Accuracy of the Orientation Estimate Obtained Using Four Sensor Fusion Filters Applied to Recordings of Magneto-Inertial Sensors Moving at Three Rotation Rates

M. Caruso, A. M. Sabatini, M. Knaflitz, M. Gazzoni, U. Della Croce, and A. Cereatti

Abstract— **Magneto-Inertial technology is a well- established alternative to optical motion capture for human motion analysis applications since it allows prolonged monitoring in free-living conditions. Magneto and Inertial Measurement Units (MIMUs) integrate a triaxial accelerometer, a triaxial gyroscope and a triaxial magnetometer in a single and lightweight device. The orientation of the body to which a MIMU is attached can be obtained by combining its sensor readings within a sensor fusion framework. Despite several sensor fusion implementations have been proposed, no well-established conclusion about the accuracy level achievable with MIMUs has been reached yet. The aim of this preliminary study was to perform a direct comparison among four popular sensor fusion algorithms applied to the recordings of MIMUs rotating at three different rotation rates, with the orientation provided by a stereophotogrammetric system used as a reference. A procedure for suboptimal determination of the parameter filter values was also proposed. The findings highlighted that all filters exhibited reasonable accuracy (rms errors < 6.4°). Moreover, in accordance with previous studies, every algorithm's accuracy worsened as the rotation rate increased. At the highest rotation rate, the algorithm from Sabatini (2011) showed the best performance with errors smaller than 4.1° rms.**

I. Introduction

Instrumented movement analysis is central for evaluating the level of mobility in populations with and without motor impairments, for diagnosis, for assessing the efficacy of innovative treatments and for optimizing athlete performance [1]. Optical stereophotogrammetry (SP) is considered the gold standard for instrumented human movement analysis since it can measure the instantaneous 3-D position of markers with submillimeter accuracy and a temporal resolution of milliseconds. When used in gait analysis, SP measurements allow to estimate spatio-temporal parameters and joint kinematics. Their main limitation is that the subject's movement is captured within a limited volume. As recently highlighted in the literature, these type of measurements, although useful to assess motor capacity, may not be indicative of the typical performance in daily-life [2],[3].

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A miniaturized Magneto and Inertial Measurement Unit (MIMU) in its full configuration integrates, in a single small and lightweight device, a triaxial MEMS accelerometer, a triaxial gyroscope, and a triaxial magnetometer. Some of their features accelerated their employment in tracking human movement. In particular, being "wearable", they can be used to record movements not only outdoor but also indoor, an advantage over location-based services depending on GPS which suffers from signal attenuation and multiple reflections. On the other hand, the use of MIMUs in this context has shown limitations [4]. Whereas, specific accelerations and angular velocities can be directly measured, MIMU 3-D orientation can be only estimated by means of sensor fusion algorithms. In theory, from a known initial condition, the simple integration over time of the gyroscope angular velocity provides an estimate of the orientation. However, the gyroscope readings are affected by a slow-varying bias which, once integrated, introduces a drift in the orientation estimate that grows unbounded over time. Accelerometer and magnetometer readings can be utilized to contain the effects of such drift. In fact, since the accelerometer measures the "specific force" (the vector difference between the external acceleration and the gravity), when stationary, the accelerometer senses only gravity, distributed on its three axes, allowing the estimate of the MIMU inclination (roll and pitch angles, also jointly known as "attitude"), which can be used to limit the drift in the estimated attitude component of the orientation. The magnetometer readings can be used to determine the MIMU orientation in the horizontal plane (yaw or "heading") and be used to contain the drift in the heading component. Although helpful, the above-mentioned observations are not sufficient to contain the effects of the drift in the orientation estimate. In fact, in dynamic conditions a moving accelerometer senses both gravity and its own acceleration and the two cannot be separated unless additional information is used. Moreover, magnetic fields, generated by electrical appliances and metal objects, are superimposed to the Earth's magnetic field thus making the use of the magnetometer critical, especially indoor [5]. Finally, electronics noise of the MIMU sensors, non-orthogonality of the sensor axes, misalignment, sensitivity to changes in temperature, further affect the quality of the reliability of the readings.

