predicting the future decline or recovery which older people may fail to explicit [3]. Numerous tests to examine mobility exist but gait speed appears as the easiest, quickest and most reliable to perform [4]. However, when measuring gait speed, researchers often require the sensor to be attached to a specific and fixed location of the body which is difficult to achieve during daily-life occupations and may not be feasible by patients themselves without the help of a trained person. Thus, it is limiting its broaden applicability in clinical setting. This is a real drawback as it has been shown that we get different results at home and in clinic. [5]. Indeed, in a confined environment, with laboratory settings, participants perform differently than in real-life daily activities [6]. For example, sit-to-stand duration is higher during daily activities than in the clinic for elderly and patients with idiopathic Parkinson's disease [7]. This demonstrates the importance of developing measurement methods that are as effective in domestic environments than in clinic. The sensor placement is thus central in the assessment of gait speed. One location which is often used is the lower limb. Indeed, due to the biomechanical role of the lower limb, it provides very accurate results in gait speed estimation [8]. However, lower-limb sensor is not comfortable in free living context and users would prefer a sensor placed on the trunk for an increased usability and comfort.
To this end, the goal of the project is to investigate the accuracy of gait speed estimation when the placement of the IMU is changed on the trunk at different comfortable locations. Our hypothesis is that we can obtain gait speed with trunk sensors using a machine learning approach.

2 Data collection

A. Measurement protocol, participants and sensors

A dataset of 15 young healthy participants recorded during 15 minutes of simulated daily activities including over-ground walking is used for this study. During the measurements, each participant was wearing six IMU's placed at different locations on the body. On Figure 1 are shown the locations of the four sensors used for the model: chest (TR), lower back at the area of L5 (L5), anterior superior iliac spine (ASIS), and an arbitrary position on the right hip (RH).

Figure 1: Location of IMU sensors on the trunk: L5, TR, RH and ASIS.

On top of that, two additional foot sensors were used to provide the gait speed benchmark (Figure 2). It was instructed to the participants to attach the foot sensors by a rubber clip to the shoes. They fixed the TR sensor using an around the

Figure 2: Picture of the IMU foot sensors used as a reference.

chest belt. L5 sensor was fixed using an elastic belt and the ASIS and RH sensor were attached directly to the trousers of the participant. Four reflective markers were mounted on TR, ASIS and L5 inertial sensors. Data from the 3D accelerometer and 3D gyroscope were recorded with a sampling frequency of 128 Hz. Barometric data were recorded using a 64Hz frequency. During the recording, participants performed daily tasks and were free to move outside the lab and between different offices. They performed the tasks in a fixed order inside a building: sitting on different chairs and sofas with different heights, walking through different offices, bending to pick up objects from the floor, working on a computer, lying, tying shoe laces, grabbing pencils from a table, picking objects from the fridge, and using stairs and lift.

B. Reference values for gait speed

Reference values for gait speed were obtained with a previously validated algorithm using IMUs on the feet which achieved an error of 1.4±5.6 cm/s in a study with healthy older and younger adults [9]. In that previous study, the method was validated using an optical motion capture system (Vicon, Oxford Metrics) with sub-millimeter accuracy [10],[11]. The foot sensors system demonstrated to be suitable for clinical application requiring objective evaluation of gait outside of the lab environment [9]. Consequently, the gait speed values provided by foot sensors are used in this study as an accurate reference.

3 Gait speed estimation method

A. Treatment of data

In order to make the detection algorithm independent from the sensor location, the vertical acceleration in the global frame was used. The sensor gives a measurement of the acceleration in the sensor frame. From these values, the data can be derived in the global frame by quaternions as in the reference study [12]. Then, the acceleration of the movement is obtained by subtracting the gravity vector from the accelerometer data. To remove the noise and artifacts included in the signal, a low-pass Butterworth filter of order 12 with a cut-off frequency of 1.3 Hz was used to filter the vertical acceleration.
Then, in order to be able to compare the acceleration signals obtained with different sensors the bias were removed from the vertical accelerations. The signals have also been aligned as some outliers (most probably due to the bad synchronization) were noticed when comparing accelerations from tr, rh and asis with respect to l5. Also, the stairs periods have been detected using the barometric data and removed from the training data because the reference is not accurate on non-flat ground (see Figure 3).

