

Trunk Orientation Estimate During Walking Using Gyroscope Sensors

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Abstract—This study proposes the use of a combination of Weighted Fourier Linear Combiner and Fourier Linear Combiner algorithms to estimate lower trunk orientation angles during walking using the three angular velocity components measured by an inertial measurement unit. The proposed method enables the determination in real-time of the rotations around three local orthogonal axes defined relative to their initial orientations (pitch, roll, and yaw). Since the method is based on the analytical integration of a Fourier series, it is suitable for the analysis of quasi-periodic movements such as gait.

INERTIAL measurement units (IMUs) have gained in popularity as a means to quantify human motion [1], thanks to their ease-of-use, robust design, low-cost, and their small dimensions. These advantages enable their use for extended periods outside the confines of a laboratory. In human walking analysis, IMUs have been frequently used to estimate spatial [2] and temporal [3] features of gait.

An IMU normally includes accelerometers and rate gyroscopes to measure accelerations and angular velocities, respectively. Theoretically, the determination of the position and orientation in space could be obtained by integrating the above signals. Unfortunately the IMU outputs, and especially those of the gyroscopes, are subject to drift over time which jeopardizes the time integration of the raw signals when estimating orientation data [4]. This problem has been overcome by using recursive filters, such as Kalman filters [5], [1]. The use of a Kalman filter associated with three measured accelerations and three measured angular velocities however, only allows accurate estimation of the lower trunk lateral (Roll) and frontal (Pitch) bending during walking (see Fig.1). The use of an additional sensor, such as a magnetometer, has been proposed to estimate the pose of IMU [6], including axial lower trunk angle (Yaw). As an alternative, this third angle could be estimated using a model of this missing additional information in the Kalman

filter [7]. In this case, the modelled variable would act as an additional non-drifting reference signal.

Fourier Linear Combiner (FLC) [8]-[9] adaptive filters have been mainly used for detection and cancelling of quasi-periodic signals such as hand tremor and heart motion [10] and for applications in microsurgery [7], [11]-[12]. Recently, they have also been proposed for the analytical integration of inertial sensor data [4] due to their ability to remove drifts. FLC filters are based on the Fourier's theorem that states that a periodic signal may be represented as a sum of sine and cosine waves at integer multiples of the fundamental frequency. From this, one can understand that the determination of the fundamental frequency is a key requirement that can limit accurate use of these filters to periodic or quasi-periodic signals with a known fundamental frequency. To overcome this limitation, Riviere and Thakor [11] proposed the Weighted Fourier Linear Combiner (WFLC) filter, which is an extension of the FLC to be used when dealing with signals of variable frequency. Since WFLC and FLC, are adaptive signal processing algorithms, they exhibit transient phenomena while adapting their parameters [13]. In these conditions, the more periodic the signal, the better the estimation of the Fourier series parameters, and thus their analytical integration will be.

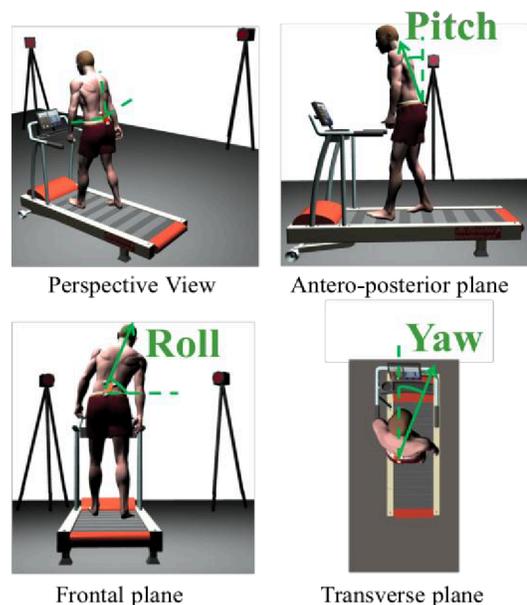


Fig. 1: Representation of the considered lower trunk orientation angles expressed in the initial unit local frame.