To overcome such variety of sources of errors and limitations, several sensor fusion algorithms have been designed to optimally estimate the orientation based on selection of most reliable observations at each time step. The majority of the published sensor fusion algorithms belong either to the family of the Kalman filters (KF) or to that of complementary filters (CF) [6]. Although several formulations have been proposed, consensus about the level of accuracy and the best performing algorithms has not been reached yet [1].

The aim of this preliminary work was to quantitatively compare the accuracy of the orientation estimates of four sensor fusion algorithms, namely the KF algorithm proposed by Sabatini [7], the KF recently integrated in the MATLAB software, the open source CF proposed by Madgwick et al. [8] and the proprietary Xsens filter. The accuracy of the orientation estimate was evaluated at three different rotation rates using the orientation provided by a SP system as a reference. To enable a "fair comparison" among the sensor fusion algorithms, we also proposed a procedure for sub-optimally determine the values of the filter parameters.

II. Related works

The scientific community has often been stirred by the challenges associated with the assessment of the accuracy of sensor fusion algorithms. Over the years, various experimental procedures have been designed to this purpose. Cutti et al. [9] and Picerno et al. [10] proposed two spot-checks for evaluating the orientation consistency as estimated by a commercial sensor fusion algorithm among a set of aligned MIMUs. Although, in the ideal case, orientation differences would be null, Picerno and colleagues found errors up to 11.4° in static conditions. Other studies provided a direct comparison among the orientation accuracy of two or more sensor fusion algorithms. Lebel et al. in [11] tested three commercial MIMU systems by using an instrumented gimbal table in a magnetic clear environment. The orientation of each system was provided by its proprietary algorithm. Algorithms from Xsens and APDM were based on the KF principles, whereas the third from Inertial Labs belonged to the CF family. For each system, MIMUs were aligned on the table center and data were collected while rotating the gimbal axes to obtain both planar (2D) and 3D motions at quasi-constant low and high rotation rates (90°/s and 180°/s) for two minutes. All the three algorithms exhibited a worsening of the performances when the rotation rate increased (mean errors compared with a SP system up to 7°), although this effect was less evident for Xsens. Madgwick et al., in their popular paper [12], compared the proposed CF with the Xsens KF during static and dynamic acquisition conducted by manually moving a single MIMU. The authors found their algorithm to perform slightly better for both conditions (rms errors 1.1° vs 1.3°). Valenti et al. in [13] collected data from a MIMU mounted on a micro aerial vehicle to evaluate their proposed CF against the CF by Madgwick et al. and the KF by Sabatini [7]. The comparison was made by using ground-truth data from a SP system. The CF proposed by the authors showed the best performance (rms errors < 1.7° for pitch and roll and rms yaw errors ≈ 16.6°), while the CF by Madgwick et al. showed the worst (rms errors < 3° for pitch and roll and rms yaw errors ≈ 76.2°). In their study, Bergamini et al. [6] tested the filters from Madgwick et al. and Sabatini as representative of the CF and KF approaches during manual and locomotion tasks. Manual tasks involved slow velocities, short time recordings and small capture volume, as opposed to the locomotion task which required a larger capture volume (likely more prone to ferromagnetic disturbances) and three minutes of acquisition without static phases. The errors ranged from less than 5.5° for the manual tasks to 21° for the locomotion tasks and they were not dependent on the sensor fusion approach, as pointed out by the authors. In [4], the proprietary KF from APDM was tested against the CF from Tian et al. described in [14]. Experiments were executed involving a robot arm both in static and dynamic conditions. The authors outlined the better performance of the CF in static conditions (1° vs 1.6° of maximum error). The dynamic tests consisted in different sinusoidal rotations generated around one axis of the MIMUs. The protocol was repeated by orienting that axis along and perpendicular to the gravity direction, and by varying the frequency (from 0.18 Hz to 5.6 Hz) and the range of the rotations (from ± 3° to ± 18°). The rms of the resulting angular velocity ranged from 2.1°/s to 150°/s. In the dynamic trials, the KF exhibited the best performance. Higher frequency and amplitude of the movement led to greater errors in accordance with the work of Lebel et al. [11]. The authors hypothesized a strong relationship between the selection of the parameter values required by the algorithms and the corresponding orientation accuracy. Finally, a recent work of Ludwig et al. [15] compared two CFs from Madgwick et al. and Mahony et al. and one KF from Marins et al. [16] by using the data collected by a MIMU mounted on a quadcopter. In this case the CF from Mahony et al. was found to be the most accurate with errors up to 11° rms. The parameters were set by means of a genetic algorithm as described in [17].

