Analysis of Human Gait Based on Smartphone Inertial Measurement Unit: A Feasibility Study

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***Abstract*—In that feasibility study we report on the capability of the inertial measurement units embedded in a smartphone to adequately reconstruct the spatio-temporal trajectory of human head during a widely used the Timed Up and Go (TUG) motor test. The data obtained with the help of a commercially available motion stereo video capture system served as the reference. We found that the trajectories reconstructed from the signals of 3-axial accelerometer and gyroscope of a smartphone matched well with those obtained by a conventional video system. In the time domain this matching was clearly high, while in the spatial domain there were inconsistencies between two methods seen at the "sit-to-stand" and "stand-to-sit" phases. In conclusion, the smartphone's sensor system efficiently reconstructed the spatio-temporal trajectories. Therefore, even relatively cheap MEMS sensors can be used for the purpose of reliable motion analysis, especially in the condition when the body effectively damps mechanical shocks and vibrations during the TUG test. Vertical human movements during walking can be measured even by inertial sensors in smartphones with rather low cut-off frequencies (15-25 Hz).**

I. Introduction

Safe locomotion is critical for personal social adaptation of the man because it provides communication, mobility, employment, and, hence, independent living. Both neurological pathologies and specific normal states, such as ageing or fatigue, exert profound impact on force, power, endurance, coordination and velocity of muscle contraction. Impaired body balance and walking often provoke falls and traumas [1]. Therefore, it is vitally important to accurately describe the movement, and to mark its most informative features, which points on the motor disorders. That would allow elaborating prognoses and, finally, preventing these motor disorders.

Reliable predicting/preventing methods that allow detecting minor deteriorations of body balance and thus the risk of traumas in sports and under ageing are already used [2]. Also, daily walking activity/ability may serve as predictor of mortality [3], morbidity, quality of life and even life span [4].

Unlike body balance, the human gait requires more complex assessment methods, such as 1) computerized walkways, and 2) motion video-capture. These two are reliably accurate in describing phases of gait, step and stride parameters, and therefore are regarded as "gold standard" for gait studies. Still, these are usually applied in laboratory setting [5].

Thus, video-based methods are accurate but costly, difficult to install and operate, and these are often vulnerable to occlusion and illumination change in home settings [6]. Therefore, we aimed at comparing of gait spatio-temporal parameters obtained with help of a commercially available smartphone attached to a head during the TUG test with referenced records from a conventional stereo video motion capture system.

The paper is organized as follows. In section II the most relevant works are presented and evaluated. It is concluded that wearable sensors, including those built in smartphones, seem perspective to analyze human gait. In section III the algorithm of inertial data processing from accelerometers and gyroscopes is presented. Section IV presents the experimental design with special attention to the inertial measurement and processing system and the TUG test. In the Results and Discussion section V we provided a series of graphical presentations of raw and processed trajectories from IMU sensors and reference video system, and conclusions.

II. Related works

In recent years, wearable sensors for gait characterization attract growing attention due to their reliable accuracy and low costs [5], for example, "smart shoes", inertial sensors (accelerometers, gyro sensors) [7], [8], [9]. Also, surveillance camera and smartphones were suggested to trace the motion and gait of a human body with light returning spheres fixed on it [10]. This method appears interesting, though complex.

Second, sensor placement appears as an important issue in gait analysis. In the video-based analysis, light returning elements are usually fixed symmetrically on the major joints (knee, heap, ankle, elbow, shoulder) and head. As for the wearable inertial sensors, they are mostly adjusted to extremities and lower back [11]. In our earlier study we proposed to adjust the light-returning element on the top of head [10]. The head is one of the most informative objects for gait analysis. Also, head is the top element of the body construct (reversed pendulum) and thus it adequately reflects all displacements of the whole body.

The other important issue in gait and body balance analysis is the motor test selected. In recent years, the Timed "Up and Go" test gains much attention from both physiologists and clinicians to assess gait in healthy controls and neurological populations, for example with Parkinsons disease (PD) [12], [13], [14], [15]. The TUG test is comprised of the chain of events which are can be regarded as a part of usual daily living activity: 1) sit-to-stand motion, 2) stand-to-go motion, 3) short (3 m) strait walk, 4) U-turn, 5) back walk, and 6) stand-to-sit motion [16]. For healthy people, execution of the TUG test usually takes 12-16 s. Also, a "long" (L-test) version of the TUG test with is proposed for clinical use [17].

