RANGE ESTIMATION SYSTEM FOR POWERED WHEELCHAIRS

Norbert Fränzel[1], Thekla Schroeder[1], Frank Weichert[2], André Weiskopf[2], Andreas Wenzel[2], Christoph Ament[1]

1 Inst. for Automation and Systems Engineering, Technische Universität Ilmenau, Germany
2 Embedded Systems, Fraunhofer IOSB-AST, Ilmenau, Germany

ABSTRACT

In this paper, we present a method to estimate a wheelchair's power consumption and therefore its battery autonomy. The wheelchair powertrain is modeled to enable a virtual driving simulation. The use of a white box model enables an adaption to other systems and configurations. This model outputs the actual battery and motor currents within a simulation for a given route and speed profile. These currents affect the battery's SoC, whose total charge depends on its temperature. To account changes of the available charge, a simplistic model of the battery's temperature dependence is introduced, that has been acquired via discharge cycles within a climate chamber. Furthermore, an *a priori* simulation uses the model to estimate the SoC after the virtual completion of a route with a corresponding height and velocity profile. Finally, the paper compares the results of the simulation with real measurements using the recorded tracks and the generated virtual routes. Since the input for the *a priori* estimation relies on virtual routes, their quality is assessed as well.

Index Terms - wheelchair, range estimation, smartphone, SoC

1. INTRODUCTION

People with different impairments of their own mobility often rely on the use of mobility aids such as electrical powered wheelchairs to maintain some degree of mobility and thusly independence. However, the users receive no detailed information regarding the vehicles range while driving nor its battery autonomy. The only source of information is quite commonly an optical status indicator showing the approximate battery state of charge (SoC) relative to a fully charged battery. However, relating this abstract battery status to a specific driving range is very difficult as the actual range depends on a number of factors, such as the user's weight, the user's manner of driving and the route characteristics [1]. In contrast to ordinary electrical vehicles used for individual mobility, the users of powered wheelchairs are fully exposed to the functioning of their means of transportation to manage their everyday life. In case of an empty battery, they are directly affected by immobility. These circumstances might lead to a self-restriction of the drivers regarding their mobility and participation in society in general. In order to overcome these limitations of powered mobility aids, a driving range estimation system is needed that can be easily adapted to the specific vehicle configuration and the user's driving habit.

Existing driving range estimation systems often rely on the previously consumed energy for a certain distance and extrapolate the remaining driving range according to the energy left in the batteries. However, this information is not reliable as it only considers the *a posteriori* observation that might often not be applicable for the further route as its parameters, such as slope and road surface, are unknown and can change. Hence, there is always the immanent risk for the driver to drive beyond the point of no return. More sophisticated prediction systems need an *a priori* knowledge of the route to estimate the total consumption based on look-up tables whereby different road types have a designated constant consumption per distance parameter. Although this prediction yields more accurate results, it cannot be considered as reliable because the specific consumption still depends on the driving style and route slope. These drawbacks can lead to erroneous estimations that impede a safe return home [2]. Other range estimation systems address the unknown parameters and influences via fuzzy neural networks [1]. Although the results are promising, this approach requires a new training and validation for every possible configuration. This might prevent a future deployment as the handling can rapidly become uneconomical due to the individual training. Even more, future adjustments to the system are initially unknown and cannot be considered thusly.

2. METHODS

In order to provide a robust and, even more importantly, adaptable driving range estimation a powered wheelchair has been equipped with sensors and a data acquisition system, the so-called Smart-Assisted-Mobility (SAM) Box. Figure 1 shows the sensors and their position. The battery sensor (Hella IBS 24V) measures current and voltage at $10\ Hz$. The Trimble DGPS consisting of the Pathfinder receiver and the GeoBeacon provides longitude, latitude, altitude and velocity.