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Many observations have confirmed that human walking frequency is subject specific but it exhibits a small variation of 3–4% in the stride interval during walking [14]. However, even if human walking data can be qualified as quasi-periodic signals [15], meaning that they repeat almost identically in every steady-state gait cycle, they cannot be assumed to be stationary. The non-stationary nature of human gait, i.e. the stride variability, data can be particularly apparent in long lasting experiments or with patients affected by gait abnormalities such as hemiplegic [16] or elderly [17]. In addition, the gait variability is used as a quantitative tool to categorize walking performance [16] in clinical applications. Therefore, if the aim is to provide a clearer picture of each individual, it is desirable to develop algorithms that do not assume a stationary signal [11], and thus that are able to self-adjust their parameters. For this purpose a very popular class of adaptive filters which minimize the least mean square (LMS) difference between the measured signal and its estimate was proposed by Widrow [13]. WFLC filters are based on the LMS algorithm and use Fourier series, which are continuously updated, to represent the measured signal. Once the Fourier series coefficients are identified they can be analytically integrated without drift due to the null mean value hypothesis that is fundamental to the Fourier series. As a consequence, WFLC seems ideal for modelling and integrating quasi-periodic human walking signals in which neither frequency nor amplitude are fixed.

This paper proposes the use of Fourier Linear Combiner adaptive filters to perform drift-free lower trunk orientation angles estimation using the three angular velocity components measured by an IMU.

I. METHODS

In order to estimate the sensor orientation angles, gyroscope measured angular velocities need to be integrated. To do this, online tracking of angular velocities will be first performed. This tracking will allow identification of the Fourier series coefficients. The identified Fourier series coefficients will then be analytically integrated.

A. Tracking of angular velocities

The WFLC is an adaptive signal processing algorithm that, at each sample of time, compares the phase of a measured signal with its estimate, and modifies the frequency weight w_{0k} [11] to reduce the difference between these two quantities. Due to its adaptive capabilities, the WFLC can be used to model a quasi-periodic signal when both amplitude and frequency are unknown and slightly time-varying. The WFLC input vector $\mathbf{x}_k = [x_{1k} \dots x_{2Mk}]^T$ is [11]:

$$x_{rk} = \begin{cases} \sin(r \sum_{t=0}^k w_{0t}), & 1 \leq r \leq M \\ \cos((r - M) \sum_{t=0}^k w_{0t}), & M + 1 \leq r \leq 2M \end{cases} \quad (1a)$$

where M is the number of harmonics and k is the number of measured samples.

The instantaneous frequency weight w_{0k} can be estimated by updating every sample using the equations:

$$\varepsilon_k = s_k - \mathbf{w}_k^T \mathbf{x}_k - w_{b_k} \quad (1b)$$

$$w_{0_{k+1}} = w_{0_k} + 2\mu_0 \varepsilon_k \sum_{r=1}^M r(w_r x_{M+r} - w_{M+r} x_r) \quad (1b)$$

$$\mathbf{w}_{k+1} = \mathbf{w}_k + 2\mu \mathbf{x}_k \varepsilon_k \quad (1d)$$

where the amplitude and phase of the input signal s_k are estimated by the so-called adaptive vector $\mathbf{w}_k = [w_{1k} \dots w_{2Mk}]^T$, ε_k is the instantaneous difference between the output of the WFLC algorithm and s_k . In general, pre-filtering is used in WFLC, to separate the low frequency component/drift from the analysed signal. Pre-filtering inherently introduces phase lag. In order to avoid the use of pre-filtering, a bias weight w_{b_k} with adaptive gain has been proposed [13], [19]:

$$w_{b_{k+1}} = w_{b_k} + 2\mu_b \varepsilon_k \quad (1e)$$

Three adaptation gains are used in the current implementation of the WFLC algorithm: the frequency (μ_0), the amplitude (μ), and the bias (μ_b). It has to be noted that it is not possible to define a theoretical time constant for the algorithm [11], [8], and that the algorithm gains must be chosen as a trade-off between convergence time and algorithm stability [13]. High values of the gains can improve tracking of the input signal but can cause the algorithm to diverge

To allow the use of high gains values, the WFLC filter has been used in conjunction with a FLC filter, which receives as input the estimate of the instantaneous frequency w_{0k} provided by the WFLC (Fig. 2) together with a different set of amplitude adaptive gains (μ_{FLC}). The tracking can then be seen as a two step process: the first step, based on the WFLC, performs the frequency weight identification with a high μ_0 value and a small μ value; the second step identifies the amplitude weights with a high μ_{FLC} value.