Additionally, the TUG test in its instrumented form (iTUG) was acknowledged informative and reliable [12].

In conclusion, wearable 3-axial accelerometer and gyroscope sensors are increasingly used to capture the spatio-temporal parameters of gait. The reliability of such systems in comparison with the reference camera-based systems is high [18]. Inertial Measurement Units (IMU) incorporated in smartphones can provide records that match registers obtained by laboratory instruments [19]. The IMU of iPod are also used as wearable inertial sensors to assess gait [20]. Therefore, IMU-based methods of human motion analysis can be used instead of complex and expensive systems and methods based on video capture and recognition equipment. We consider high performance inertial modules as superfluous for gait features analysis especially for the fixing point at a head. Humans skeleton and muscles act as a physical damper smoothing strong acceleration signals generated at every step performed. Characteristic frequencies of such a motion are below 10 Hz. Thus cheap commercial-off-the-shelf MEMS sensors might be used in these applications.

III. Inertial data processing algorithm

In order to analyse the trajectory of an object the data obtained from inertial module should be processed. First, systematic errors are removed. Then, the coordinate axes are rotated to be aligned to the global frame using the orientation relative to the gravity vector. After that, gyroscope data are integrated to obtain the rotation angle; accelerometer data are filtered and double integrated to obtain the trajectory. Double integration of acceleration leads to huge errors in trajectory. However, for short duration motion containing repeatable parts, like for motion during the TUG test, the errors might be significantly corrected.

A. Biases subtraction

Biases of accelerometers and gyroscopes might be found analysing the raw data corresponding to no motion conditions. For the TUG test this can be done during the sitting on the chair before and after the test (SS_0 and SS_1 periods correspondingly).

For automatic recognition of these still periods the k-point moving variance of the gyroscope signal is compared with a threshold. The number of samples is $k = 50$ for 0.5 second window size. The maximum duration of a standstill period using for further analysis was limited to 10 seconds.

To estimate the accelerometer biases on 3 axes, the referenced gravity vector $g = [0\,0\,9.82]$ is transformed into the sensor coordinate frame and subtracted from the measurements. Then the biases are calculated as the mean difference between the measured and reference values:

$$acc_{bias} = \frac{1}{N_{SS0}} \sum_{i=1}^{N_{SS0}} (acc_i - q_i \otimes [0\, g]^T \otimes q_i^*)$$

where acc_{bias} – systematic error, $acc_i = [x_i' y_i' z_i']$ – accelerometer measurements in the sensor's coordinate frame, N_{SS0} – number of samples in SS_0, q_i – orientation quaternion, [0 g] – referenced gravity vector in quaternion representation, $\otimes$ – the quaternion multiplication operation.

The gyro biases are estimated as the mean value over the period SS_0.

Thus, both accelerometer and gyroscope systematic errors are calculated and must be subtracted from the raw measurements.

B. Orientation estimation

The implemented orientation filter is based on the nonlinear complementary filter proposed in [21]. The filter state is a quaternion q representing the orientation of the device relative to the reference coordinate system. The reference coordinate system is chosen so that the Z axis is co-aligned with the gravity.

Each measurement from the inertial sensors (either gyroscope or accelerometer) is sequentially sent to the filter input along with the measurement timestamp and sensor type. Then the update of the filter state is performed.

The correction $\dot{q}$ of current orientation quaternion is calculated as follows:

$$\dot{q} = \frac{1}{2} q \otimes \omega_g, \tag{1}$$

where q – the unit quaternion reflecting the orientation of the device body frame relative to the reference frame, ω_g – the gyroscope measurements in quaternion representation (with a scalar part equal to zero).

After finding the correction quaternion $\dot{q}$, the previous estimated orientation could be updated according to:

$$q_n = q_{n-1} + \dot{q} \cdot T, \tag{2}$$

where T is the time between two consecutive measurements. Finally, the normalization of the quaternion is performed after the update procedure.

