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Towards an IMU Evaluation Framework for Human Body Tracking

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Abstract. Existing full-body tracking systems, which use Inertial Measurement Units (IMUs) as sensing unit, require expert knowledge for setup and data collection. Thus, the daily application for human body tracking is difficult. In particular, in the field of active and assisted living (AAL), tracking human movements would enable novel insights not only into the quantity but also into the quality of human movement, for example by monitoring functional training. While the current market offers a wide range of products with vastly different properties, literature lacks guidelines for choosing IMUs for body tracking applications. Therefore, this paper introduces developments towards an IMU evaluation framework for human body tracking which compares IMUs against five requirement areas that consider device features and data quality. The data quality is assessed by conducting a static and a dynamic error analysis. In a first application to four IMUs of different component consumption, the IMU evaluation framework convinced as promising tool for IMU selection.

Keywords. IMU, human body tracking, evaluation framework.

1. Introduction

In recent years, sensor miniaturization has been a driver for product innovation in many areas. The miniaturization of Inertial Measurement Units (IMUs) for instance enables numerous applications including the tracking of moving objects by computing orientation [1,2]. In the field of human movement analysis, the integration of IMUs in wearable full-body tracking systems has been realized by a few specialized manufacturers and start-ups [3], such as Xsens (Xsens Technologies B.V., Enschede, The Netherlands), Enflux (Enflux, San Francisco, United States) or Rokoko (Rokoko Electronics, Copenhagen, Denmark). In general, all these systems aim at assessing people's movement outside the laboratory [4,5]. In particular, in the research field of Active and Assisted Living (AAL), mobility for older people means independence and participation in social life. Furthermore, the functional ability of being mobile, including exercise, promotes healthy aging and postpones frailty [6]. In order to avoid injury and maintain functional ability, it is important that exercises are performed in a proper way. Exercise monitoring of older people at their homes could benefit from wearing an IMU-based full-body tracking system. The quality assessment of exercise performance could not only provide meaningful feedback to the users themselves but it could also help supervising entities like trainers or doctors to adjust training according to the users' abilities. Functional training has been supported technologically in various AAL projects for better quality of life and health of older people [7,8]; however, only few have considered IMUs as sensor technology so far [9,10]. The required expert knowledge of

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existing full-body tracking systems for setup and data acquisition as well as their fixed configuration of IMU placements is unsuitable for the target group of older people. Thus, we decided on implementing a human body tracking system where number, position, and hardware can be chosen according to application requirements.

Available IMUs on the market differ in various aspects including component composition. The range of products starts at basic packages, for which casing, battery and data transmission have to be added separately, up to turnkey solutions. Some of the turnkey solutions are even capable of outputting their orientation directly. Due to the variety of options, IMUs have to be selected based on criteria.

Existing works stated some criteria related to IMU selection such as power consumption and sampling rate [1,11-13]. However, none considered data quality of the IMU measurements, which is a crucial factor since all further processing steps depend on it.

Thus, this paper introduces an evaluation framework for wearable IMUs used in human body tracking that considers both, hardware features and data quality. In order to assess its performance, the framework is applied to IMUs with different component composition. Based on the results of the application, possible improvements and adaptations of the framework should be identified and discussed.

2. Methods

2.1. IMU evaluation requirements

In recent years, considerably little effort has been investigated in the comparison of IMU performance with respect to human motion analysis. Ahmad et al. [1] identified form factor, data accuracy, response rate, and the degree of freedom (DOF) when selecting IMUs for various applications. Data accuracy was described to be dependent on the selected sensor fusion which reduced sensor drift and other errors introduced by the sensors. During the development of their own IMU for the analysis of Parkinson's disease symptoms, Rodríguez-Martín et al. [11] stated several IMU requirements, including long, unsupervised runtime, minimum power consumption, wearable form factor and connectivity to other devices. Within their work, they compared twelve commercial IMUs including the Xsens MTw and the Physilog 3 as wireless body tracking sensors. The conducted comparison relied purely on market analysis without looking at data samples of the actual devices. A latest design methodology for motion capture wearables, called *Octopus*, is exclusively based on review of publication and a market research [13]. It considers connection, attachment method, and the physical properties of the device such as shape, dimensions, weight, housing material and color.