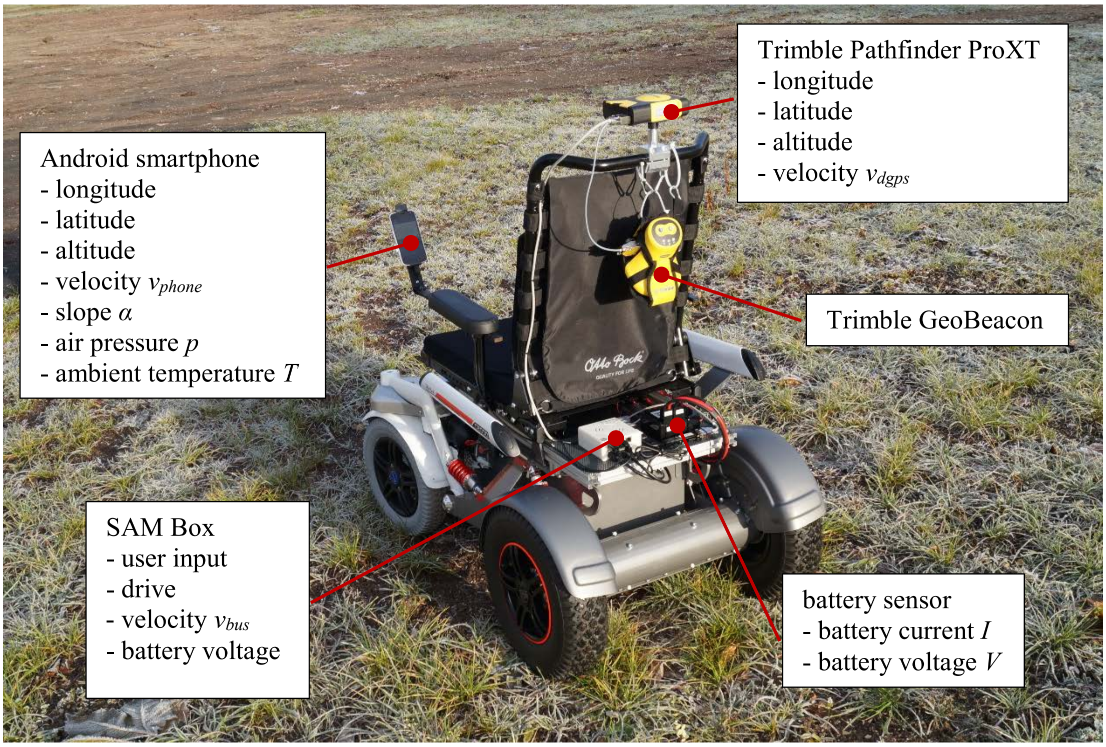

Fig. 1: Wheelchair with sensors and SAM Box

2.1 SAM Box

The SAM Box is a rapid prototyping system especially designed for the development and evaluation of assistance systems for wheelchair users. It connects to the vehicle bus and is capable of real-time data manipulation. This unit offers two CAN ports, four USB 2.0 ports, one 100 Mbit Ethernet port, eight analog inputs and eight digital inputs/outputs. The SAM Box is a heterogeneous system, i.e. it contains two different modules. The first module is responsible for the wheelchair bus interface and its data manipulation. The second module is an embedded Linux system that commands the first one. The use of the Linux systems enables to take advantage of the Linux ecosystem with software repositories and already available software libraries. Furthermore, the standardized access of input/output resources eases the software development. It is even possible to transfer Simulink models directly to the SAM Box and access the sensors and the vehicle bus data via dedicated library blocks that have been developed for the SAM Box. Hence, model based design can be easily deployed in the context of an assisting system for mobility aids and thusly reduce the time needed for their actual implementation [3].Within the scope of this paper, it facilitates the data acquisition, whereby it synchronizes measurements from different sources including the wheelchair control and stores them for later processing. The wheelchair control offers the actual velocity and the user input via joystick. The battery voltage is accessible through the vehicle bus, but it is not considered due to its low resolution and slow update rate. The DGPS and the battery sensor are connected to the SAM Box, where their output is processed and stored.

2.2 Android Smartphone

The Android smartphone runs an application designed to serve both as a graphical user interface to visualize measurements and as an interface to the smartphone’s sensors. Modern smartphones offer commonly a GPS receiver and an inertial measurement unit. Since the used phone has an ambient air pressure sensor, its measurement are stored as well. Furthermore, the processing power enables the computing of complex algorithms. As the market penetration rate of smartphones is steadily growing, they suggest themselves for the application within assisting systems [4]. The smartphone’s integration in the measurement system enables the evaluation of its sensor’s capabilities and thusly an assessment of its suitability for a future stand-alone operation in the context of a residual driving range prediction. The smartphone connects to the SAM Box via USB. This interface provides energy for the smartphone and an information exchange through the Android Open Accessory Protocol [5].