The filter state update on the accelerometer data is performed in the similar way. Before the update, the estimated offset (systematic error) is subtracted from the measurements of the accelerometer. Then the corrected accelerometer measurement a_{corr} is normalized. And the orientation correction ω_a, which should be applied to align measured acceleration vector with the gravity, is calculated as:

$$\omega_a = k_a \cdot (a_{corr} \times g_{est}),$$

where $g_{est} = q \otimes [0\ 0\ 1]^T \otimes q^*$ is the reference normalized acceleration vector of the gravity transformed into the body coordinate frame, k_a is the weight coefficient of accelerometer measurements. The coefficient value k_a is either $k_a = 2$ under conditions of low dynamics or $k_a = 0.5$ under conditions of high dynamics. The distinction between these states is determined automatically by comparing the energy of gyro measurements with a predefined threshold.

For the orientation update the calculated value ω_a is placed into the equation (1) instead of ω_g, then the correction quaternion is calculated and the quaternion of orientation is updated using the formula (2).

Using the estimated orientation the corrected sensors measurements are transformed from the sensor local frame

$(X'Y'Z')$ into the reference static coordinate system (the global frame XYZ).

$$\begin{pmatrix} 0 \\ x \\ y \\ z \end{pmatrix} = q \otimes \begin{pmatrix} 0 \\ x' \\ y' \\ z' \end{pmatrix} \otimes q^* \tag{3}$$

To get the linear acceleration a, the gravity vector g is subtracted from the accelerometer measurements.

C. Velocity and position estimation

The velocity estimation v_n is obtained using integration of the linear acceleration according to:

$$v_n = v_{n-1} + a_n \cdot (t_n - t_{n-1}),$$

where a_n – the linear acceleration at the moment t_n.

The linear acceleration contains at least two types of errors: a) not perfectly excluded bias and b) random errors. In practice for the time periods of dozens of seconds the random error component prevails due to its nature – the flicker noise.

The unconsidered bias leads the integration error (the velocity) to be growing linearly in time. And the random error bends this straight line.

However, some corrections to improve the integration result might be done. For the sensor fixed on a foot, ZUPT (zero velocity update) technique might be applied. In case of fixing the sensor on a head, the most convenient correction is the following.

Knowing that SS_0 and SS_1 are the still periods with the velocity equal to zero ($v = 0$), the velocity correction during the TUG test activity is calculated as the linear interpolation between the values at the end of SS_0 and the beginning of SS_1 periods. Then this correction is subtracted from the velocity estimation. The velocity during SS_0 and SS_1 is explicitly set to zero.

To get the position estimation the velocity is integrated.

$$x_n = x_{n-1} + v_n \cdot (t_n - t_{n-1}).$$

D. Z-coordinate motion correction

As it was said, due to the double integration of a noisy acceleration signal the calculated coordinates are not accurate in long term aspect.

For gait analysis the step duration and Z-coordinate variations of a head during walking periods are vital. In order to extract the vertical oscillations the following data processing method similar to a high pass filtering is proposed.

First, the Z axis data are filtered by a low pass filter, and a trend curve is constructed. Then the difference between this trend and not filtered data is analysed.

To get the short time variations of the position, its low frequency component is calculated using two consecutive median and moving average low pass filters:

$$z_{trend} = \sum_{i=n-w_{ma}/2}^{n+w_{ma}/2} medfilt(z).$$

The size of the filter window is set to $w_{medfilt} = 100$ samples for the median (approximately 2 steps time interval) and $w_{ma} = 25$ samples for the moving average filter.

IV. Experiment description

A. Reference video positioning system

In our study, we used the Videoanaliz Biosoft 3D setup (Biosoft LTD, Moscow, Russia) as the reference positioning system. It is commercially available and actively used in Russia [22]. The concept of motion stereo video capture system is shown in Fig. 1.