As it appears from the comparative analyses published during the last ten years, literature is inconclusive about the identification of the best algorithm and filtering approach (CF or KF). It is worth pointing out that the parameter values chosen in each work were different due to the different experimental conditions, different hardware, different environments, and no standard approaches for their selection were adopted. In this work we proposed a procedure for automatically determining the parameter values for each algorithm without using the knowledge of the orientation reference. Differently from the above-mentioned works, all selected algorithms were stressed to estimate the orientation in a wide range of angular velocities (from 120°/s to 380°/s rms). Finally, since the KF integrated in MATLAB has been made available from the latest release (R2018b), to the best of our knowledge, in the literature there are still no studies involving this filter.

III. Matherial and Methods

A. *Experimental Set Up*

Two MTx MIMUs (Xsens) were aligned on a wooden board. The board was also equipped with seven reflective markers attached as illustrated in Figure 1. The Local Coordinate System (LCS) of the board was defined by the three central markers and aligned to the LCS of the MIMUs. The four markers redundancy was exploited to estimate the orientation by means of the Singular Value Decomposition technique (SVD) [18]. An optical Vicon T20 system (software Nexus 2) with 12 cameras was used to obtain the gold standard orientation. One force platform integrated in the Vicon system was also used to synchronize MIMUs and optical systems by generating a mechanical shock.

B. Experimental Protocol

MIMUs and optical data were collected at 100 Hz. Before starting the experiments, a 5-minute warm-up was performed to limit the temperature influence on the sensor readings. Recordings started with the board placed horizontally on a tripod, over the force plate. A first vertical mechanical shock was generated to define the initial synchronization instant. After one minute of static acquisition to ensure the convergence of the filters and to enable the estimate of gyroscope biases, the operator executed a dynamic trial by continuously changing the board orientation to span the three rotational DoFs. The board was then repositioned on the tripod for one minute and finally the operator generated a second mechanical shock to define the final synchronization instant. This protocol was repeated for three rotation rates conditions: slow (angular velocity rms = 120°/s for 70 s), medium (260°/s rms for 45 s) and fast (380° rms/s for 30 s). The movements were executed in a volume of approximately 1 m^3.

C. Filters

The algorithms selected for the comparison were a popular constant gain CF (MAD, [8]), an extended KF (EKF, [7]), the MATLAB KF (MKF), and the proprietary Xsens KF (XKF, v1.7). MAD was implemented following the original formulation while EKF was adjusted to increase the weight of the accelerometer and magnetometer contribution during the static conditions. MKF was used as defined by "ahrsfilter System object". The XKF, instead, being embedded in the Xsens software, was used as a black box.

All algorithms were based on quaternions, which is an efficient four-term representation of the orientation. It allows to avoid singularities such as Gimbal Lock and it is not computationally demanding [6]. The orientation of the coordinate system embedded with the MIMU with respect to the global coordinate system (defined to have two axes aligned with the gravity and the magnetic North) can be expressed as follows:

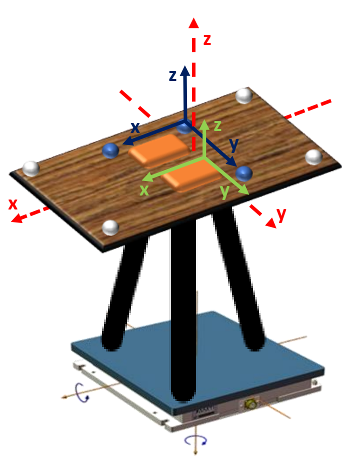

Figure 1: a wooden board (whose axes are represented in red) was attached on a tripod (height 1.5 m) on a force plate. The three central markers (blue) were used to define the SP Local Coordinate System. The MIMU Local Coordinate System is represented in green.