Based on this research, we created a demand profile for IMUs in human body tracking. In addition, we considered a role model for the framework since the usage of such full-body tracking systems require expert knowledge, which complicates the independent usage, e.g. for AAL applications, and the predefined number and positions of IMUs decrease the flexibility of applications. Hence, the full-body tracking system that uses wireless IMUs, namely the Xsens MVN Awinda [14] is considered as role model. Finally, the identified requirements for human body tracking are divided into five areas:

Form factor: Wearable IMUs for wireless body tracking are available in different dimensions. Nevertheless, they should be appropriate for unobtrusive integration into clothes. The Xsens MVN Awinda uses Velcro straps to attach the IMUs onto predefined body segments. Each IMU comes with dimensions of *47x30x13mm* and weights *16g* [15]. Integration can be additionally possible using clips or other simple methods of fastening [1,13].

Mobility: The maximum possible operating time depends on battery capacity, sampling rate and the means of data transmission. A runtime of *6 h* at *60 Hz* with wireless transmission is considered as threshold for the framework since high-end systems like Xsens MVN Awinda work with these specifications [14]. Ideally, the battery is rechargeable via Universal Serial Bus (USB).

Data acquisition: For immediate feedback to users, near real-time data processing should be targeted, i.e. showing a latency time of at most *100ms* [16]. Furthermore, wireless data transmission should be considered for avoiding cables and, thus, difficult setup. For example, Bluetooth Low Energy (BLE) is most widely supported by consumer smartphones and meets the requirement of fast data transmission. The supported sampling rate of the IMU should be at least *60 Hz* , being higher than the suggestion of *40 Hz* by [11]. An API for monitoring the hardware's health status and for customization of applications is a basic requirement. This should enable access to the IMU's raw data.

Additional features: The price of each IMU should be of concern since we plan to develop a full-body tracking system to consist of at least five IMUs [4]. Considering the current prices of smart wearables such as smartphones, we expect that people might be willing to spend the same amount for a wearable IMU-based full-body tracking system, being priced up to €500 [17], i.e. the price of a single IMU should not exceed *€ 100*. In addition, the possibility of building a sensor network should be possible so that multiple IMUs can interact with each other for synchronization purposes.

Reliable recognition of human motion: This requirement area includes the verification of how robust and reproducible the data provided by the IMU is for full-body tracking. Most commonly, IMUs with 6-DOF, which comprise a 3D accelerometer and a 3D gyroscope, or 9-DOF IMUs, which add a 3D magnetometer, are used [1]. Thus, at least 6-DOF IMUs should be required. Further sensors, like the magnetometer or the barometer are optional for consideration in orientation estimation. With respect to data quality, a static and dynamic error analysis support the evaluation of IMUs by identifying error behavior of the IMUs and rank the devices upon these results (see subsection *2.2*).

The more requirements of the framework are fulfilled by the IMU under investigation, the more appropriate it should be for the task of body tracking.

2.2. Static and dynamic error analysis

Static and dynamic error analysis were used for the objective evaluation of the data quality of each IMU.

The **static error analysis** aims at evaluating the amount of inherent noise in the sensor readings, particularly, the gyroscope drift error. For a static and undisturbed position, the IMU is fixed onto a table and data is recorded for *120 min* without movement at room temperature. If available, the IMU's internal calibration routine is used to dampen the noise. To quantify the residual noise occurring while the sensor experiences no movement, an Allan variance analysis is conducted as described in El-Sheimy et al. [18] determining two types of error quantity: the random walk and the bias stability. The Angle Random Walk (ARW) or Velocity Random Walk (VRW) is the