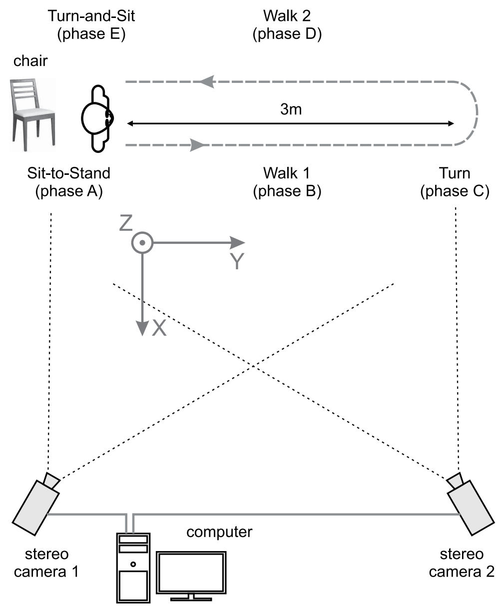

Fig. 1. TUG test environment

The system includes two synchronized video cameras Baumer TXG (90 Hz) connected to a computer via Firewire-1394 interface. The stereo cameras register the motion of a reflecting ball (balls). The ball can be fixed to an object with an adhesive film.

To increase the sensitivity of the tracking two additional infra-red backlight projectors were installed. After saving stereo video in AVI format, the specific Biosoft commercial software is used to reconstruct the motion.

The software performs automated identification of labels (reflecting balls) on video, computation of their coordinates in 3D, construction of a 3D model of a subject and kinetogram (with the option to superimpose it with original video). The data can also be exported to the TXT and MS Excel formats for further analysis.

Spatial resolution of the reference video positioning system for low dynamic objects with velocities less than 3 m/s is estimated to be ≈0.2 cm for Y and Z axes, and ≤1 cm for X axis (the axes are noted corresponding to the scheme on Fig. 1).

B. Inertial measurement and processing subsystem

In the experiments described below Xiaomi Mi4 smartphone equipped with STMicroelectronics LSM6DB0 sensor module was used. The inertial module includes a 3-axis accelerometer, 3-axis gyroscope and Cortex-M0 core. Though Xiaomi Mi4 contains a magnetometer, it was not used for a trajectory restoration, since magnetic field is very disturbed indoors.

LSM6DB0 characteristics are presented in Table I.

TABLE I. CHARACTERISTICS OF LSM6DB0 INERTIAL MODULE

Parameter	Value
Linear acceleration measurement range	±8 g
Linear acceleration sensitivity	0.244 mg/LSb
Angular rate measurement range	±2000 dps
Angular rate sensitivity	70 mdps/LSb
Noise characteristics and LPF settings	N/A

Although LSM6DB0 can independently fuse the data from all embedded sensors by iNemo Engine software and provide the result to the Android OS, all the processing within the investigation was carried out using raw data from accelerometer and gyroscope in order to use previously developed advanced algorithms [23], [24], [25] and to demonstrate the hardware independence.

The raw data sampled at 100 Hz were collected using Sensor Fusion software provided by the University of Linkoping, Sweden [26] and then processed by the scripts in Python.

C. TUG test description

The TUG test is composed of a series of consequent motions in a relatively small room [14]. Before the test the subject 1) freely rested on a chair (still period), 2) then, by the command the subject stood up (the sit-to-stand phase), 3) walked 3 meters forth (walking phase), 4) turned back (U-turn phase), 5) walked back to the chair (back walk phase), 6) turned back in front of a chair and sit down (turn-stand-to-sit phase), 7) still period. General design of the TUG test is presented on Fig. 1.

The smartphone was fixed on the back of the head of a researcher by the tight knitted hat as presented in Fig. 2. The smartphone did not change its orientation relatively to the head while the researcher moved.

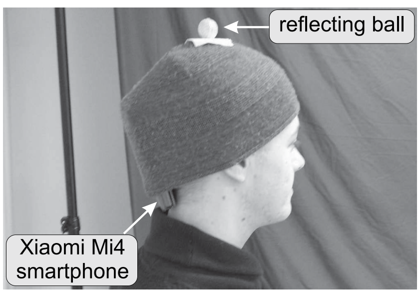

Fig. 2. Xiaomi Mi4 smartphone fixed on the back of the head of a researcher

V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Inertial data analysis

The data from 3D-accelerometer and 3D-gyroscope collected in TUG test were processed according to the methods described in Sec. III.