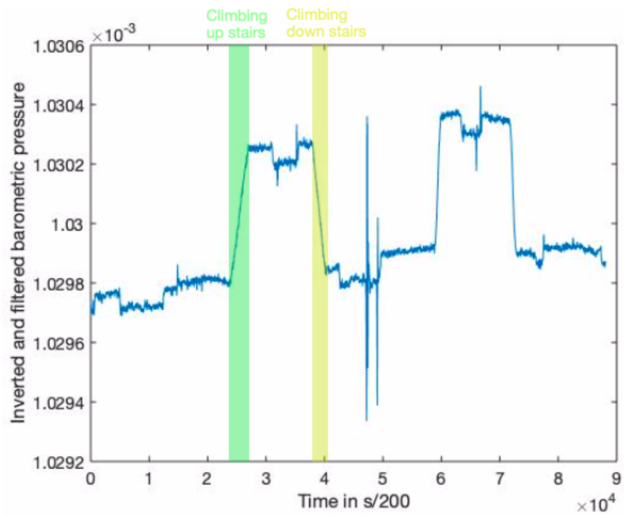

Figure 3: Barometric pressure data with stairs detected periods (up in blue and down in yellow). Second high elevation change corresponds to the participant taking the lift which has a flat ground.

To this end, the barometric pressure signal was first up-sampled from 64 Hz to 200 Hz. The signal was then inverted as the displacement is inversely associated with barometric pressure. Additionally, a low-pass filter of order 12 with a cut-off frequency of 1.3 Hz was applied. The stairs periods could therefore be detected and removed from vertical acceleration. Lastly, it was noticed that the reference algorithm had an issue in detecting some steps for a short time for certain subjects (subject 1, 5, 10, 11 and 14) hence these parts were identified and removed.

Same parts were removed from the foot and belt sensors to keep a high correlation.

B. Feature selection

Identifying and extracting highly correlated features for gait speed estimation is highly important as the accuracy of the estimation will partly depend on that.

In the original study about the unsupervised assessment of walking speed and duration [12], 11 features were selected out of 18 features by the backward elimination method [13]. Here, the same 11 features were extracted from the filtered acceleration signal and are listed in Appendix I (section 7).
Each feature was computed over a window size of 2 s and the window is moving 1 second at each time. Among the 11 features, 6 are directly related to the acceleration signal: the mean ($x_{k,1}$), standard deviation ($x_{k,2}$), maximum ($x_{k,3}$) and minimum value ($x_{k,4}$) as well as the sum of absolute values ($x_{k,5}$) and sum of squared values ($x_{k,6}$).
Three features have been extracted from the integration of the acceleration signal: the mean velocity ($x_{k,7}$) and its minimum ($x_{k,8}$) and maximum values ($x_{k,9}$).

Finally, in order to provide 2 additional features based on the periodicity of the signal, the fast Fourier transform of the acceleration signal was computed and then the first dominant frequency as well as its amplitude were extracted.

Additionally, the Pearson's correlation coefficients were computed to see which of these features provided the highest correlation with gait speed. The Figure 4 shows that the sum of squared values of acceleration, sum of absolute values of acceleration and the first dominant frequency are the most correlated features with gait speed in comparison to other features. The sum of squared values demonstrates a correlation coefficient of 0.9045. This high correlation finding further confirms that the proposed features are good to predict gait speed.