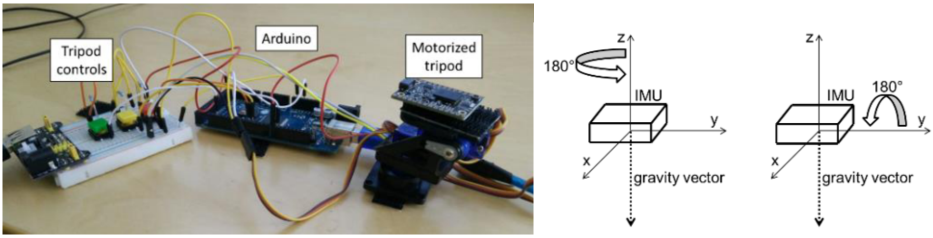

Figure 1. Left: Motorized tripod (on which the device under test is mounted) with additional Arduino micro controller unit and manual controls; Right: IMU rotations about z- and y-axis.

influence of high-frequency noise. The bias stability is dependent on the influence of low-frequency noise mainly coming from the sensor's electronics. With the bias changing over time, this metric tells the best expected bias stability (BS) from this IMU. Of both quantities, the root mean square error (RMS) over x-, y- and z-axis is calculated, for which lower numbers imply better results.

By conducting a **dynamic error analysis**, the performance of the sensors in motion is assessed and compared to simulated data. To move the IMU in a controlled manner, a motorized pan-tilt tripod and an Arduino board is used to conduct counterclockwise z- and y-rotations of *180°* (see *Figure 1*). All rotations are performed at a programmed speed of *166.7°/s* that roughly resembles a natural limb rotation. To mark beginning and end of the sequence, rotations at maximum speed of the motors around the z-axis are executed giving clearly distinguishable impulses in the data. If necessary, the IMU's frames are mapped to a right-handed coordinate system, where the positive vertical z-axis points upwards, the positive y-axis to the right, and the positive x-axis frontwards. Sensor fusion algorithm such as described by [19] are used to calculate quaternions representing the orientation of each IMU over time. For comparison, the entire motion sequence is simulated using the spherical linear interpolation (SLERP) of quaternions which is commonly used to smoothly animate 3D rotations [20]. The calculated and simulated quaternions are applied to rotate a unit vector, resulting in an ideal and an actual trajectory. The idea is to determine the error by using the distance function $\phi(q_1, q_2)$ that computes the angular deviation between two quaternions [21]:

$$\phi(q_1, q_2) = \cos^{-1}(2\langle q_1,\ q_2\rangle^2 - 1) \tag{1}$$

The denotation $\langle q_1,\ q_2\rangle$ corresponds to the inner product of the two quaternions q_1 and q_2. The range of the distance function is between *0* and *π*, where *0* means that the compared rotations result in the same orientation. Values close to *π* represent maximal angular deviation from simulated orientation.

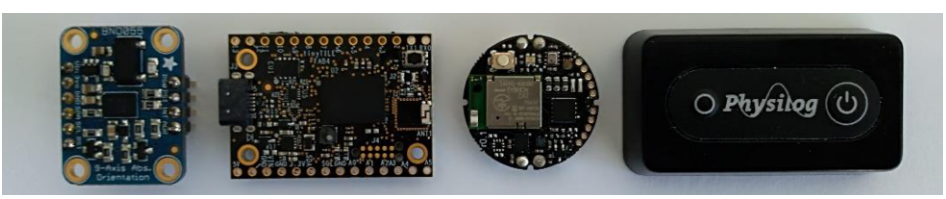

Figure 2. IMUs of different components composition from left to right: BNO055 board, Intel Curie board, MetaMotionC and Physilog 5.

3. Results

In this section the first application of the framework is presented showing the fulfilments of the requirements and the ranking of the static and dynamic error analysis (*Table 1*). Thus, four IMUs were selected based on their component composition. The BNO055 board [22] and the Intel Curie board [23] represented basic packages that can be integrated into low-level prototypes. In this case, "low-level" means that the IMU requires additional hardware, like power supply and casing. The MetaMotionC [24] and Physilog 5 [25] represented turnkey solutions that work out of the box and come with complementary software. We chose these devices due to their small size, wide availability, and their differing component composition.