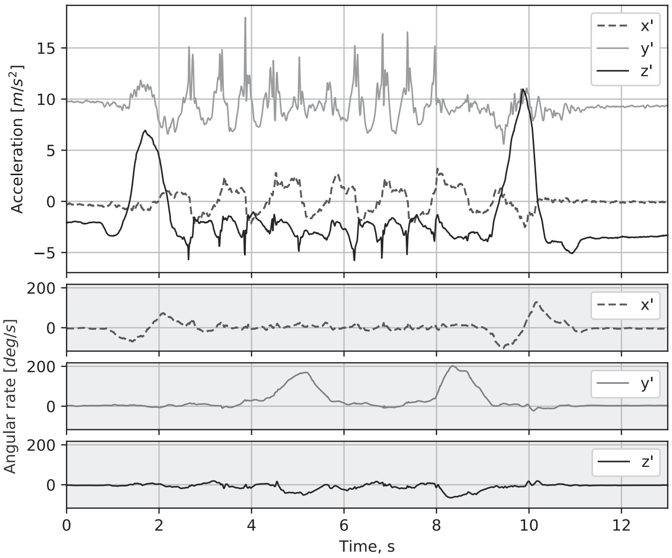

Fig. 3. Raw inertial data (3 spatial components of acceleration and rotation rate)

Raw data are presented in Fig. 3.

X', Y' and Z' axes are the internal axes of the inertial module and are not aligned with the global frame.

Since the smartphone was fixed not vertically, the mean values over the internal Z' axis of the accelerometer in statics are shifted from zero level to ≈-3 m/s^2 (as presented in the upper plot in Fig. 3).

After the calibration of accelerometer and gyroscope using the data within the still period prior to the phase A of the TUG test the biases of the accelerometer and gyroscope were subtracted (Sec. III-A). Then, using the estimated smartphone's orientation, 3D-measurements were rotated to fit the global frame according to the method described in Sec. III-B. The result is shown in Fig. 4.

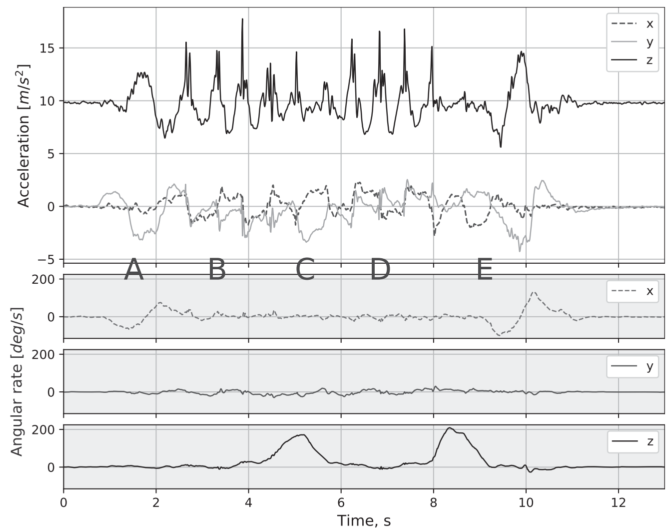

Fig. 4. Inertial data in the global frame (3D acceleration and rotation rate)

X and Y axes are oriented horizontally, Z axis is directed up. Thus only the Z-component of acceleration vector contains the gravity. And the biases of the gyroscope are excluded from the raw data.

All phases of the TUG test can be clearly identified on Fig. 4:
- still period (0–0.7 s);
- phase A (Sit-to-Stand, 0.7–2.2 s);
- phase B (Walk 1, 2.2–4.4 s);
- phase C (Turn, 4.4–5.6 s);
- phase D (Walk 2, 5.6–8 s);
- phase E (Turn-and-Sit: turn 8-9.2 s and "sit" 9.2–10.3 s);
- still period (11–13 s).

The periods of rising from a chair and sitting down on a chair are characterized by the alternate signals over X axis of angular rate, left turns – by two peaks over Z axis of angular rate, performed steps – by Z axis acceleration signal.

The trajectory was obtained by double integration of the unbiased acceleration data. The motion of the head over Z coordinate in time (see Sec. III-C) is presented on the upper plot in Fig. 5 by the solid line.