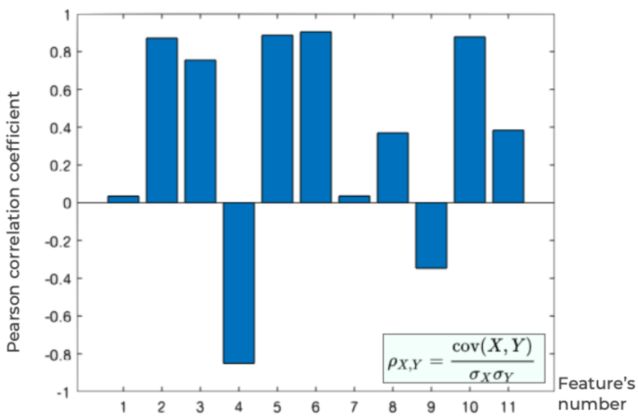

Figure 4: Pearson correlation coefficient between different features and Gait speed reference for one subject.

C. Training and testing

The chosen regression algorithm for the training of the model is the Gaussian process regression (GPR).
Indeed, according to previous works [12], [14] and a study which compared the relative performance of Gaussian process regression, Bayesian Linear Regression (BLR) and Least Square Regression (LSR) for gait speed estimation [15], the GPR model seems to be the best. In this study [15], GPR performed increasingly better than BLR under the same conditions. By contrast LSR showed much larger error with higher variance. Their results showed that GPR had a lower average root mean square (RMS) prediction error when compared to BLR and LSR across all subjects. Therefore, GPR was chosen because it is non-parametric and thus the regression is driven by the data.

A quadratic kernel was chosen since the same mentioned studies on gait speed estimation obtained good results using it and because it allows us to model data that vary at multiple scales [16].

For the training, the data were first loaded and processed for each of the 15 subjects and the features were extracted for L5, trunk, right hip and ASIS, and stored in a table (see Figure 5) which has the features as columns and the samples as the lines. The last column contains the gait speed reference provided by the foot sensors. Thus, for each subject a table X that contains 4 matrices is obtained, one for each sensor (X is of size [4x Nb_samples x12]).

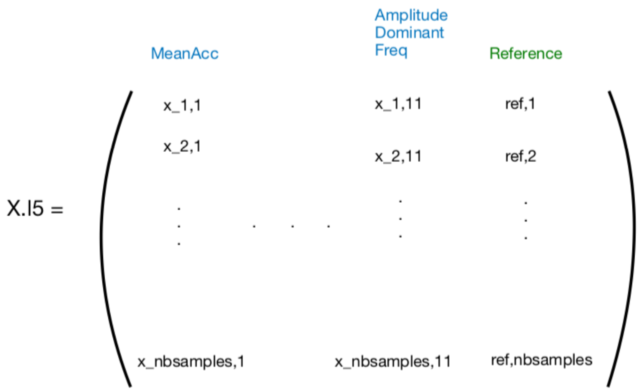

Figure 5: Organization of data of matrix X.l5.

Secondly, because this study uses a leave-one subject-out strategy, for each group of 14 subjects all the data of one sensor were stored in a table by stacking the participants' data. In total, there are 15 tables of 14 stacked participants data again having the features as columns and the samples as lines. Then, the data were ready to be trained and tested.
Subsequently, GPR algorithm was used to build the model with MATLAB Regression Learner toolbox with a 5-hold cross validation to prevent from overfitting. A model was acquired for each group of 14 subjects so for 15 groups, and for each sensor so in total there are 60 models.

These models were tested on the remaining subject for each sensor so each model was used to predict 4 gait speeds.

Training and testing was performed with and without locomotion periods but as better results were obtain with locomotion periods, only those are reported in the following.

4 Results

A. Intermediate results

Some intermediate results were obtained and support the validity of our hypothesis.

1. Acceleration signals comparison

On Figure 6, the vertical acceleration signal is plotted for the 4 sensor's locations for one subject. Qualitatively, it can be observed that the acceleration signals are similar which encourages us to follow in that direction.

