

## Measuring Skiing Speed – Possibilities of Machine Learning

Patrick Carqueville<sup>1</sup>, Aljoscha Hermann<sup>1</sup>, and Veit Senner<sup>1</sup>

<sup>1</sup> Technical University of Munich, TUM School of Engineering and Design, Professorship of Sport Equipment and Materials, Boltzmannstr. 15, Garching, 80574, Germany

**INTRODUCTION:** Whether as an input parameter for adaptive safety components, such as a mechatronic ski binding, or as a pure feedback parameter: measuring the speed of skiers is a meaningful and challenging task. The combination of global navigation satellite systems (GNSS) and inertial measurement units (IMU) has been exploited extensively in the literature. Kalman filters are amongst the most advanced fusion algorithms. However, those algorithms are prone to satellite signal outages. Signal outage results in drifting values, as examined for example by Gao et al. [1]. For an adaptive safety system that takes the skiing speed into account, it must be possible to determine the speed over a long period of time, even in the case of satellite masking. Therefore, the use of state-of-the-art Kalman filters seems not suitable for this purpose. This work shows an explorative approach to use LSTM networks to determine the skiing speed – with IMU data as input data and the 3D speed of GNSS antennas as the targeted output. Therefore, two different GNSS-IMU setups are compared, one attached to the ski and one mounted on the helmet.

**METHOD:** In a field test at Hausberg, Garmisch Patenkirchen, Germany, 46 minutes of skiing data were collected with the two setups. The first setup (ski\_sys) consists of a 6-degrees-of-freedom (dof) IMU positioned underneath the right ski boot and a 25 Hz GNSS antenna attached to the front of the right ski. The other system (helmet\_sys) consists of a 6dof IMU and a 10 Hz GNSS antenna mounted on the helmet. All hardware was manufactured by 2D Messsysteme GmbH, Karlsruhe, Germany. The IMU sampling frequency of both setups was 1000 Hz.

Table 1: Speed Accuracy and number of received satellites of GNSS Systems.

System	SpAccu [km/h]			Satellite number		
	Min	Avg	RMS	Min	Max	Avg
ski_sys	0.14	0.41	0.43	8	16	15
helmet_sys	0.32	0.60	0.61	14	23	19

One LSTM model was trained per setup. Both artificial neural networks (NNs) consist of two LSTM layers and two dense layers with a total number of 14,529 trainable parameters. For the training of both LSTM models the 3D-speed data of

the GNSS and the IMU data were resampled at 200 Hz. The last 100 timesteps were taken into account for the training of the 3D speed. The 46 Minutes of field data were split into 60 % training data, 16 % validation data, and 24 % test data.

Results: The minimum (min), average (avg), and root mean square of the speed-accuracy (SpAccu) parameter given by the GNSS module as well as the min, maximal (max), and avg satellite number for both GNSS are documented in table 1. The NN-output for the test data is shown in Figure 1. The trained model for ski\_sys reaches a Pearson correlation coefficient (PCC) of 0.94 and a mean squared error (MSE) of 5.8 km/h. The model for helmet\_sys reaches a PCC of 0.82 and an MSE of 9.9 km/h.

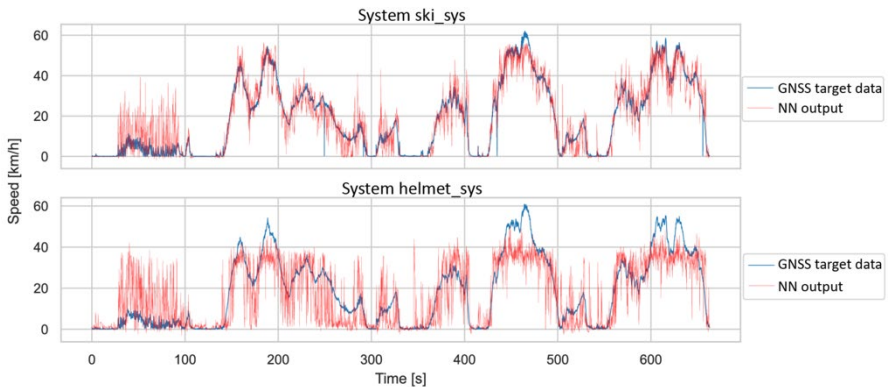


Fig. 1: Comparison of GNSS target data (3D speed) with neural net outputs for the system ski\_sys on the top and helmet\_sys on the bottom.

DISCUSSION: Overall, the system ski\_sys performs much better than helmet\_sys. This may be due to the damping effect on the IMU data by the body. This is observable in the raw data of the IMUs, in which the signal amplitudes of the helmet\_sys system differs less strongly between phases of high and low speed compared to the signal of ski\_sys. This assumption, however, indicates that the slope properties have a significant influence on the accuracy of the ski\_sys system. In order to be able to comprehensively assess the suitability of such a system for determining the skiing speed, further tests are necessary.

1. Gao, J., Petovello, M.G. & Cannon, M.E. GPS/Low-Cost IMU/Onboard Vehicle Sensors Integrated Land Vehicle Positioning System. J Embedded Systems 2007, 062616 (2007). <https://doi.org/10.1155/2007/62616>