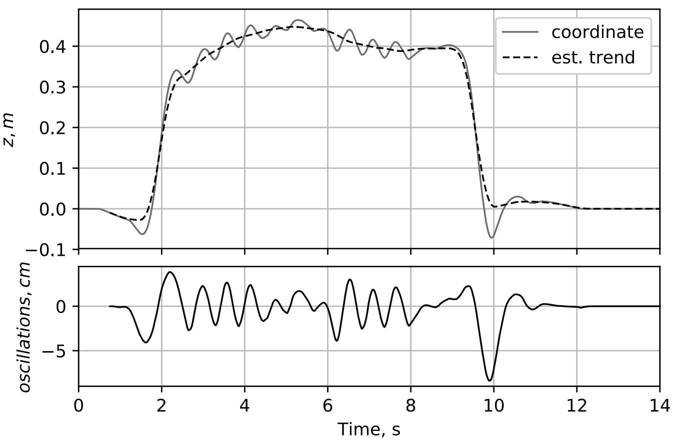

Fig. 5. Z axis coordinate motion of the head of a pedestrian (restored by means of inertial system)

To determine the amplitude of vertical displacement of the head the technique described in Sec. III-D was applied. The low pass filtered trend is marked by a dashed line (upper plot in Fig. 5). The extracted vertical oscillations of the head are presented in the bottom plot in Fig. 5. The head displacement in the Walk phase is $\approx$5 cm.

B. Comparison with reference video positioning system

The movement of the head of a researcher was also registered by the reference video stereo camera system. Curves for X, Y and Z coordinates are presented in Fig. 6. The path length along Y axis was $\approx$2.9 m. Characteristic cross section views in YZ and XY planes are shown in Fig. 7 and Fig. 8. Curves corresponding to the phases A, C and E are very specific.

To compare the IMU-based calculations with the reference trajectory, the motion of the head along Z axis was filtered and processed in the same way as for the inertial signal. The result is presented in Fig. 9.

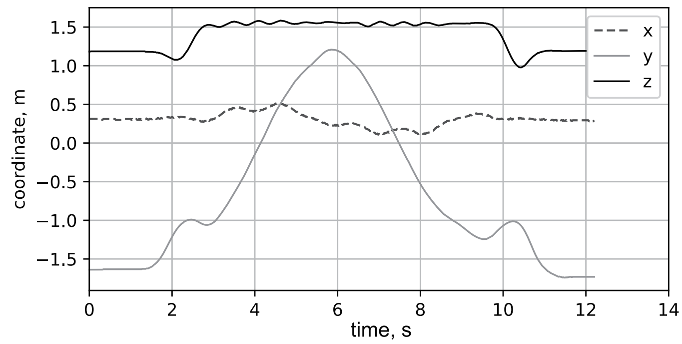

Fig. 6. X, Y and Z relative coordinates of the head of a pedestrian within the TUG test (reference video positioning system)

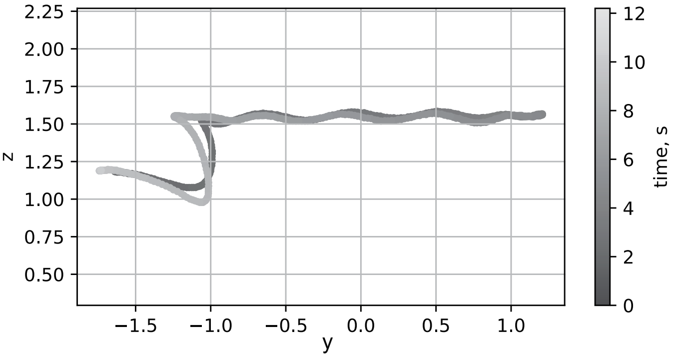

Fig. 7. Characteristic motion of the head of a pedestrian during the TUG test (YZ vertical plane, reference video positioning system)

The form and the amplitude of vertical oscillations of the head registered by the reference video positioning system and restored by the inertial data processing are very close to each other (see Fig. 10).

The main difference between the solid and dashed lines corresponds to the moment of fast sit-to-stand and stand-to-sit transitions (2-nd and 10-th seconds). The fronts of the generated acceleration signals during this motion are too steep. And the internal digital filtering system (inside the smartphone: embedded in LSM6DB0 or Android OS, might be adaptive filtering) seems to make them more flat.

However, all the tiny vertical oscillations of the head were "caught" by the inertial data processing algorithm.

C. Applying the proposed method for longer TUG tests

To test the proposed method for teh longer TUG procedure, the same researcher was asked to make $\approx$20 steps in each Walk phase. The result of Z coordinate motion is presented in Fig. 11.