$$q = [\cos(\theta/2),\ n_x\sin(\theta/2),\ n_y\sin(\theta/2),\ n_z\sin(\theta/2)]^T. \qquad (1)$$

where $\boldsymbol{n} = [n_x, n_y, n_z]^T$ is the rotation axis and θ is the angle about which the rotation occurs (angle-axis representation).

The MAD exploits the complementary filter approach where the orientation computed from the gyroscope recordings is fused with that computed first from the accelerometer and then from the magnetometer readings without considering any statistical description of the noise. The fusion process is governed by the weighting factor β. A larger value of β gives more weight to the orientation computed from the accelerometer and magnetometer, to limit the orientation drift, but makes the resulting orientation more sensitive to body acceleration and ferromagnetic disturbances. The MAD requires a second parameter ζ, which represents the rate of convergence, to remove the drift of the gyroscope bias over time.

The EKF is a direct KF where the absolute orientation is estimated within an optimization framework. The predicted state obtained by integrating the angular velocity is then updated with the accelerometer and magnetometer readings taken as measurements for the KF. The tunable parameters are the noise standard deviations (SDs) of the three sensors whose ratios govern the weighting process (for further details refer to equation of the Kalman gain reported in [7]). Differently from the MAD, which exploits the magnetometer only to update the heading component of the orientation (a ferromagnetic disturbance would not affect the attitude), the EKF does not decouple the updates due to the accelerometer and those due to the magnetometer, which is however without any relevant effect in most situations of interest [5][6]. One of the main features of KFs consists in the possibility of augmenting the state vector with variables that allow to keep track of the ferromagnetic disturbances, body acceleration components, etc. To limit the drift in the heading component it is necessary to know the North's magnetic direction. However, when the MIMU is moving near to an additional external magnetic field, the estimate of the North's magnetic direction is hampered, and the distortion is generally unpredictable. The EKF attempts to tackle this problem by assuming that the distortion is a time-variant bias superimposed to the magnetometer readings. In the present EKF implementation, the state vector was augmented with the three components of the magnetic bias, whereas the gyroscope biases computed during the initial static phase were subtracted from the gyroscope readings.

The MKF and the XKF, are based on the indirect KF formulation proposed by Luinge et al. [19] and extended by Roetenberg et al. [20]. In the indirect KF formulation, the optimization is carried out by minimizing the uncertainty of the estimated orientation error rather than the uncertainty of the absolute orientation as done in the direct KF, [21]. In MKF and XKF the accelerometer and magnetometer readings are combined with the gyroscope to obtain two additional updates: the gravity direction estimated from both accelerometer and gyroscope and the global magnetic vector estimated from both magnetometer and gyroscope. The two pieces of information are included within the measurement vector to compute the orientation error update. In MKF the state vector is augmented with the gyroscope bias, the acceleration errors (the deviation from the gravity), and the magnetic disturbances.

D. Parameter Values Definition

All the filters implemented (MAD, EKF and MKF) required *ad-hoc* tuned parameters to work properly. A major problem when using the sensor fusion algorithms is to find the most suitable values for the parameters required [4],[11],[15],[17]. In fact, proper parameter selection depends on numerous factors, the most important being: sensors noise characteristics [12], type and velocity of motion [9],[11],[20], severity of the linear accelerations and ferromagnetic disturbances [20], and convergence speed [22]. The "optimal" values are usually chosen following a *trial and error* approach, by minimizing the difference of the estimate and the available orientation reference [6],[13]. This approach was also adopted by Madgwick and colleagues in [8], even if they proposed an equation to estimate the optimal value of the parameter. As sensor fusion algorithms can perform very differently depending on the specific set of filter parameter selected, to enable a meaningful comparison among different algorithms, it was necessary to define a common strategy for a sub-optimal determination of the parameter values specific for the hardware and movements tested. The optimization strategy was designed to work without relying on information about the actual MIMU orientation.