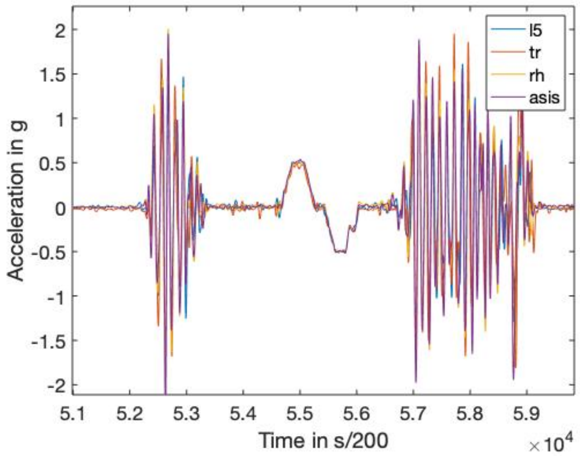

Figure 6: Vertical acceleration for subject one (09.09.2018/9MW/Real-life) with 4 sensors: L5, Tr, RH, ASIS.

Additionally, quantitative results confirm this observation. First, by computing the root mean square error between each vertical acceleration minus the acceleration provided by l5, one can quantify the difference between the signals. On Figure 7, there is little variation between acceleration from different sensor location which shows that it is likely that gait speed can be obtained from different location of sensors. Second, the RMS, median and IQR of the signal's difference are reported in Table 1. The median of RMS and IQR are relatively low for each signal compared to l5 and are the smallest for RH. Regarding the median of the error, it is almost zero which is expected as we removed the bias between the signals.

2. Attenuation coefficients

Another good way to compare the signals of different locations is to compute the attenuation coefficient (AC). They are computed using the following formula (as in [17]) and results are provided in Table 2.

$$AC = (1 - \frac{RMS_{a,i}}{RMS_{a,L5}}) * 100(\%) \qquad (1)$$

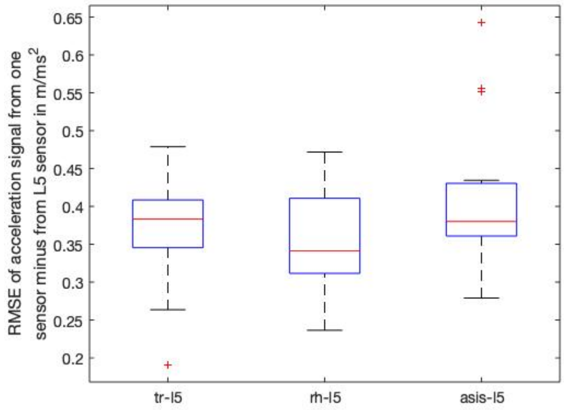

Figure 7: Boxplot of RMS values of tr-l5 acceleration signal, asis-l5 acceleration signal and rh-l5 acceleration signal.

Table 1: The RMS, median (bias), and IQR (precision) of the error between acceleration signal from one sensor and acceleration signal from l5 in m^2/s. For each of these three parameters the median and IQR values were reported.

	RMS (m^2/s)		Median (m^2/s)		IQR (m^2/s)	
	Median	IQR	Median	IQR	Median	IQR
tr-l5	0.38	[0.35; 0.41]	-0.01	[-0.01;0.00]	0.24	[0.21; 0.27]
rh-l5	0.34	[0.31;0.41]	-0.01	[-0.01;0.00]	0.23	[0.21,0.27]
asis-l5	0,38	[0.36;0.43]	0.01	[-0.00;0.01]	0.27	[0.23,0.32]

They represent the relative increase or reduction of the vertical acceleration from L5 to the sensor of interest. A positive attenuation coefficient means that there is a reduction of the acceleration from L5 to the sensor while a negative coefficient means that there is an amplification of the signal. A low coefficient indicates that the sensors are very similar.

Here, we observe that they are all amplifications of the vertical acceleration from L5 to right hip, trunk and ASIS. According to these results, the right hip seems to be closer to L5 than the other sensors which is in accordance with what has been observed when computing RMSE of accelerations. Overall, these percentages are relatively small so it is again encouraging for the hypothesis.

Table 2: Median and interquartile range of attenuation coefficient computed for RH, TR and ASIS regarding L5.

