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Getting the angles straight in speed skating: a validation study on an IMU filter design to measure the lean angle of the skate on the straights.

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Abstract

To assist speed skaters in improving their skating performance, we would like to provide them with real time feedback on the orientation of the skate within a single stroke. While of course the forces generated by the skater on the ice determine the acceleration of the skater, the orientation of the skate determines in which direction this force, and thus acceleration, is headed. In this study we focus on the validation of the lean angle measurements of the skate, which distributes the push-off forces over the global vertical and transverse component. To measure this angle, an inertial measurement unit (IMU) would be a logical choice, but two aspects render measuring with commercially available IMUs and their filters on an ice rink rather difficult, first the ferromagnetic materials in the vicinity of the IMU and secondly the large linear accelerations. In this paper we therefore propose filters that bypass these problems. In total three complementary filters with adaptive gain were validated with a motion capture system. The filter based on the assumption that the lean angle can be reset to zero (upright) when there is no change in steer angle of the skate, showed the most accurate results (mean RMSE error of 5.3^0 and 3.6^0, for the left and right skate respectively). Integrated into the filter is an IMU based stroke detection, which as a stand-alone system could provide feedback on stroke frequency, stroke length, contact time or double stance phase time. It is concluded that an IMU used with this filter can provide individual elite speed skaters reliable feedback on their skate lean angle.

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Keywords: Speed Skating; IMU; Validation measurements; Lean Angle;

1. Introduction

Lean, steer and pitch, these are the three angles which together determine the orientation of a skate on the skate rink. While of course the forces generated by the skater on the ice determine the acceleration of the skater, the orientation of the skate determines in which direction this force, and thus acceleration, is headed. The lean angle of the skate distributes the force on the skate into a global horizontal and vertical direction, while the steer angle directs the forces in either the forward direction of the rink or the sideways direction (Figure 1). With pitch we refer to the pitch angle of the skate shoe. Pitch only occurs at the end of push-off, when the klapskate opens, and in the repositioning phase, while the skater repositions his skate in the air for the next stroke.

For the purpose of providing speed skaters with real-time feedback within a stroke to improve their skating performance, we would like to determine the skate orientation. The orientation can firstly provide insight into the direction, and therefore effectiveness, of the skate push-off, secondly the lean angle proved to be related to velocity in previous studies (Yuki et al. 1996). Up to now, no determination of the orientation of the skate in speed skating was established yet, except for (Yuda et al. 2004; Yuki et al. 1996), who performed measures of the lean angle at specific points in the stroke by a camera analysis. In this study we focus on validation of the lean angle of the orientation measurements with an IMU over the complete stroke.

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An Inertial Measurement Unit (IMU), when filtered with the right algorithm, is an exquisite choice to continuously measure orientation with low interference. These systems are light weight, small sized and low cost. Unfortunately, disturbances on an indoor rink hamper the functioning of the commercially available orientation measurement units and their filters (van der Kruk 2013). Ferromagnetic materials in the vicinity of the IMU on the skate, e.g. the cooling pipes under the ice, disturb the local magnetic field and thereby render the first problem for the filtering algorithm. Second problem to address is motion dynamics. During speed skating, the skate moves uninterruptedly, either by gliding over the ice, or by repositioning the skate after retracting the skate from the ice (Allinger & Bogert 1997). This causes linear accelerations which disturb gravity-based algorithms. Contrary to studies in walking or running, where the foot has no velocity during push off, there is no static condition in speed skating to reset the drift of the IMU. In addition, when the skater passes through the curve, the centrifugal forces interfere with the measurements. Accurate measurements of the orientation of the skate with an IMU can therefore only be tackled by determining an algorithm which can by-pass these interferences.

The Extended Kalman Filter (EKF) is an accepted basis for the majority of the orientation filter algorithms and is the most applied one in commercially available orientation sensors. However, tuning the variables in the filter is a precise and difficult job, and the result is sensitive to changes in the environment. This can become a problem in speed skating when different rinks, each with their own cooling system, produce different noise levels for the sensors or when the difference in dynamics in speed skating between short and long distances call for a different gain in the EKF. The common alternative to the EKF is a Complementary Filter (CF) because of its simplicity and effectiveness. A complementary filter fuses accelerometer, magnetometer and gyroscope data for orientation estimation such that low pass filtering is applied on accelerometer and magnetometer data and high-pass filtering on the gyroscopic data (Mahony et al. 2008; Valenti et al. 2015; Madgwick et al. 2011). An adaptive gain, making the filter an Adaptive Gain Complementary Filter (ACF), improves robustness of the filter during dynamic motion.