The procedure implemented for selecting the parameter values exploited the assumption that the two MIMUs aligned and attached to a rigid body should have the same orientation. For each algorithm, the parameter values were determined by minimizing the orientation difference between the MIMUs for each rotation rate condition. Moreover, since experiments were conducted within a small volume of capture free from magnetic objects and at least 1.5 m from the ground level, we decided not to tune the magnetometer parameters associated to the severity of the magnetic disturbances.

For instance, in the MAD filter, the sub-optimal values of the parameters the β and ζ were searched within the interval [0, *p*], where 0 describes an ideal gyroscope without noise and bias drift, and *p* is an arbitrary opposite extreme.

For the EKF, the tuning was performed on the values of the SDs of accelerometer and gyroscope to test different ratios. The magnetometer SD was set to the constant value of 0.5 µT. The sub-optimal values for the gyroscope SD was searched within the interval [0, 5] °/s. A SD equal to 0 °/s meant that the final orientation estimate was based only on the gyroscope readings, modelled as ideal. Similarly, the research interval for the accelerometer SD ranged from 0 mg to 50 mg. The parameter which governed the estimate of the magnetic bias was set as suggested by Sabatini in [7].

In general, the MKF allowed for the tuning of eight parameter values, that is two for the gyroscope and three for the accelerometer and three for the magnetometer. However, to reduce the search space dimension, the tuning was limited to only two parameters: the gyroscope variance and the decay factor for linear acceleration which were found to be the most sensitive.

Preliminary investigations carried out by the authors have supported the hypothesis that the parameter values which minimized the relative orientation differences are those that provided low absolute orientation errors (computed as described in the next paragraph). Figure 2 shows the results obtained for the MAD in the case of high rotation rate.

E. Data Processing, Orientation Estimation and Error Computing

The signal processing and the orientation estimation was performed in MATLAB, R2018b. To remove high frequency noise, marker trajectories were low-pass filtered using an anti-causal zero-phase Butterworth filter of the 6th order (cut-off frequency set to 6 Hz as suggested in [6]). The gold standard orientation of the LCS (q_{SP}) was defined using the