3. MODELLING

The modelling for the range estimation covers three aspects. Firstly, the interaction of the wheelchair with its environment, i.e the route with its characteristics, has to be considered. Secondly, the user behavior requires at least a simple representation and, lastly, the link between the user input and the resulting velocity needs a model of the vehicle’s powertrain.

3.1 Environment Interaction

Since the longitudinal motion of the vehicle is the dominant domain for energy conversion from electric energy stored in the batteries to the mechanical energy, a point mass with the mass m and the frontal area A_f, see fig 2., is an applicable representation of the wheelchair [6]. For the same reason, the modelling reflects only the longitudinal movement and the associated changes in altitude. Hereby, m accounts for both the mass of the empty wheelchair and the individual mass of the driver with additional luggage.

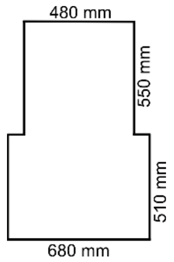

Fig. 2: Frontal area of wheelchair

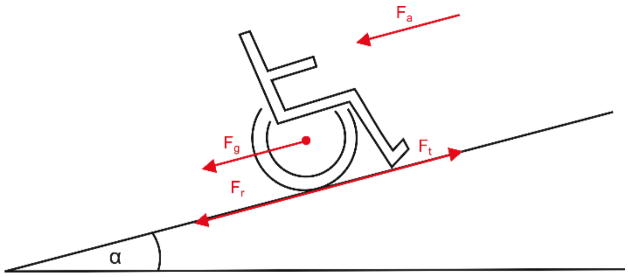

Fig. 3: Forces acting on the wheelchair

The forces acting on the wheelchair, see fig. 3, are mainly the rolling friction force

$$F_r = f_r \cdot m \cdot g \cdot \cos\alpha,$$

with f_r as rolling friction coefficient, the force caused by gravity while driving up- or down-hill

$$F_g = m \cdot g \cdot \cos\alpha$$

and the aerodynamic friction force

$$F_a = c_d \cdot A_f \cdot v \cdot \frac{\rho}{2},$$

with c_d as drag coefficient, v as the vehicle's velocity and ρ as the air density. The friction and gravity forces depend either on the route parameters, i.e. the slope and the rolling friction coefficient, at a given position x or on the current velocity. As the actual rolling friction coefficient is not known, a constant value of 0.03 is assumed as mean approximation according Naunheimer [7]. The route's slope can either be measured or retrieved via maps, which yields $\alpha(x(t))$. The traction force F_t is the propelling force of the powertrain. Thusly, the following equation describes the movement of the wheelchair:

$$\dot{v} = \frac{1}{m}\left[F_t(t) - F_r(x(t)) - F_g(x(t)) - F_a(v(t))\right], \text{ with } x(t) = \iint_0^t \dot{v}\,(\tau)d\tau.$$

3.2 User Behavior

The user behavior regarding the driving style is *a priori* unknown. However, the model requires set points for the desired velocity along a given route. These set points are often referred to as the driving cycle. In general, the combination of four distinct phases form such a driving cycle, like the European Urban Driving Cycle or the Extra Urban Driving Cycle [8]:

- cruise $v(t) = v_{cruise}$,
- stop $v(t) = 0\ \frac{m}{s}$,
- acceleration $\dot{v}(t) = a_{acc}$ and
- deceleration $\dot{v}(t) = -a_{acc}$.

Since the interaction between the wheelchair and the environment relies on the vehicle position on the route, the desired velocity as commanded by the virtual driver is related to the position $x(t)$ as well. The driving cycle generation considers the desired velocity for the cruise v_{cruise} that is the prevailing phase and the acceleration, respectively the deceleration, with a constant a_{acc}. Both parameters are adjustable to reflect different driving styles. The algorithm reduces the speed to v_{turn} for every turn at the route by a deceleration followed by an acceleration phase, see fig. 4.