In this paper we validate the lean angle estimation in speed skating measured by an IMU and determined by an Adaptive Gain Complementary Filter on the straight parts with an optical motion capture system(Qualisys 2015). Furthermore, two algorithms are tested, which improve the ACF filter for the application in speed skating, by adding a correction per stroke, based on established knowledge on the dynamics of speed skating. With this we want to provide useful feedback for speed skaters on the orientation of their skates. The algorithms are designed to be applied in real-time measurements.

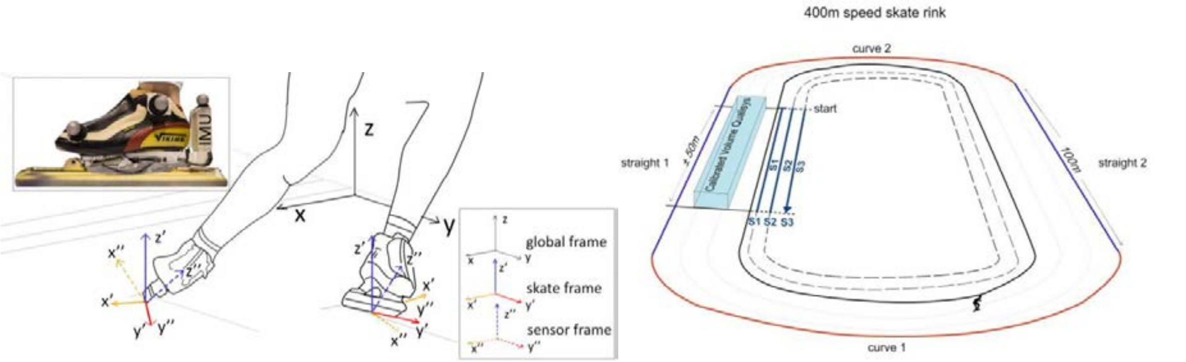

Figure 1 a) the three frames in speed skating, defined by the orientation of the skate; the global frame is a Newtonian frame aligned to the rink b) experimental set-up in the ice rink of Thialf (van der Kruk et al. 2015); 50m of the straight part were measured by the Qualisys motion capture system. The participants skated three consecutive rounds where one straight part of each (S1,S2,S3) was used for validation of the measurement system.

2. Method

2.1. Adaptive Gain Filter (VAL1)

The filter described in Valenti et al. was employed in its original form as the adaptive gain filter and will further be referred to as VAL1 (Valenti et al. 2015). Input to the filter are the unfiltered data of the gyroscope, accelerometer and magnetometer. In this complementary filter first an estimation of the orientation in quaternion form is made by the gyroscope data. This estimation is then corrected by two steps: first the roll and pitch are corrected by an estimation of the accelerometer, second the yaw is corrected by the magnetometer data. In this paper the cut-off frequency for this correction was determined by the procedure described by Yu et al.(Yu et al. 1999). An adaptive gain compares the non-gravitational accelerations to the gravitational forces. If the non-gravitational forces rise and the error magnitude exceeds a certain threshold, the filter will rely less on the accelerometer output. This improves estimations in dynamic situations.

2.2. Self-Designed Filters

The filters are designed based on a reset point, where the estimation is reset to zero (upright). Although the lean angle is validated in this paper, the pitch angle is of influence on the lean angle estimation and is therefore also mentioned in this section.

The following assumptions were made for the design of the additional two filters:

I. When the skater places his skate on the ice, the skate is closed, so the pitch angle is zero.
II. Since speed skating is a cyclic motion, we assume that the integral of the lean angular velocity, which determines the leaning of the skate, is approximately zero over one stroke.
III. When the skate is perfectly upright (zero lean angle), it is impossible to have a change of heading. Therefore, the lean angle is zero when the change in steer is zero.

With these assumptions two filters were designed. The first filter is based on assumptions I and II (VAL2), the second filter is based on assumption I and III (VAL3). The filters start with an estimation of the orientation at time *t* via the VAL1 filter. The reset steps of the filter are explained in Figure 2.

2.3. Stroke Detection algorithm

Stroke detection is necessary for the filters VAL2 and VAL3 to recognize the start and end of a stroke. When the skate is in contact with the ice, a high frequency noise appears in the accelerometer signal of the IMU, due to the structure of ice surface. By detecting this noise, an algorithm was made to perform stroke recognition via an IMU (Figure 2).