The curvature of the dashed line in the upper plot demonstrates double integration errors (mostly in velocity calculation part). However, the technique of the construction of the low pass trend and further plotting the difference between the trend and the unfiltered trajectory yields the same result for vertical head displacement – 5 centimetres.

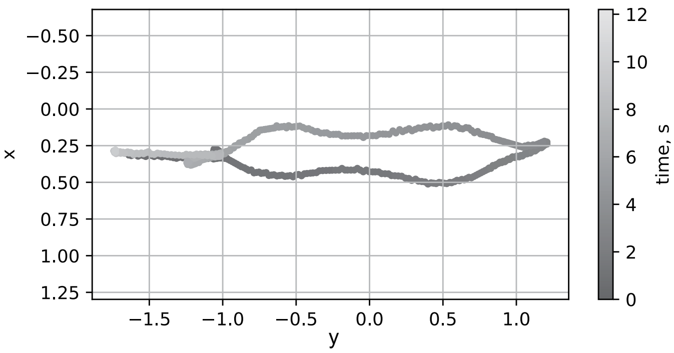

Fig. 8. Characteristic motion of the head of a pedestrian during the TUG test (XY horizontal plane, reference video positioning system)

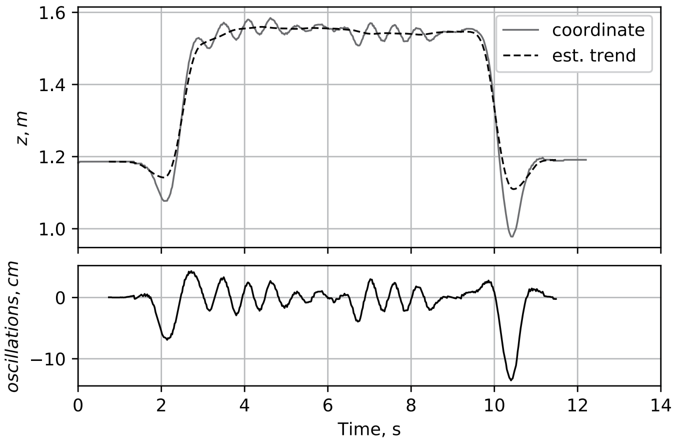

Fig. 9. Motion of the head of a pedestrian during the TUG test (Z-coordinate, reference video positioning system)

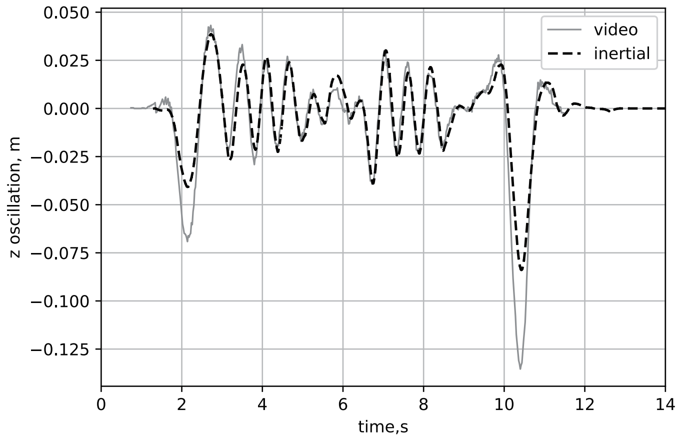

Fig. 10. Comparison of the restored Z axis trajectories for both methods: reference video positioning system and IMU-based approach

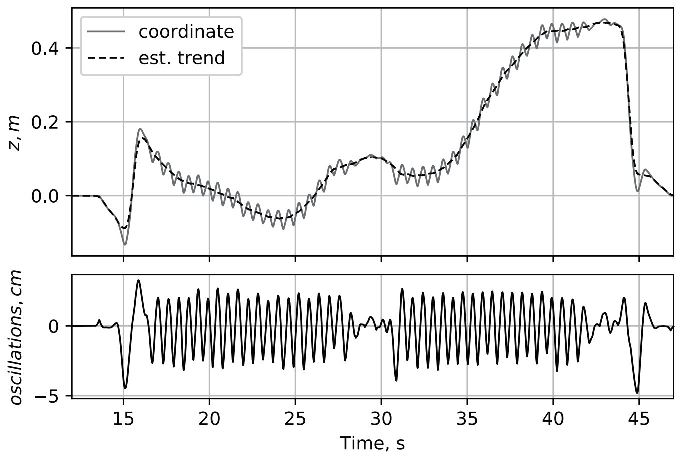

Fig. 11. Z axis head height oscillations of a pedestrian for a longer 20 steps TUG test