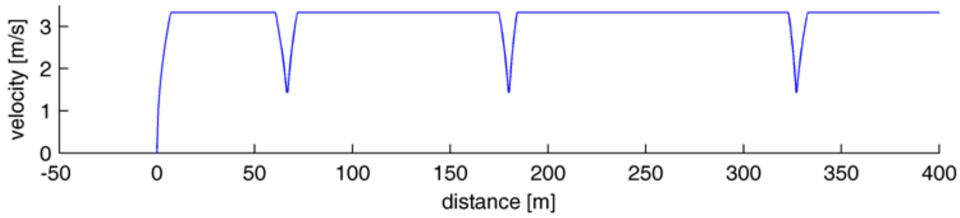

Fig. 4: Part of a virtual driving cycle

3.3 Powertrain

The wheelchair powertrain is the link between the user input and the environment interaction. The vehicle control relates the joystick commands to a desired speed and adjusts the motor voltage accordingly.

3.3.1 DC Motor

The application of Kirchhoff's law yields a simplistic model of the motor, see fig. 5.

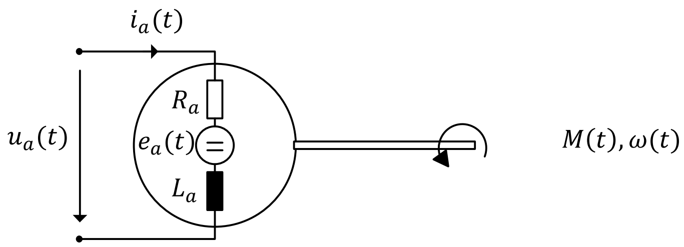

Fig. 5: Model of the DC motor

The motor parameters relate the torque $M(t)$ to the current $i_a(t)$ and the voltages $u_a(t)$, respectively $e_a(t)$ to the revolution per second $\omega(t)$. A gear applies that torque to the wheels and causes finally the propelling force F_t. Although the wheelchair has two motors, the powertrain model contains only one. A multiplication accounts for the second one. This approach neglects the effects of curved trajectories, but it eases the simulation and their impact on the range is small compared to the longitudinal movement [6]. The effectively flowing current from the battery is determined with a power balance.

3.3.2 Battery

The wheelchair has two $12\ V$ lead acid batteries with a nominal C_5 capacity of $93.5\ Ah$ and a C_{20} capacity of $110\ Ah$ at $20°\ C$. The indices refer to the discharging time to reflect Peukert's effect. These capacities in reality depend on more factors such as the battery temperature and the usage history [9]. As the effects of the usage history are not within the scope of this paper, the model neglects it and new batteries have been used for this work. Equation

$$n = \frac{\log t_{C_5} - \log t_{C_{20}}}{\log i_{C_5} - \log i_{C_{20}}}$$

calculates the Peukert exponent that is used to determine the available capacity for the actual discharge current. The quotient k represents the ratio of the depleted charge until a terminal voltage of $10.5\ V$ at a certain temperature to the nominal capacity, see tab. 1. A $24\ h$ resting time before the discharge allows an equal temperature distribution within the battery.

Temperature [°C]	Charge [Ah]	Time [hh:mm:ss]	k
30	93.01	04:58:23	0.9885
20	94.09	05:01:52	1
10	84.75	04:31:54	0.9007
0	76.44	04:05:14	0.8124
-10	71.49	03:49:21	0.7591

Tab. 1: Temperature dependency of the available charge

A third order polynomial can approximate the measurement. Together with the Peukert exponent, the available capacity C can be determined and thusly the state of charge.

$$SoC(t) = \frac{C - \int_0^t i(\tau)d\tau}{C}.$$

4. USER INTERFACE

The range estimation system requires a route with start, end and eventually turns. The user behavior algorithm creates a driving cycle according to the waypoints and the desired velocity. Additionally, a height profile represents the altitude along the route. In order to enable an *a priori* driving range estimation for wheelchair users, a graphical user interface (GUI) has been developed, see fig. 6. Currently, this GUI runs only on desktop computers to prove the concept. It demands at least a start and an end point. Additionally the user is allowed to enter two stops between the start and end.