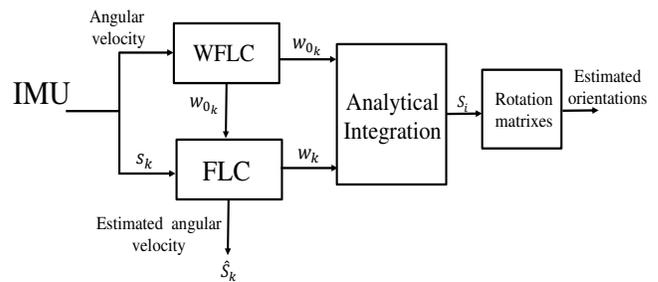


Fig. 2: Block diagram of the proposed approach.

B. Calculation of orientations from gyroscopes data

a) Integration of gyroscope data

The estimates of orientation require an integration of gyroscopes data. Tan and his colleagues [4] recently illustrated how the identified Fourier series can be analytically integrated at each sample time using the following equations:

$$w_{i_{r_k}} = \begin{cases} -w_{r_k}/(r w_{0_k} f_s), & 1 \leq r \leq M \\ w_{r_k}/((r - M) w_{0_k} f_s), & M + 1 \leq r \leq 2M \end{cases} \quad (2)$$

where w_i is the vector containing the Fourier series integrated amplitude coefficients, and f_s is the sample frequency.

The instantaneous estimate s_{i_k} of the integral of the measured angular velocity can then be obtained as follows:

$$s_{i_k} = w_{i_k} \cdot x_k \quad (3)$$

b) Automatic start-stop detection

The importance of a correct estimate of the frequency weight w_0 to avoid indeterminate values of \dot{w} is evident from (2). Estimating values of w_{0_k} that are close to zero, such as in the case of reduced oscillations, (obtained for example when a subject stops walking), would lead the WFLC algorithm to diverge. To overcome this problem, the duration during which the WFLC algorithms can properly be run must be detected. A windowed algorithm based on *a priori* determined threshold T_r is proposed. The threshold is determined using the mean value and standard deviation of the first 20 samples of a given signal:

$$T_r = \bar{s}_{1...20} + 2SD(\bar{s}_{1...20}) \quad (4)$$

The mean value of the signal calculated over a moving window of 20 samples is compared to T_r at each sample of time, and used to start or stop the WFLC and FLC algorithms. If the algorithms are stopped then the last values of w_0 and w are held in order to avoid the WFLC divergence.

c) Lower trunk orientation angles

IMU motion occurs in three-dimensions, thus the three unit local axis (x, y, z) fixed to the device move relative to the global frame. Consequently, the estimated integrals ($s_{ix_k}, s_{iy_k}, s_{iz_k}$) of the angular velocities around each axis need to be expressed in the unit local frame (ULF), i.e. the initial local frame defined at the first sample time (Fig. 3). Instantaneous lower trunk orientations angles (Y_k, P_k, R_k) in the ULF can be obtained through rigid transformation. This assumption is justified by the fact that the angles are relatively small and that the motion is quasi-periodic and thus do not lead to singularities in the rotation matrices.

C. Human walking data collection

Ten healthy subjects (5 males, 5 females, age range 24-64 years, stature range 1.60-1.94m, and mass range 69-90kg) participated in the study after giving informed consent. An IMU (Freesense, Sensorize srl) was mounted on the lower back of the subjects so that the axes of the unit local frame (ULF) were aligned with the anatomical axes of the lower trunk (see Fig. 3). In addition, three markers were attached to the unit case and defined a marker-cluster local frame (MLF).

Subjects were asked to walk at their self-selected “natural” walking speed (as determined by ad hoc preliminary trials) on a motorized treadmill for 35s. Angular velocity data were collected from the IMU ($f_s=100\text{sample}\cdot\text{s}^{-1}$) while the marker trajectories were tracked by five infrared cameras (MX, Vicon, $f_s=100\text{sample}\cdot\text{s}^{-1}$).