Form factor: The dimensions of all four devices are sufficient (*Figure 2*). However, the BNO055 and Curie provide no attachment to the body. This could be circumvented by using 3D printed parts. For the MetaMotionC, the 3D-printed case provided by the manufacturer was used. Physilog provides a rubber clip with each device.

Mobility: The Physilog comes with a USB-chargeable battery included in the casing. BNO055 and Curie have to be powered externally, although the Curie provides a charging circuit. The MetaMotionC does not provide an integrated rechargeable battery and is instead powered by a coin cell.

Data acquisition: Except BNO055, which supports only *I²C* communication, all investigated IMUs support BLE transmission. Regarding API, libraries are freely available for all boards except Physilog.

Additional features: The Physilog is the most expensive one of the selected IMUs with *€ 499* per device, which would sum up to *€ 2,495* for a full-body tracking system. All others were within the required price range. The support for multiple sensors is limited. Solely Physilog and MetaMotionC provide basic synchronization by allowing IMUs to start and stop simultaneously.

Table 1. Application of IMU evaluation framework to four IMUs: 'X' marks fulfilment of requirement and the rank of each IMU is given from *1* (best) to *4* for static and dynamic error analysis.

	Physilog 5	MetaMotionC	BNO055	Intel Curie
Form Factor				
Application to clothes	X	X		
Size < *47x30x13 mm*	X	X	X	X
Weight < *16 g*	X	X	X	X
Mobility				
Battery life > *6 h*	X	X		
Chargeable battery	X	X		
USB charging	X			X
Data acquisition				
Bluetooth data transmission	X	X		X
Sampling rate > *60 Hz*	X	X	X	X
API available		X	X	X
Additional features				
Price less than *€ 100*		X	X	X
Multiple sensor network feasibility	X	X		
Reliable recognition				
6-DOF IMU	X	X	X	X
3-DOF magnetometer	X	X	X	
Barometer	X	X		
Static error analysis – RW	*2*	*1*	*4*	*3*
Static error analysis – BS	*1*	*2*	*3*	*4*
Dynamic error analysis	*1*	*2*	*3*	*4*

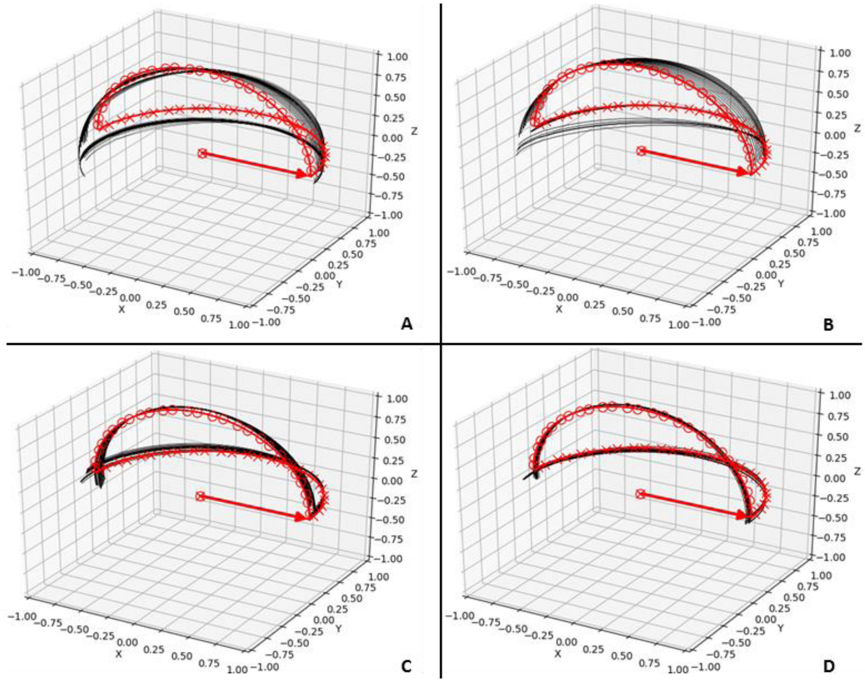

Figure 3. IMU-based trajectory of unit vector of (A) BNO055, (B) Intel Curie, (C) MetaMotionC and (D) Physilog 5 (black) and SLERP-simulated trajectory of the same unit vector (red marked with X and O).