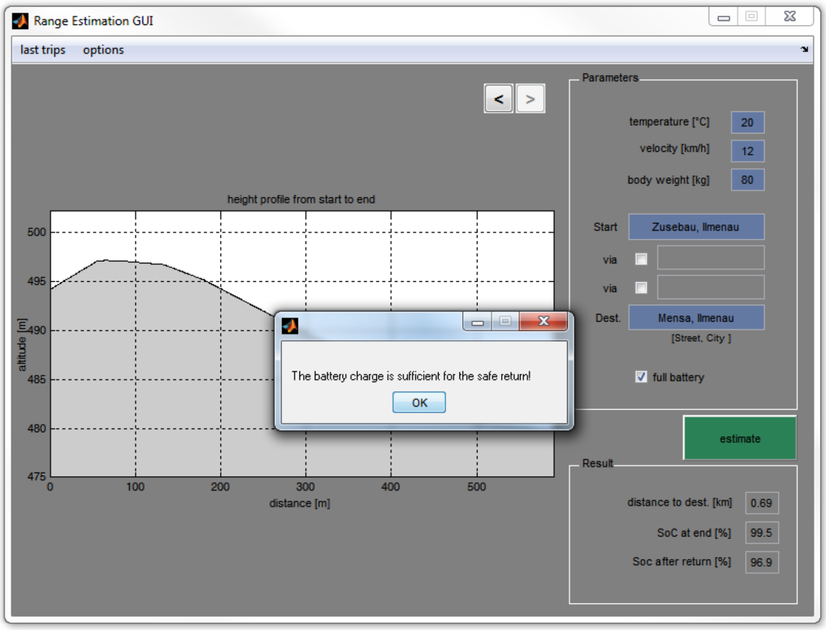

Fig. 6: GUI for the range estimation system

The route generation is provided by an online service. The GUI sends four points (start, end and two stops) to Google servers and receives a set of waypoints (longitude, latitude, distance) describing the route and the turns. This information is accessible via the Google

Directions API [10]. The system sends these positions again to Google servers to receive a height profile between them with the help of the Google Elevation API. If the checkbox "full battery" is not checked, the simulation considers the SoC from the previous simulation, which enables estimation of even more complex routes. Furthermore, the GUI offers the option to simulate the direct drive back from the end to the start without the additional stops.

5. RESULTS

The evaluation of the developed system compromises three parts. In order to verify the model, measurements have to be compared with the simulation results. In consequence, the sensor data needs a reviewing to incorporate the best data sources.

5.1 Sensor Accuracy

For the verification of the accuracy, the vehicle's velocity and position is measured with different sensors. Fig. 7 shows the velocity acquired from the smartphone GPS, the wheelchair's bus and the Trimble DGPS as a reference, whereby the GPS values are interpolated between each measurement.