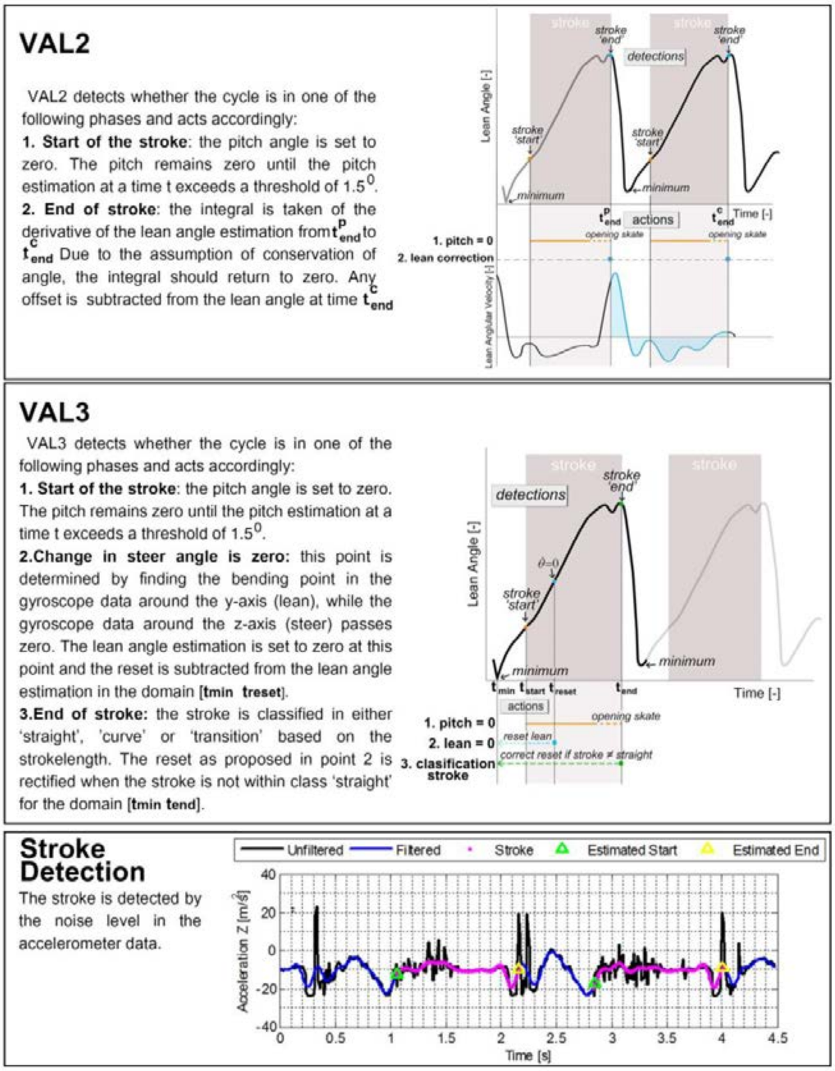

Figure 2 The infographics show the explanations of the filters VAL2 and VAL3 and the stroke detection algorithm. The graphs are divided into detections and actions. The detections set certain events (a.o. t_{end}, t_{reset}, t_{start}), the actions reset the current lean angle or reset the lean angle in a certain domain.

2.4. Experimental set-up

The validation of the filters was done with a data set recorded on the indoor ice rink in Thialf Heerenveen (januari 2015). Four passive markers on each skate were captured by 20 Qualisys motion capture cameras over 50m of the straight part to determine the reference orientation(Qualisys 2015)(300Hz). The number of strokes captured on each straight part varies depending on the participant. Data of three straight parts (S1,S2,S3) in three consecutive rounds of two elite speed skaters at a speed of 10.3m/s were used (Figure 1). The Qualisys orientation data were low passed filtered. Furthermore, the participants skated on instrumented skates with an integrated IMU on the bridge (see Figure 1) (100Hz) (Shimmer3 2015). The instrumented skates measured the forces (van der Kruk et al. 2015). The instrumented skate and Qualisys system were synchronised via a digital start and end pulse. As the initial condition, the orientation measured by Qualisys at *t=0* (start of S1) was taken.

2.5. RMSE

The accuracy of the three filters was determined by a sample wise root mean square error (RMSE) between the orientation measured by the Qualisys system and the value estimated by the filters with the IMU data for each complete stroke. A stroke was defined as the time were the skate was in contact with the ice (contact time). This was determined by the force data measured with the instrumented skate. The IMU results were validated for both the left and the right skate. Due to a different pattern of the left and right stroke on a full round (both are mainly on the medial side on the straights, but when entering the curve, the left skate changes to the lateral side, while the right skate remains on the medial side), we have treated their validation separately.
The contact-time determined with the instrumented skate was also used to verify the IMU stroke detection algorithm. The start and end point of the stroke were verified on one full round (curve and straight) for the two participants (50 strokes).