	RH/L5	TR/L5	ASIS/L5
Averaged median of AC in %	-10.36 %	-14.17 %	-10.70 %
Averaged IQR of AC in %	[-18.3;-3.4]	[-21.9;-6.3]	[-13.9;-4.1]

B. Estimated gait speed compared to reference

On Figure 8 we can see a plot (and its zoom on Figure 9) of the predicted gait speed versus the reference gait speed for one subject trained on the L5 sensor and tested on the trunk. It can be observed that the estimated and reference values are in close agreement.

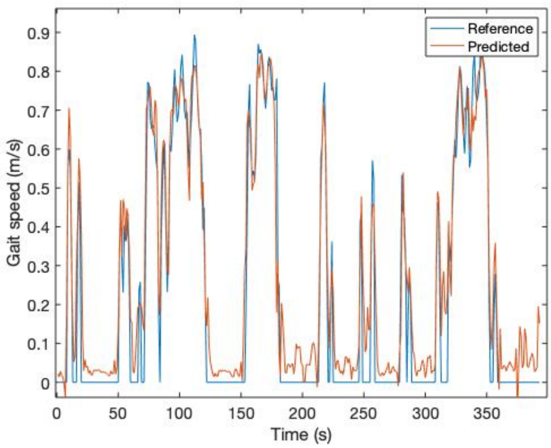

Figure 8: Estimated gait speed by the proposed method (in blue) versus the reference gait speed provided by foot sensors (in orange) for one participant.

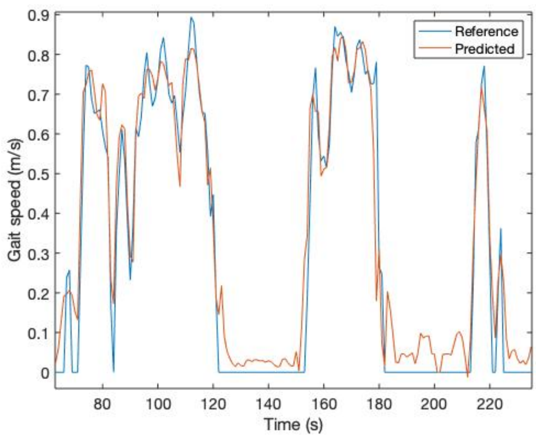

Figure 9: Zoom of Figure 8

In order to have a more quantitative analysis of the results, the median and IQR of the root mean square error have been computed and plotted as boxplots on Figure 10 and reported in Table 3. They represent the error between the prediction and estimated gait speed when trained on 14 subjects and tested on the remaining subject for each sensor. For instance, the first blue boxplot on the left is the RMSE of the prediction trained on the features extracted from L5 sensor and tested on values provided by L5 sensor as well.

First of all, it has been observed that RMS errors were lower for bigger datasets so they were lower when staking the subjects than when training and testing on one subject. Indeed, GPR improves with bigger datasets.

Secondly, we can see that for all combinations, the RMS of the error is mainly between 0.14 m/s and 0.2 m/s. With values under 0.2 m/s we can consider that the assumption is valid. It is possible to estimate gait speed with sensors placed around the belt. We also observe that the best predictions are obtained when tested on the trunk which will be discussed in the following.

Lastly, the mean and standard deviation of the error of prediction were also computed and then their median and IQR. These computations are provided for data trained on L5 in Table 3. The median of mean are close to zero when tested on each sensor. Regarding the STD, it is overall lower than 0.17m/s and is the smallest for trunk sensor.

5 Discussion

The method based on IMU sensors placed at four positions around the belt was able to predict gait speed in real-life conditions. Accuracy of the method was investigated against an already approved gait estimation method based on foot sensors. Our method is an improvement in comparison to two foot sensors as it offers more comfort to the user as well as a better usability.

First, the vertical acceleration in the global frame was very similar between different locations around the trunk and even smaller differences were observed after alignment of the signals. Analysis of attenuation coefficient and Pearsons's correlation coefficient showed high correlations between signals that were extracted from different sensors. Hence, the hypothesis of similarity between the vertical accelerations produced by different sensor locations seems valid.