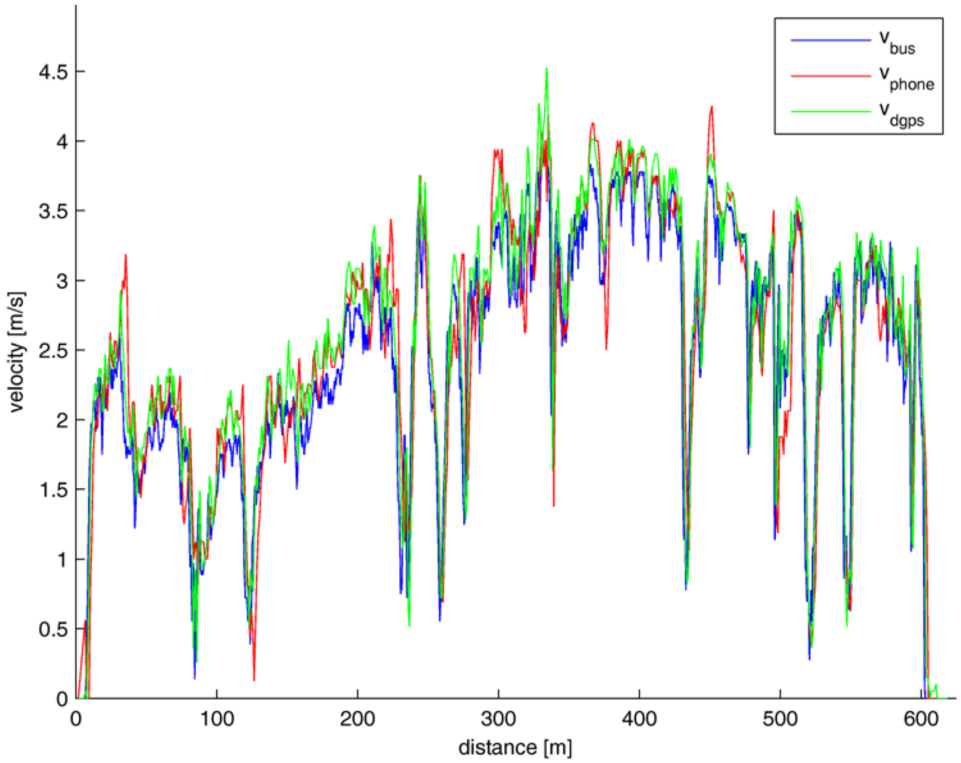

Fig. 7: Wheelchair velocity during a test drive

Although the velocity readings via CAN bus are updated more often, the velocity acquired via (D)GPS is higher at most times. As the later use of the DGPS sensor seems not to be reasonable within an assisting system, the smartphone GPS will be used for the velocity measurement. The same applies for the wheelchair's position. Fig. 8 shows the latitude and longitude of the wheelchair during a test drive (left) and its the altitude (right) that is referenced to the start position. The 2D GPS data of the two GPS sensors is comparable and yields a good estimation for the vehicle's driven distance. However, the 3D fix information differs notably. In general, GPS data is liable to interference and atmospheric errors. With respect to the altitude, the design of the global positioning system limits its accuracy [12]. Within this paper, the altitude estimation relies simply on the slope measurement and the velocity provided by the smartphone GPS. Although it is still erroneous, the results are better as the GPS' altitude and, the most important advantage, this estimation is not subject to sudden changes caused by environmental influences, see fig. 8.

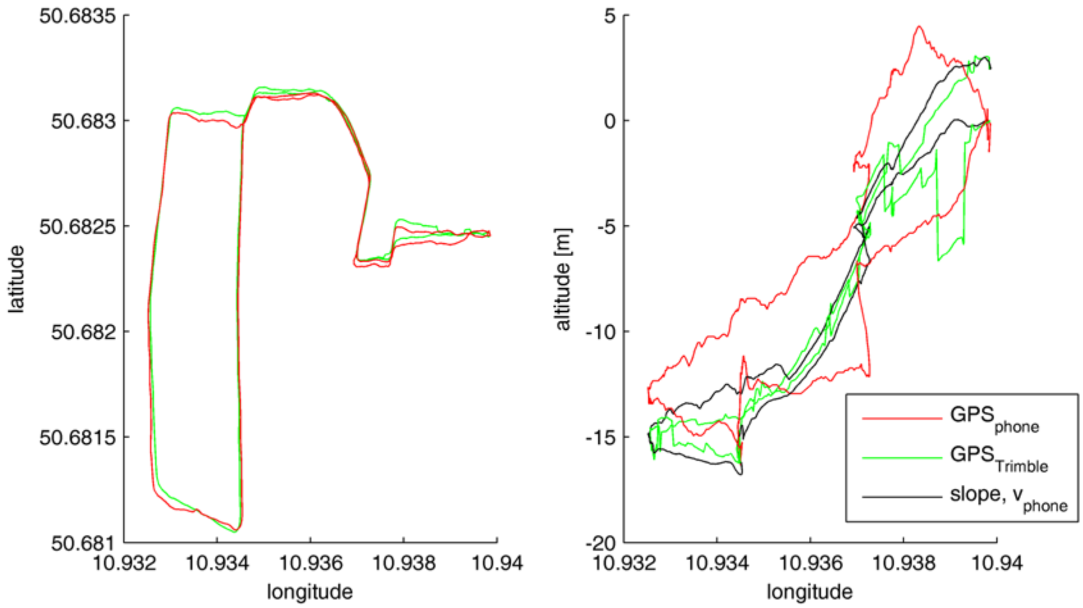

Fig. 8: Wheelchair position during a test drive

5.2 System Model

The position information is used to extract the height und velocity profile of the test drives. Their usage as an input for the simulation model allows its validation. Fig. 9 shows the simulation input and its results compared to the measured values for one test drive.