3. Results

3.1. Stroke Detection

The start of the stroke was detected with an error of 0.002s (SD:0.08s) and 0.02s (SD:0.08s) for respectively the left and right stroke. The end of the stroke was detected with an error of respectively -0.02s (SD:0.02s) and -0.01s (SD:0.01s).

3.2. Filter validation

The estimation on lean angle of the three different filters and the measured lean angle for each recorded area (S1, S2, S3) for both the left and the right skate are shown in Figure 3. The RMSE errors are given in Table 1. The designed filter VAL3 shows improved estimations for the lean angle compared to the VAL1 filter. The VAL1 has a mean RMSE error of 15.3^0 and 10^0 for respectively the left and the right skate, the filter VAL3 has a mean RMSE error of 5.3^0 and 3.6^0.
The VAL2 filter also shows improved estimations in 3 out 4 data sets compared to VAL1. The lack of robustness of this filter is evident in the left stroke of participant 1: one wrong correction affected the remaining data set.

Table 1 RMSE error (in degrees) for two participants for the three straight parts on three consecutive rounds (S1,S2,S3) for each left (L1,L2) and right (R1,R2) stroke. The number of strokes varies with speed and may depend on the participant, due to the fixed measurement volume.

Participant 1

RMSE [^{0}]	**S1**		**S2**		**S3**		**mean**	**S1**		**S2**		**S3**		**mean**
stroke	L1	L2	L1	L2	L1	L2		R1	R2	R1	R2	R1	R2	
VAL1	4.5	6.7	1.0	0.4	39.7	34.3	**14.4**	1.0	0.1	0.7		9.1	11.7	**4.5**
VAL2	0.9	78.8	77.8	81.4	85.3	91.5	**69.3**	1.0	0.2	0.8		8.9	2.2	**2.6**
VAL3	4.8	0.5	3.4	6.6	3.9	3.4	**3.8**	1.0	0.2	2.8		7.8	4.2	**3.2**

Participant 2

RMSE [^{0}]	**S1**	**S2**	**S3**		**mean**	**S1**	**S2**	**S3**	**mean**
stroke	L1	L1	L1	L2		R1	R1	R1	
VAL1	11.8	34.6	10.2	7.8	**16.1**	4.0	24.2	18.3	**15.5**
VAL2	11.8	14.5	9.4	2.1	**9.5**	3.9	3.0	14.9	**7.2**
VAL3	0.8	13.0	12.9	0.7	**6.9**	4.0	0.2	7.4	**3.9**

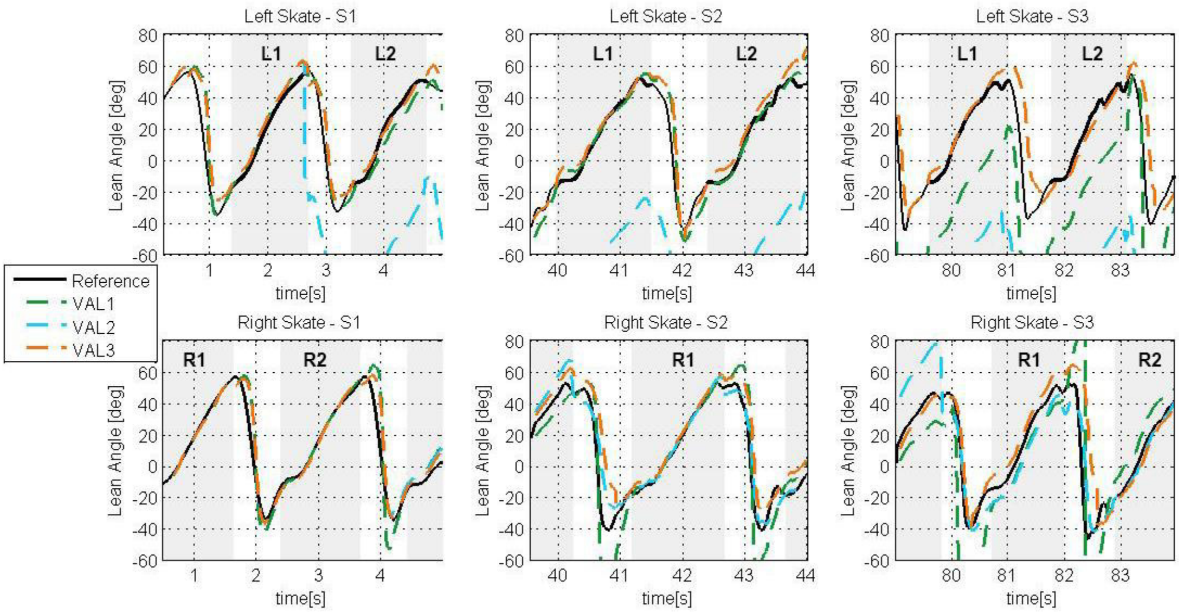

Figure 3 Measured lean angles with Qualisys (Reference) and the three ACFs (VAL1,VAL2,VAL3) for the three straight parts of the three consecutive rounds (S1,S2,S3) for participant 1. The grey areas indicate when the skate is in contact with the ice (measured via the instrumented skate).