As previously mentioned, the independence of the algorithm is possible as it relies on the vertical acceleration in global frame. To ensure free sensor location and orientation during the measurements, the participants placed the sensors themselves on the different sites. The accuracy was first evaluated by computing the RMSE between estimated gait speed prediction and gait speed reference. It showed that the RMSE is in average below 0.2 m/s. This is comparable to what has been obtained with other validated gait speed method such as wrist-sensor's based method [18] which achieved a median [Interquartile Range] of root mean square error of 0.05 [0.04–0.06] (m/s) and 0.14 [0.11– 0.17] (m/s) for walking and running. Our method can therefore be used for gait speed assessment in home settings. The estimation's accuracy comes from good correlation of the proposed features with gait speed as well as a powerful regression algorithm.

Other metrics have also been studies: the mean and standard deviation of the difference of gait speed. The median and IQR of the three error metrics are provided for models trained on L5 in Table 3. They allow to investigate where the error is coming from. If the median of the mean is not zero, it means that there is a systematic bias that can be corrected. In our case, we observed a median of the mean of -0.02m/s in aver-

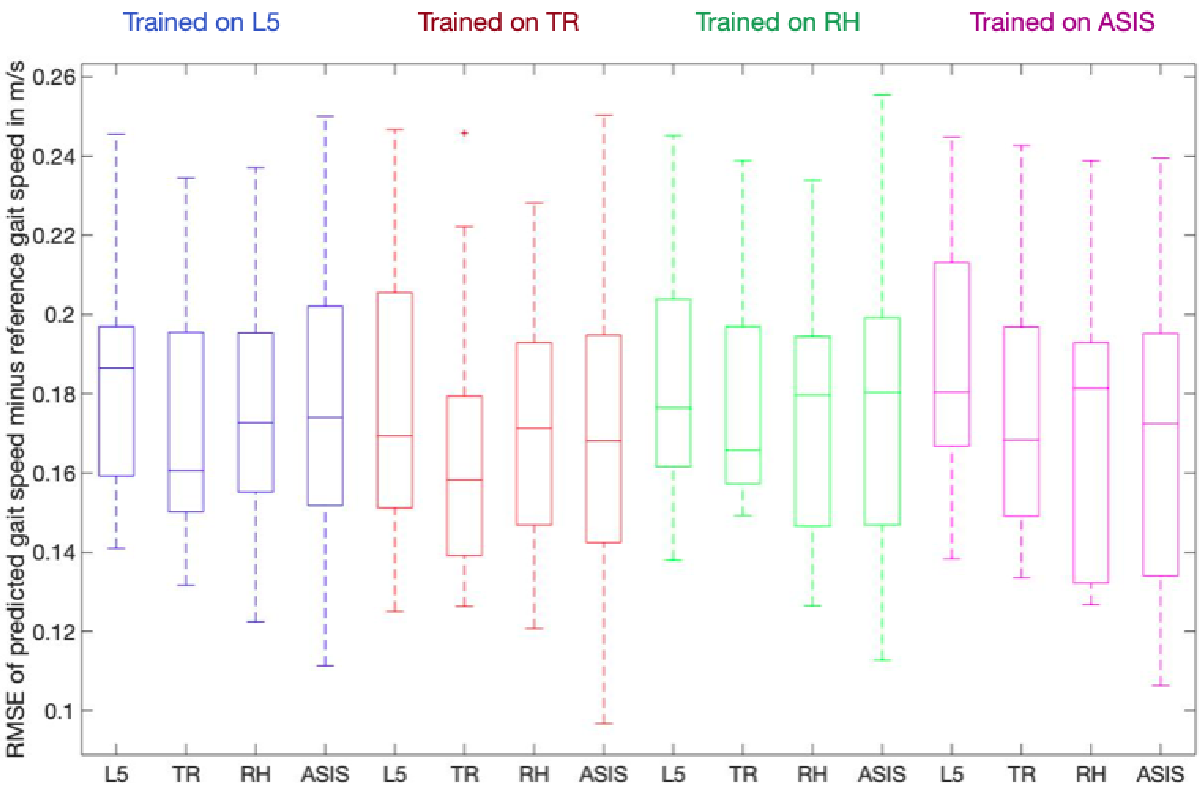

Figure 10: Boxplot of the RMSE between gait speed estimated by training and testing on each sensor and reference gait speed