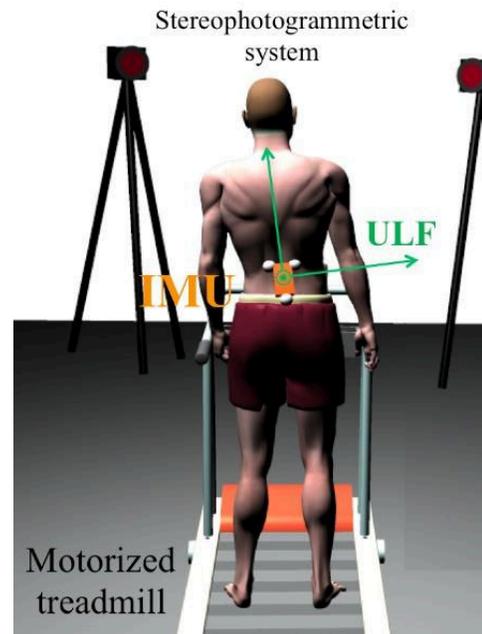


Fig. 3: Experimental setup used for the algorithm validation. Initial posture is used to define the ULF.

Yaw, pitch and roll angles, describing the orientation of the sensor in the ULF were estimated from the IMU data using the proposed methodology, and those describing the orientation of the MLF, were reconstructed from stereophotogrammetric data. The time-invariant offset of the MLF orientation relative to the ULF orientation was mathematically removed through a rigid transformation. In this way both instruments could be assumed to provide yaw, pitch and roll angles in the same lower trunk anatomical frame. It has to be recalled that both ULF and MLF are affected by the same skin artefacts during the movement and their accuracy in representing the lower trunk movements might hence be limited.

D. Input data values

The values of the algorithm parameters were chosen following the literature and the authors' experience (see section I. A). The number of harmonics is typically fixed to $M=1$ in the literature and $0 < \mu < \mu_{FLC} < 1$ must be satisfied to ensure stability [11]. Based on the authors' experience the following parameters values were chosen: $\mu_0 = 1e^{-4}$, $\mu = 0.08$, $\mu_{FLC} = 10\mu$, and $\mu_b = 1e^{-6}$. The initial estimate of the frequency weight required by WFLC algorithm was set to $w_0 = 4\pi$, while amplitude weights were set equal to zero.

E. Assessment of accuracy

To assess the accuracy of the proposed approach, its outputs were compared to the orientation angles estimated from measured stereophotogrammetric system data. Root mean square difference (RMSD), and correlation coefficient (r) were calculated for the comparison.

II. RESULTS

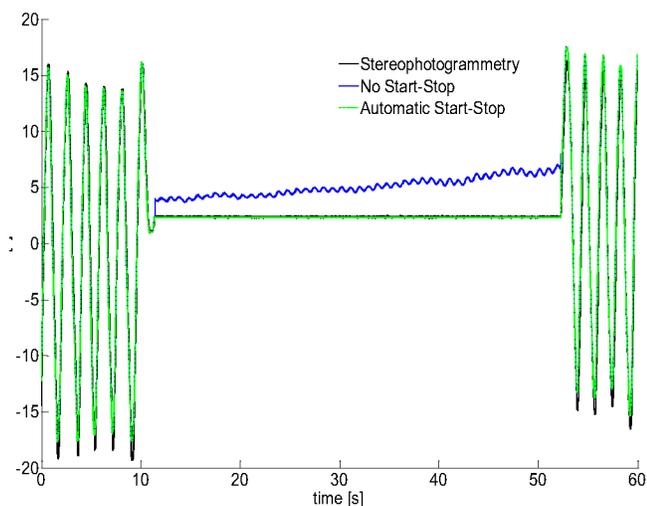


Fig. 4: Experimental illustration of the proposed method obtained with a planar motion of the IMU. Black lines correspond to measured data. Green and blue lines indicate algorithm estimates with and without the start-stop detection, respectively.

An experimental illustration of the application of the start-stop automatic detection obtained with a planar motion of the IMU is shown in Fig. 4. The IMU was moved back and forth manually with an amplitude of 30° on a plane at a frequency close to 1Hz. The green line indicates that by using start-stop automatic detection, the algorithm is able to maintain a constant value of orientation angle by stopping the update of the filter parameters while the WFLC estimation tends to diverge when oscillations stop (blue line). It should be noted that the algorithm rapidly re-

converges with the measured data once the oscillations are again present.

Fig. 5 exemplifies the ability of the WFLC algorithm in tracking the measured angular velocities.