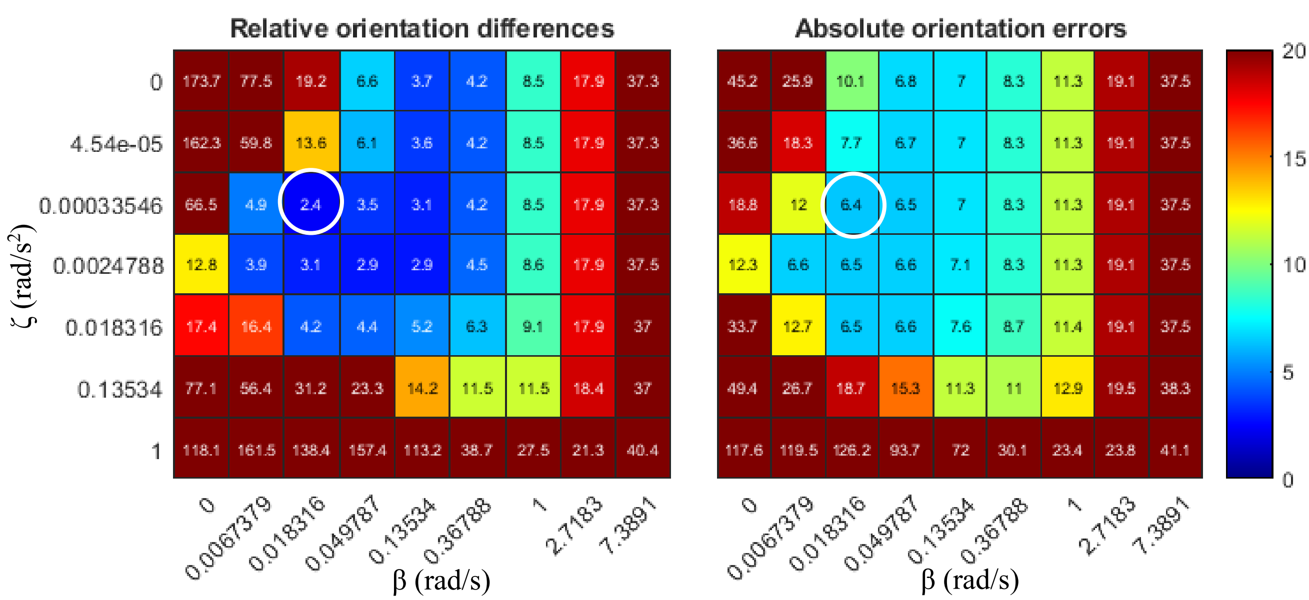

Figure 2: heatmaps of the relative orientation differences vs absolute orientation errors averaged over the two MIMUs for MAD (fast rate). In this case the two selected values of β and ζ minimized both the relative differences and the absolute errors. All the units are in degrees.

three central markers, as described in Figure 1 and its orientation with respect to the SP global coordinate system (GCS) was obtained by means of the SVD technique. Data analysis was restricted between the synchronization points.

Each algorithm was fed with the magneto-inertial data acquired with the two MIMUs to compute the absolute orientation (q_m). Since the GCS and the MIMU systems were not aligned, the orientation computed by each system was referred to its initial frame.

For each algorithm the quaternion error was computed for each MIMU and for each rate condition separately, in the quaternion form as follows:

$$\Delta q = q_m^{-1} \otimes q_{SP}. \qquad (2)$$

Then, Δq was decoupled into the attitude and heading components (Δq_{att} and Δq_{head}) to discriminate the different error contributions provided by accelerometer and the magnetometer in correctly estimating the gravity and the Magnetic North directions, as proposed by Bergamini et al. in [6]. The attitude and heading orientation errors were obtained from the scalar components of Δq_{att} and Δq_{head}. The orientation accuracy was computed as the rms value of the attitude and heading orientation errors (RMS_{att} and RMS_{head}) evaluated only during the dynamic trial. Since no substantial differences were observed between RMS_{att} and RMS_{head}, for sake of brevity, the orientation accuracy was expressed by computing the root sum square of the latter values.

IV. Results

TABLE I reports the orientation accuracy for each algorithm separately for the two tested MIMUs and for each rotation rate condition. For ease of reading, the results for the two MIMUs were averaged and shown for each algorithm and for each rotation rate condition (Figure 3). The computation times required by MAD, EKF, and MKF to compute the orientation starting from a data set of 25400 samples are 0.53 s, 4.15 s, and 7.29 s, respectively (Intel® Core™ i7-6500U CPU @ 2.50 GHz).

V. Discussion

Based on the findings of the present study, all the tuned filters exhibited similar accuracy. In fact, the differences between the maximum and minimum filter errors amounted to 2.1°, 1.3° and 2.3° ad low, medium and high rotation rates, respectively. Moreover, the accuracy of the orientation estimate obtained with all filters resulted in general better than that reported in previous studies (rms errors smaller than 6.5°), even at high rotation rate (angular velocity rms ≈ 380°/s). This circumstance can be explained by the fact that the sub-optimal parameter values were defined on the specific rotation rate condition. It is important noting that when comparing orientation errors, differences smaller than 0.5° are not considered as relevant, being of the same amplitude as the errors affecting the gold standard orientation [6].