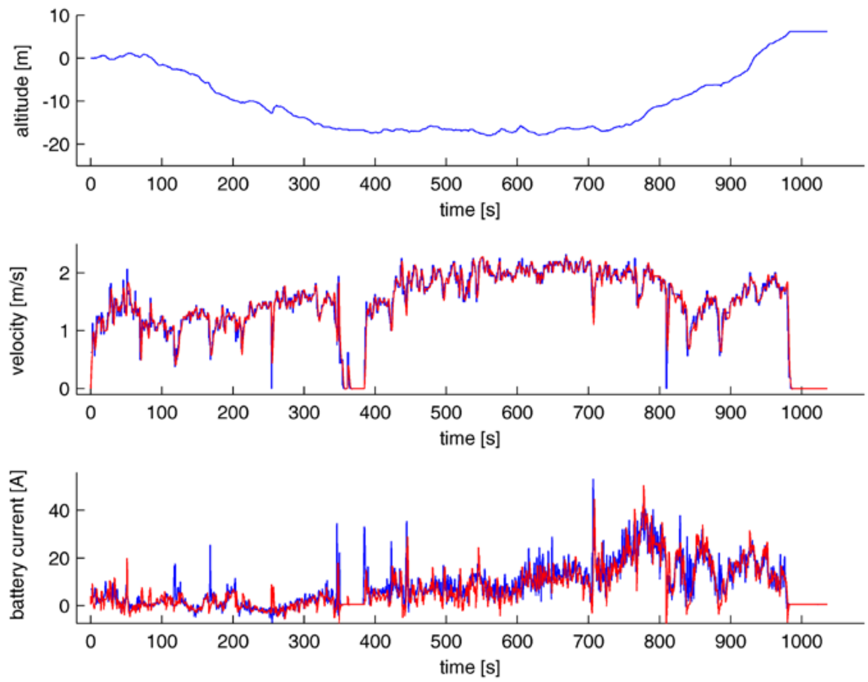

Fig. 9: Simulation results in red, measured data in blue.

The battery model relies on the simulated current for the SoC estimation. As the real SoC cannot be determined, the validation concentrates on the battery current. Its verification enables the future deployment of other battery models as well. The simulation outputs almost the same current as measured. The mean difference in the total depleted charge is 6% over all 11 test drives. This is an acceptable result considering the model uncertainties and the simple altitude measurement.

5.3 Virtual Routes

As the exact route profile is *a priori* unknown, the differences between real tracks and the generated profiles need some consideration. Fig. 10 shows a driven route and its pendant using the Google APIs as described afore.

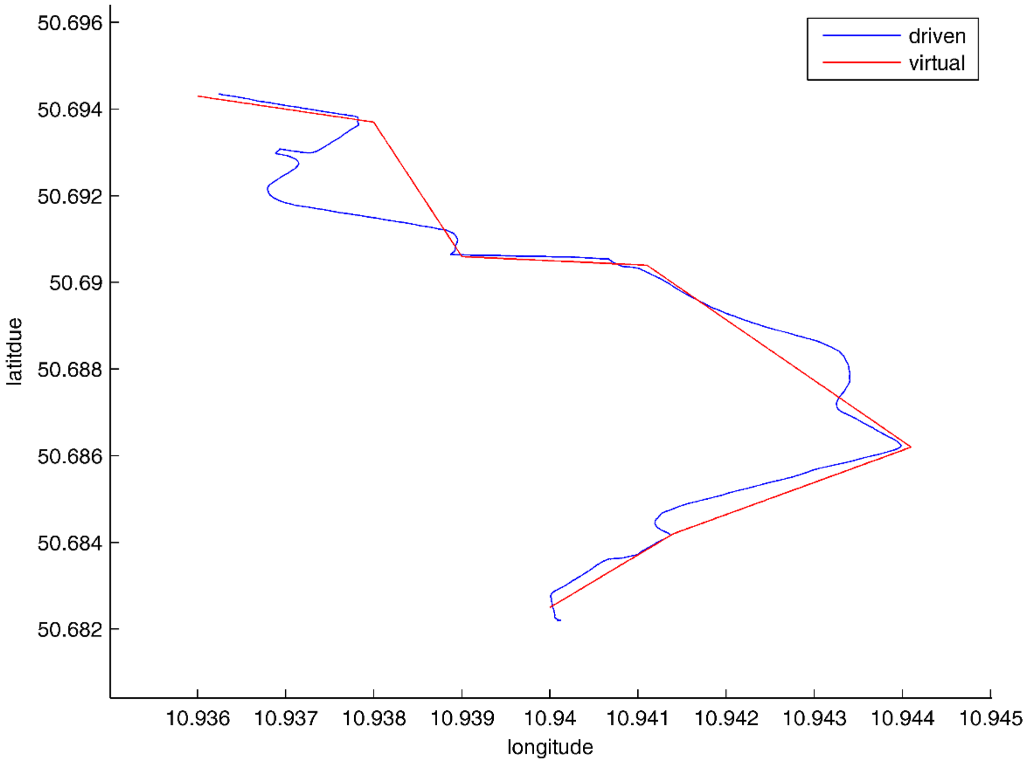

Fig. 10: Simulation results in red, measured data in blue.