Reliable recognition of human motion: All four selected IMUs provide the mandatory 3-DOF gyroscope and accelerometer. Additional sensors are available on the Physilog, MetaMotionC and BNO055. The results of the static and dynamic error analysis are given in *Table 2*. The best results related to bias stability came from the Physilog measurements (RMS for gyroscope and accelerometer of *7.19 °/h* and *0.12 °/h*, respectively). MetaMotionC provided the lowest amount of random walk (RMS for ARW and VRW of *0.0055 °/s/√Hz* and *0.0001°/s/√Hz*, respectively). For the dynamic error analysis, the calculated orientation was compared to the orientation data simulated with SLERP (*Figure 3*). The resulting maximal and mean angular orientation deviations are shown in *Table 2*. The lowest deviation was achieved by using the Physilog data, with the MetaMotionC coming close. The BNO055 was ranked third, and the largest error by a clear margin came from fusing the Curie data (see *Table 1)*.

Table 2. *Static error analysis*: RMS of random walk in °/s/√Hz and of bias stability in °/h over the x-, y- and z-axis; *Dynamic error analysis*: maximum and mean angular orientation derivation to SLERP-simulated orientation data ranging from *0* to π (*= 3.14*).

	Physilog 5	MetaMotionC	BNO055	Intel Curie
Bias stability				
Gyroscope:	7.19	7.43	7.95	7.54
Accelerometer:	0.12	0.27	0.29	0.50
Random walk				
ARW:	0.0068	0.0055	0.0455	0.0069
VRW:	0.0002	0.0001	0.0002	0.0002
$\boldsymbol{\Phi(q_1, q_2)}$				
Maximum:	1.12	1.19	1.58	3.14
Mean:	0.35	0.37	0.43	1.09

4. Discussion and conclusions

The introduced IMU evaluation framework was applied to four IMUs with different component composition. Results indicated that the turnkey solutions MetaMotionC and Physilog are better due to device features and data quality. Considering the basic packages BNO055 and Curie, which ranked behind the turnkey solutions, they differed extremely from the other two products in their component composition, i.e. battery and casing would have to be added additionally. However, the framework could even distinguish between the basic packages and the turnkey solutions by identifying the missing components when observing the requirements in the areas mobility and data transmission.

The binary marking of fulfilments gave an overview of how often each IMU meets the requirements. The two measures random walk error and bias stability as part of the static error analysis of the framework for evaluating data quality proved to be useful and in accordance with the results of the dynamic error analysis. With respect to the dynamic error analysis, the novel usage of SLERP does not require special equipment and provides at the same time reliable reference data, although, it is important to mention that the generated reference orientation is idealized.

If required for a more detailed evaluation, weighting of the requirements could easily be included. This would allow emphasis on application-specific aspects, for example, favoring mobility over form factor. In addition, the framework could be extended by defining exclusion criteria for IMUs as a first step, such as minimal component composition. If required, application-specific thresholds for the error quantities of the static error analysis could be added as requirements. Furthermore, in a framework extension, it would make sense to rate bias stability more important than random walk since it relates to the non-linear gyroscope drift, while random walk can be reduced by applying additional filters in the orientation estimation process.

The current IMU evaluation framework provides useful requirements and assessment methods to evaluate IMUs objectively for human body tracking. Particularly, the orientation simulation by using SLERP proved suitable for a first assessment of the IMU's performance during dynamic motions.

The next step will be the development of a full-body tracking system based on results of the IMU evaluation framework. This system will be used for the application in AAL projects for monitoring physical activity. Particularly, in order to provide an advanced support for older people to maintain their functional abilities as long as possible, the quality of exercise at home will be monitored considering, for example, back and leg axis stability.

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