age which is negligible (and can be corrected). The standard deviation reflects the random error on which we cannot act as it is intrinsically linked to the method. In our case, the averaged median of the STD is equal to 0.15m/s. That value is not too high but is clearly responsible for the error of prediction and shows the weaknesses of the model as the reliability of the system is of the order of this error.

One could expect that the best predictions would be observed for a model trained and tested on the same sensor. However, this is not the case as we can see that for every sensor the best prediction is observed when tested on the trunk. One explanation could have been that the trunk sensor is attached with an around the chest ”belt” while L5 sensor is fixed using an elastic belt and the ASIS and RH sensor are attached directly to the trousers of the participant. The trunk ”belt” may provide a more stable attachment.

ASIS and RH may be exposed to some artificial motion due to the trousers’ movement that comes with a less stable attachment. Also, the RH sensor is placed near the abdominal muscles that could induce a light movement of the sensor that doesn’t reflect gait speed. The elastic belt maintaining L5 sensor could as well induce some noise as unwanted oscillations could be present when moving.

This hypothesis was investigated by plotting the FFT of the acceleration signal for a few subjects as shown on Figure 11. One cannot conclude that there are more oscillations for L5, ASIS and RH because there is only one peak. There are some small peaks near the main frequency but as there are present for each sensor, they don’t explain why even when training on l5, rh and asis, we obtained better results testing on TR. While we suspected that additional oscillations were responsible for this incoherence, the FFT plots discard this assumption. Therefore, there might be other reasons that are not apparent. Regarding L5, the reason could be that the elastic band oscillates with the same frequency but affects the intensity of the signal and could amplify the oscillation.

Another issue that was first observed is that for each plot, there was only one outlier which lied inside a range between 0.3 m/s and 0.35m/s. This outlier corresponded to training without subject 5 and testing on subject 5. One possible reason for these outliers may be the lack of synchronization between the proposed trunk-based speed estimation method and the reference foot sensors system. This has been verified by performing an alignment of estimated and reference gait speed on subject 5 only which reduced the RMSE. Also, after removing subject 5 from training and testing sets, the RMSE decreased of 0.03m/s in average. Thus, subject 5 was removed from training and testing sets.

Table 3: The RMS, mean (bias), and IQR (precision) of the error between gait speed estimated and reference when trained on L5 and tested on each sensor in m/s. For each of these three parameters the median and IQR values were reported. Results are reported only for L5 sensor as similar conclusion can be extracted from results on RH, TR and ASIS regarding the mean and STD.

	RMS (m^2/s)		Mean (m^2/s)		STD (m^2/s)	
	Median	IQR	Median	IQR	Median	IQR
Tested on L5	0.19	[0.16; 0.20]	-0.04	[-0.06;-0.01]	0.17	[0.16; 0.18]
Tested on TR	0.16	[0.15;0.20]	-0.01	[-0.03;0.01]	0.14	[0.12,0.18]
Tested on RH	0.17	[0.16;0.20]	-0.02	[-0.03;0.01]	0.15	[0.13,0.17]
Tested on ASIS	0.17	[0.15; 0.21]	-0.03	[-0.04;-0.01]	0.16	[0.15,0.22]