The figure illustrates the biggest challenge for the estimation. The proposed system interpolates linear tracks between the waypoints that cannot reflect the real situation. Curved roads are not considered. Hence, the virtual routes are shorter than the real ones. Furthermore, the lowered road curb is not necessarily close to the crossroad. This prolongs the real tracks even more. In consequence, the simulation drive depletes less charge than the real drives. During four test drives, this together with the afore mentioned sensor and model errors accounted to a mean error of 11%, whereby the maximum is 25% and the minimum is 3%.

6. CONCLUSION

The range estimation system is capable of estimating the battery current and thusly the driving range. However, the accuracy depends dramatically on the quality of the virtual routes and the accuracy of the model parameters. In order to deploy the proposed system in the context of a future assisting system, a safety factor has to be introduced to ensure the driver's safe return home. Although the first evaluation shows promising results, a thorough test with more routes and different parameters is required to assess the quality of the proposed system in more detail. Future work will concentrate on the improvement of the virtual routes to account for curves. The rolling friction coefficient is currently not know, thusly a constant mean value is assumed *a priori*. The range estimation might yield better results if this coefficient is adjusted according to the specific road types, which could be retrieved via detailed maps.

REFERENCES

[1] P. Chen and Y. Koh, "Residual traveling distance estimation of an electric wheelchair", in *5th International Conference on Biomedical Engineering and Informatics (BMEI)*, pp.790,794, 16-18 Oct. 2012, doi: 10.1109/BMEI.2012.6513075

[2] C. Adam and G. Wanielik, „Map-based Driving Profile Simulation for Energy Consumption Estimation of Electric Vehicles," in s *15th International IEEE Conference on Intelligent Transportation Systems*, Anchorage, USA, 2012.

[3] C. Veigl, C. Weiß, K. Kakousis, D. Ibáñez, A. Soria-Frisch and A. Carbone, "Model-based Design of Novel Human-Computer Interfaces", *Biosignals and Biorobotics Conference (BRC)*, 2013

[4] N. Armstrong, C. D. Nugent, G. Moore and D. D. Finlay, "Developing smartphone applications for people with Alzheimer's disease", in *10th IEEE International on Information Technology and Applications (ITAB)*, Corfu, 2010.

[5] Google Inc., „Android Open Accessory Protocol", http://source.android.com/accessories/protocol.html, 2014.

[6] L. Guzzella and A. Sciarretta, "Vehicle Propulsion Systems", Springer, Berlin, 2013

[7] H. Naunheimer, B. Bertsche, J. Ryborz, W. Novak and P. Fietkau, "Automotive Transmissions: Fundamentals, Selection, Design and Application", Springer, Heidelberg, 2010.

[8] K. Kraschl-Hirschmann and M. Fellendorf, "Estimating Energy Consumption for Routing Algorithms", in *Intelligent Vehicles Symposium*, Alcalá de Henares, Spain, 2010.

[9] L. Jongkyung, K. Youngroc, C. Hanju, „A New Battery parameter identification considering current, SOC and Peukert's effect for Hybrid Electric Vehicles", in *Energy Conversion Congress and Exposition*, Phoenix, USA, 2011.

[10] Google Inc., https://developers.google.com/maps/documentation/directions/, 2014.

[11] Google Inc., https://developers.google.com/maps/documentation/elevation/, 2014.

[12] J. H. Kim and S. Sukkarieh, „A baro-altimeter augmented INS/GPS navigation system for an uninhabited aerial vehicle", in *The 6th International Symposium on Satellite Navigation Technology Including Mobile Positioning & Location Services*, Melbourne, Australia, 2013.

ACKNOWLEDGEMENT

This study was supported by the Development Bank of Thuringia and the Thuringian Ministry of Economic Affairs with funds of the European Social Fund (ESF) under grant 2011 FGR 0127.

CONTACTS

M. Sc. Norbert Fränzel	norbert.fraenzel@tu-ilmenau.de
Dipl.-Ing. Frank Weichert	frank.weichert@iosb-ast.fraunhofer.de