4. Discussion

4.1. Validation

The VAL3 filter showed a remarkable improvement for the lean angle estimation in speed skating, compared to the standard VAL1 filter (Table 1). The question rises whether it would be accurate enough to provide (elite) speed skaters with real-time feedback on their orientation. While the exact relationship between the orientation and the performance is unknown, for now the variation within a subject can set the accuracy requirement for the lean angle. Figure 4 shows the lean angles of the two participants at several speeds measured by Qualisys. It illustrates that the lean angle varies in a range of 9^0 within a subject. The mean RMSE found in this study for the VAL3 filter falls within this variation and therefore appears to be accurate enough to provide a skater with useful feedback. For real-time feedback however, the accuracy on stroke level is important. On this level, the VAL3 estimations showed RMSE values of the measured angle of about 13^0 in two of the strokes. Both these strokes show increased noise in the gyroscope data, by which the wrong reset point was determined. These erroneous reset points can however be recognized as outliers and rejected in future use, when the individual repetitive motions are taken into account.
Besides the direct feedback on lean angle, the orientation of the skate will be used in the determination of the direction of the push-off. Since the angle is then integrated into a rotation matrix, an error in lean angle will have impact on the global force estimation. Whether the found accuracy is then still valid remains a topic for future work.

4.2. Application

When providing skaters with feedback, it is important to decide on what would be an interesting variable for a skater to work with. Currently the exact relationship between lean angle and performance is unknown. However Yuki et al. showed that the lean angle of the skate on the straights increases with velocity(Yuki et al. 1996). This implies that skaters can be trained on increasing their angle. Furthermore, based on physics, we foresee that whenever the skate has a negative lean angle, the forces that are put on the skate by the skater, will be directed in the opposite direction of motion. It seems therefore plausible that this negative angle should be minimized. It is however unclear whether this would at all be possible and what its influence on the steer angle would be. With an IMU and the VAL3 filter we are able to investigate this on the ice rink.
The algorithm for stroke detection proved to be accurate in both the curves and the straight parts. With this the skater can be provided with feedback on, among other things, his stroke frequency, stroke length, contact time or double stance phase time. Furthermore, the algorithm provides classification of the strokes in either Straight part, Transition stroke or Curve. All of these variables can be of interest to a trainer or skater.

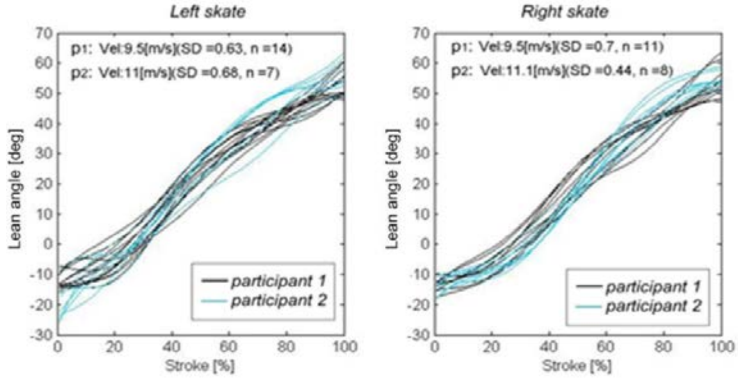

Figure 4 Lean angle measured by the Qualisys system in the study of (van der Kruk et al. 2015) for two participants. Of participant 1, 14 strokes for the left and 11 strokes for the right skate are presented at a mean speed of 9.5m/s (SD=0.68m/s). For participant 2, 7 strokes for the left and 8 strokes for the right skate are presented at a speed of 11.1m/s (SD=0.5). The variations within a subject are around the 9^0.

5. Conclusion

The lean angle of the skate in speed skating can be measured reliably with an IMU combined with an adequate filter. The complementary filter based on the assumption that the lean angle can be reset to zero when there is no change in steer angle of the skate showed the most accurate results (Table 1). Integrated into the filter is a stroke detection algorithm, which as a stand-alone system could provide feedback on stroke frequency, stroke length, contact time or double stance phase time. An IMU in combination with the VAL3 filter can provide individual elite speed skaters with reliable feedback on their skate lean angle.

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