In accordance with previous studies, orientation estimate accuracy worsened as the rotation rate increased [4],[23], with the exception of the EKF which seemed to be less sensitive to the rotation rate. At low rotation rate, the MKF exhibited the worst accuracy (rms error equal to 5.1°

TABLE I: orientation accuracy for each algorithm at each rotation rate (the root sum square errors between the MIMUs are in bold).

	slow			*medium*			*fast*		
	#1	*#2*		*#1*	*#2*		*#1*	*#2*	
MAD	5.4	2.9	**4.2**	5.3	4.5	**4.9**	7.6	5.2	**6.4**
EKF	4.7	1.9	**3.3**	4.6	3.8	**4.2**	5.5	2.6	**4.1**
MKF	5.6	4.5	**5.1**	4.2	2.9	**3.6**	6.8	5.1	**6.0**
XKF	3.6	2.3	**3.0**	4	3.3	**3.7**	5.8	4.4	**5.1**

All the units are in degrees.

compared to rms < 3.5° for the second largest value); at medium rate the MAD was the less accurate (errors equal to 4.9° compared to rms < 4.2° for the second largest value). At high rotation rate the worst accuracy was observed for the MAD and the MKF (6.4° and 6°). The EKF was the only algorithm achieving an orientation error smaller than 4.1° rms at high rotation rate. Overall, the best accuracy was observed for the EKF and the XKF. However, it is worth noting that a direct comparison with the proprietary XKF is difficult mainly for two reasons: a) it runs on the CPU of the MIMU at internal sampling frequency of 1800 Hz (18 times higher than the other filters); b) filter parameters values are not accessible and cannot be tuned. While the higher internal sampling frequency is expected to help the filter performance especially for high rotation rates, the factory calibration of the filter parameters cannot account for motion specificity as implemented for the other tested filters. This implies that the slightly worse accuracy achieved by the XKF at high rotation rate cannot be directly attributed to the filter structure.

Among the KF family, the MKF showed the lowest accuracy at both low and high rotation rates. This may be explained since the MKF required the definition of eight parameter values and the tuning was limited to only two of them for computational reasons. The high computation time required by the MKF is due to the large dimensions of the state vector (12 elements vs 7 for the EKF).

Finally, it is worth pointing out that the orientation computed using the magneto-inertial data of the MIMU #2 was in general more accurate than the MIMU #1 for all filters and velocities. This trend may be partially justified by the fact that the y-axis offset of the MIMU #1 gyroscope presented a higher deviation from an ideal gyroscope (1.7 °/s vs 0.7 °/s for the MIMU #2 y-axis). It can be expected that the gyro-bias compensation strategies implemented in the various algorithms, using the same filter parameters values for both MIMUs, were not very effective in dealing with the high bias values of the MIMU #1. Further studies are needed

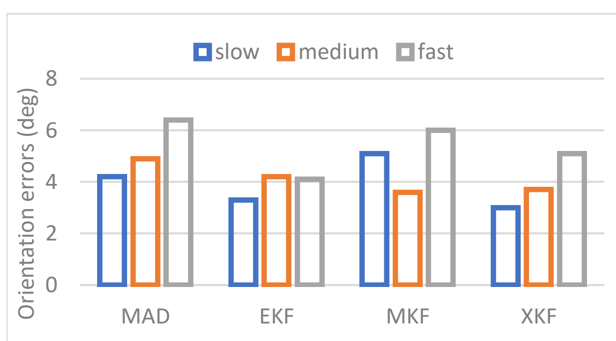

Figure 3: effect of an increased rotation rate on the sensor fusion accuracy.

to improve the filters performance when the parameter values are tuned differently for each MIMU, according to the different noise characteristics.

VI. Conclusion

The findings of the present study suggest that, under sub-optimal conditions, all filters analyzed showed reasonable performance (rms errors < 6.4°). Among the implemented algorithms, the EKF was the best performing, with errors smaller than 4.1° rms.

A key aspect of the present study is the implementation of a procedure for the determination of the values of the filter parameters. The filter parameter values determined according to a common strategy enabled a fair comparison among the different algorithms. When real-time is a requirement, an important aspect to consider in selecting the most appropriate filter is the computation time. The MAD exhibited a lower accuracy at medium and high rotation rates, but on the other hand, it is the algorithm with the lowest computational burden and the simplest to use having only two parameters to be set. In general, filters with a large number of parameters allow for a better modelling of the different sources of errors but are more difficult to tune due to the mutual influence of the parameters on the final orientation estimate.

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