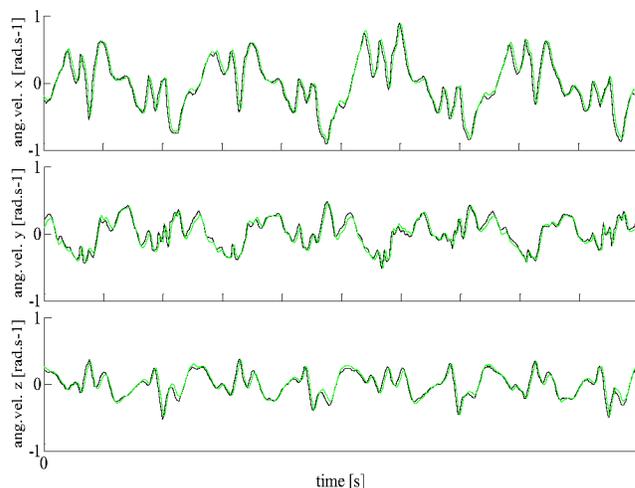


Fig. 5: Angular velocities estimated by the WFLC (blue line) and measured by the IMU (black line) during a 5s window extracted from one randomly chosen trial.

Fig. 6 shows the typical behavior of the proposed method: after a short adaptation time (≈ 5 s), the proposed algorithm is able to estimate accurately the sensor orientation angles in the ULF. In addition, the first 5 seconds of the motion correspond to the acceleration phase of the treadmill. Nevertheless, the estimate of sensor orientation angles during this adaptation time seem not to impact RMS and correlation coefficients calculated for all trials and during all their duration (Table 1). For all orientation angles and all trials, the mean RMS difference was lower than 1° (Table 1). The r values show a very good correlation between measured orientation angles and their estimates.

TABLE I

SUMMARY OF RESULTS OBTAINED OVER 10 WALKING TRIALS

	Yaw	Pitch	Roll
RMSD	$0.5 \pm 0.1^\circ$	$0.9 \pm 0.1^\circ$	$0.9 \pm 0.6^\circ$
r	0.9 ± 0.1	0.9 ± 0.0	0.8 ± 0.1