D. Possible extracted features for gait disorders analysis

Gait is a rather complex motion for analysis because it provides dozens of parameters [9]. Vienne et al. extracted as little as 57 parameters from gait analysis and classified them in 7 groups. Among these are:

1) springiness (e.g., step time),
2) sturdiness (e.g., step length, range of motion, vertical acceleration),
3) smoothness (e.g., anteroposterior acceleration of lower back, maximum acceleration or speed of all body parts),
4) stability (e.g., mediolateral range of motion of the lower back),
5) steadiness (e.g., variation coefficients a of all part and all directions),
6) symmetry (e.g., right-left symmetry of parameters of springiness and sturdiness),
7) synchronization (double stance time, phase coordination index).

As it follows from this list, only few parameters can be extracted by means of only one sensor (fixed on a head). However, such important parameters as time of step or stride, time of turning, time of sit-to-stand and stand-to-sit phases are easily read from the trajectories.

Similarly, Mico-Amigo et al. have recently shown that using a single body-fixed sensor allows distinguishing PD-associated gait from that of healthy controls [27]. In this study, gait was assessed under either self-paced (self-selected speed, SSS) and as-fast-as-possible (fast speed, FS) condition during 5 meter long walk that equals 7 steps. Over 160 kinematic parameters were extracted using accelerometers and gyroscopes. Among the most valid parameters for the SSS condition were the following: relative root mean square (RMS) of vertical displacement, relative displacement at the start of movement, range of anterior-posterior velocity, and relative RMS of vertical acceleration at the pre-last step. As for the FS condition, duration of the middle step and angular velocity around the medio-lateral axis of the last step appeared as predictors for PD [27]. It would be wise to apply this 5 meter walk paradigm to the TUG test to discriminate between PD patients and healthy controls, because 3 steps paradigm gives lesser data for analysis. Additionally, gait speed, stride length, variability, cadence, foot angles and clearance are valid for instrumented gait analysis [28].

As these characteristic events are very important for diagnostics of the symptoms of parkinsonism, such as bradikinesia, freezing, shuffling slow steps, we regard our result as sufficient to apply a smartphone IMU to record PD-specific events (features) from the spatio-temporal trajectory obtained from the only one body segment. Alternatively, one can consider of applying several IMU sensors on various parts of the body for a more profound analysis of the above listed parameters.

VI. Conclusion

In a panoramic review [29] published in 2016 the authors stated that only "surprisingly low percentage of 6% of the studies" included high level technologies for the assessment of Parkinsons Disease. Obviously, the accuracy of MEMS-based inertial devices was unsatisfactory to register the human motion and to extract the gait features.

Human body mechanically damps shocks and vibrations during walking, and the head is a perfect instrument to reflect the process. The characteristic frequencies of this smoothed motion are rather low and can easily be registered by cheap MEMS sensors with LPF cut-off frequency of $\approx$15-25 Hz. Thus we proposed to use IMU equipped smartphones (or stand alone light weight sensors wirelessly connected to a smartphone) to measure the vertical motion of the head and to use it for gait analysis. The corresponding inertial data processing method includes: sensors biases subtraction, IMU module orientation estimation, velocity and position estimation and Z-coordinate motion high pass filtering.

Now, as it was demonstrated, a single inertial 3-axial sensor embedded in a smartphone allows reconstruction of spatio-temporal trajectories of the head during the TUG test with the accuracy comparable with that of a commercial motion capture video system.

This result seems promising to elaborate an easy-to-do, low-cost, at-home, single-sensor method either to discriminate between PD patients and healthy controls, to evaluate the effect of anti-PD therapies, or to monitor current motor condition of PD patients. Longer walk (5-10 meters) with greater number of steps (10-20 steps) seems more reliable for better segmentation of the walk and capture gait signatures.

Acknowledgment

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