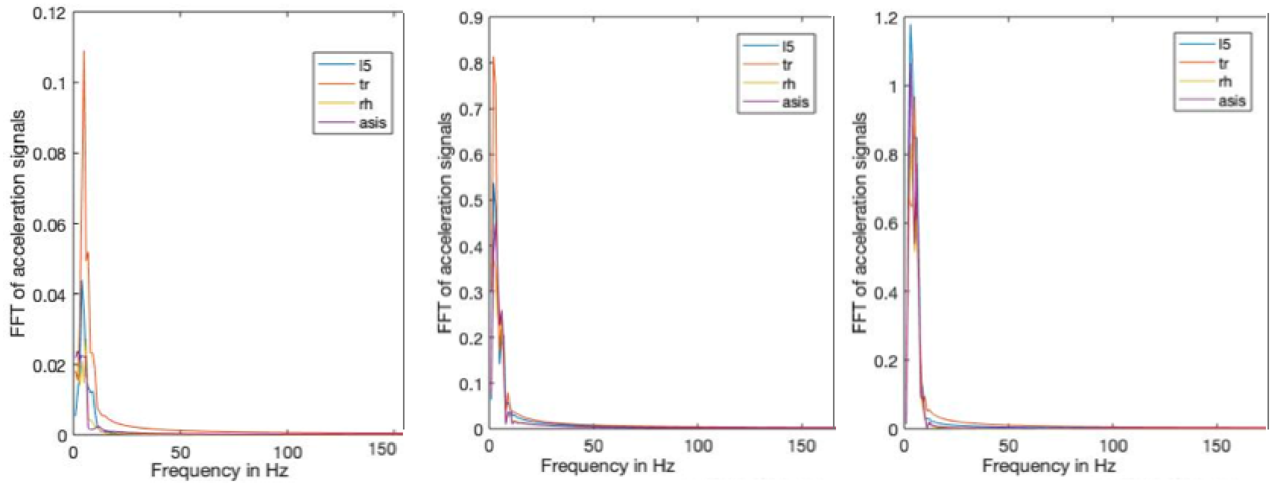

Figure 11: FFT of the acceleration signals for L5, TR, RH, ASIS

6 Conclusion

This study showed that a good estimation of gait speed can be derived from single IMUs sensors placed on L5, trunk, right hip or ASIS. The novelty of this approach is that the method is independent of the position of the inertial sensor. This is possible thanks to a machine learning regression algorithm as well as features extracted from the vertical acceleration in global frame. As measurements were performed in home-environment conditions, this gait estimation method offers new perspectives for daily-life gait speed assessment. The robust implementation and validation of this approach would however necessitate a larger amount of data including a wide array of atypical gait patterns. One possible idea for future developments could be to target subjects with gait impairments in order to see if the assumption is still valid and how it affects the accuracy of the prediction.

7 Appendix I
Formulas of selected features

The selected features are listed down below with their formula. The first 6 are extracted from the low-pass filtered vertical acceleration signal in global frame (a); the 3 following are extracted from the vertical velocity in global frame (v) and the last 3 are extracted from the FFT of a (f). In the following formulas, each sample i is denoted a,i and each window is of size N samples. The following formula then provide the feature value for a window k at time t_k.

- Mean acceleration

$$x_{k,1} = \frac{1}{N} * \sum_{i=1}^{N} a_i \tag{2}$$

- Standard deviation of acceleration

$$x_{k,2} = \sqrt{\frac{1}{N-1} * \sum_{i=1}^{N} |a_i - x_{k,1}|^2} \tag{3}$$

- Maximum acceleration .

$$x_{k,3} = \max a_i \tag{4}$$

- Minimum acceleration

$$x_{k,4} = \min a_i \tag{5}$$

- Sum of absolute values of acceleration

$$x_{k,5} = \sum_{i=1}^{N} |a_i| \tag{6}$$

- Sum of squarred values of acceleration

$$x_{k,6} = \sum_{i=1}^{N} a_i^2 \tag{7}$$

- Mean velocity

$$x_{k,7} = mean \int a(i)di \tag{8}$$

- Maximum velocity

$$x_{k,8} = \max \int a(i)di \tag{9}$$

- Minimum velocity

$$x_{k,9} = \min \int a(i)di \tag{10}$$

- First dominant frequency

$$x_{k,10} = f_{max,1} \tag{11}$$

- Amplitude of the first dominant frequency

$$x_{k,11} = A_{f_{max,1}} \tag{12}$$

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