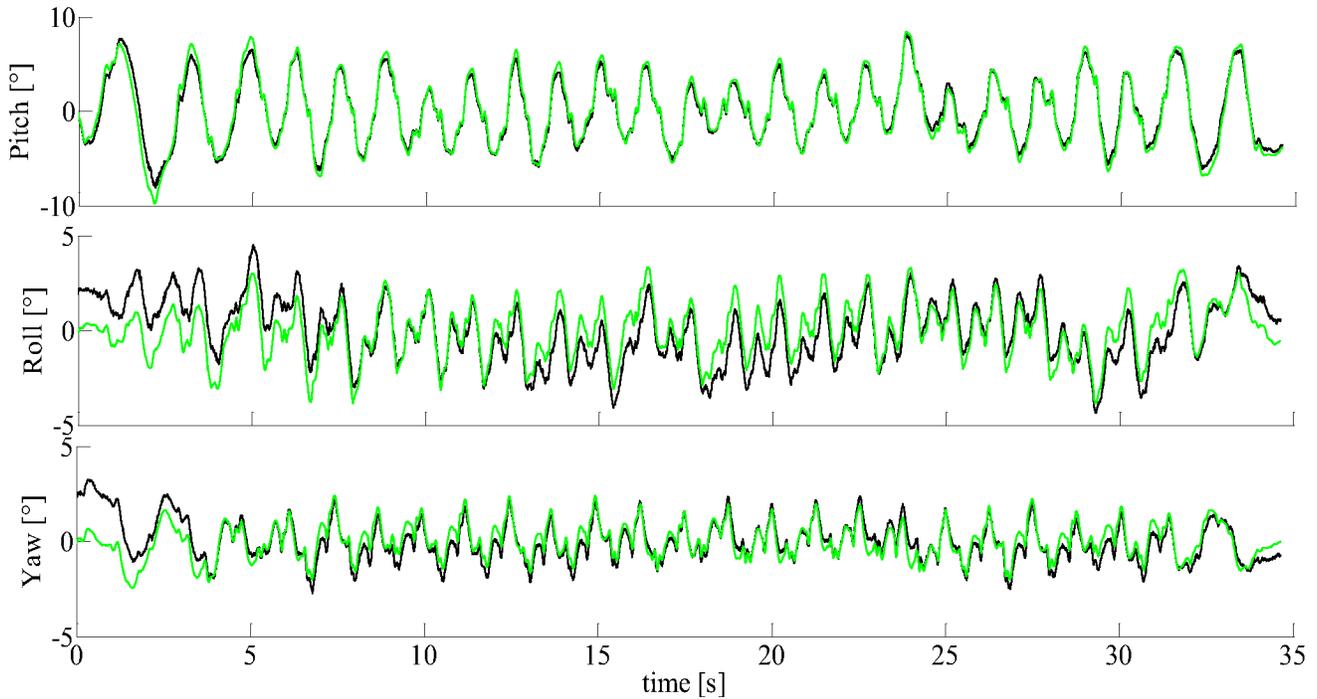


Fig. 6: Sensor pitch, roll and yaw angles as obtained for one randomly chosen trial. The black lines represent the angles obtained from the stereophotogrammetric system and the green lines the output of the proposed algorithm.

Fig. 7 shows the evolution of the frequency estimate provided by the WFLC adaptive filter, as obtained from the angular velocity measured around the x -axis of the sensor. As is clearly apparent in the figure, the frequency is updated at each sample time and converges rapidly from the initial guess.

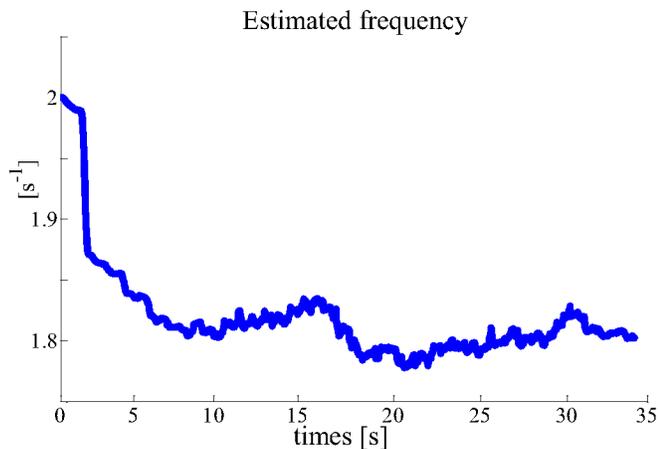


Fig. 7: Representative estimate of the frequency obtained with the WFLC algorithm and measured angular velocity along x -axis of the sensor.

III. DISCUSSION

The proposed method provides estimates of the variation of lower trunk lateral (pitch) and frontal (roll) angles, during

walking on a treadmill, that are comparable to the stereophotogrammetric system resolution, i.e. 0.5° [15]. The accuracy of the estimate obtained with the proposed method for these two orientation angles is similar to that obtained using a Kalman filter for a similar task [1]. We believe however, that a Kalman filter is more robust for un-periodic motions since its output does not require any assumptions of the signal characteristics. Axial rotation of the lower trunk (yaw) can however, also be accurately estimated with the present method whereas this is not the case with methods based on a single IMU and using a Kalman filter [1]. IN addition, the possibility of estimating in real time the sensor orientation opens the way to a number of applications requiring, for example, a bio-feedback to the subject [18].

The use of FLC adaptive filters has increased in the last two decades, with the development of several implementations to extend its field of application [11]. The WFLC algorithm generally adapts to a single frequency present in the analyzed signal [11], [17]. For the case of a signal modulated by two or more frequencies close in spectral domain, the performance of the WFLC can be degraded [11], [17]. To overcome the problems associated with a modulated signal, a very popular Band-limited Multiple Fourier Linear Combiner (BMFLC) [17], [19] that can track band limited modulated signals was proposed. The BMFLC filter requires an *a priori* determined set of frequencies. In walking analysis application the fundamental frequency can have high variations from trial to trial. As a consequence, the WFLC algorithm, which is able to track the frequency change (Fig. 7), was chosen in this study. In this context, the proposed algorithm may not provide the

best estimate of lower trunk orientation angles however it appears to be robust enough to handle human walking variability. Finally, the frequency estimate could provide interesting interpretation of gait variability [16] and this particular aspect will be addressed in the future.

IV. CONCLUSION

This study proposed the use of a combination of WFLC and FLC adaptive filters to estimate of the lower trunk orientations during treadmill walking. The proposed method can be used for estimating lower trunk lateral, frontal, and axial rotations during walking for a prolonged period of time. Future work will consist in validating our method with other quasi-periodic tasks such as squatting, rowing, running, or swimming. The limitations on the use of this method with other motor-tasks and for the estimation of variables other than lower trunk orientation angles need further investigation.

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