INTELLIGENT PEDESTRIAN POSITIONING IN VIENNA: KNOWLEDGE-BASED KALMAN FILTERING

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ABSTRACT:

In this paper the prototype of a map-independent knowledge-based Kalman filter ('WiKaF') for optimal pedestrian positioning is presented. The WiKaF concept, its system architecture and the integrated sensors are described. The multi-sensor system comes from the NAVIO project (another project for pedestrian navigation in Vienna) and contains a Dead Reckoning Module DRM III, a barometer PTB 220, a digital compass HMR 3000 and an eTrex Summit GPS receiver. The two main components of the position module are introduced. At the present time the knowledge-based component is responsible for the pre-filtering process of the measurement data which includes a first step of outlier detection. In a further step the central Kalman filter derives the optimal position of the pedestrian. For support in dead reckoning scenarios the filters system equations connect the multi-sensor output with a causal motion model. The combination of knowledge-based component and Kalman filtering preliminary aims at an increasing reliability of the filter. At the end of the paper test results in outdoor and indoor scenarios are presented. It is obvious that in many parts WiKAF works track stable but also requires further improvement in extensive dead reckoning scenarios.

1. INTRODUCTION

The increasing market of mobile information systems for pedestrians (e.g. information systems for city tours or public buildings) requires the precise and reliable provision of the current position. In contrast to the well established vehicle navigation systems which use the combination of position sequences with digital maps (map-matching techniques, see Czommer, 2001) pedestrians frequently move outside from digitally acquired roads / trajectories. Typical scenarios are represented by pedestrian zones, parks, shopping passages and the indoor area like public buildings. Within these environments the pedestrian can move nearly randomly which gives him a much higher degree of freedom like a vehicle. Consequently in many cases a simple transfer from vehicle to pedestrian navigation is not possible.

This paper deals with pedestrian positioning in passive environments, this means there's no fixed positioning infrastructure available. In this case absolute and relative position sensors must be integrated into the user's mobile device (e.g. a PDA). Using a multi-sensor system from another navigation project (NAVIO, see Gartner et al., 2004) the prototype of a 'map-independent knowledge-based Kalman filter' (WiKaF) is presented. The basic system architecture of WiKaF and the technical details of the sensors are described in Thienelt et al. (2005a and 2005b).

Figure 1 shows the multi-sensor system. It consists of

- a Dead Reckoning Module (DRM III from Point Research, 2007),
- a barometer PTB 220 (Vaisala, 2007),
- a digital compass HMR 3000 (Honeywell, 2007) and
- an eTrex Summit GPS receiver (Garmin, 2007).

In principle the DRM is a separate full operable multi-sensor system for pedestrian positioning consisting of a GPS receiver, a step counter, a barometer and a gyro with own integrated (unfortunately black-box) algorithms for data fusion (see Thienelt et al. 2005a). In WiKaF only its raw signals (e.g. from the step counter) are used. In addition the full DRM is used to map trajectories for comparison with the WiKaF results (see Section 4.1).

Figure 1. Multi-sensor system from the NAVIO project.

In the following the two main components of the position module are described. At the present time the knowledge-based component is managing the pre-filtering process of the measuring data. This includes a first step of outlier detection (e.g. multipath effects in GPS and magnetic disturbances of the digital compass). Using the prepared measuring data the succeeding central Kalman filter is then responsible for the optimal estimation of the pedestrians position. To provide maximum support in dead reckoning scenarios the filters system equations contain human motion models which enable a short-term prediction of future states of the pedestrian (e.g. his position, velocity and heading) and a smoothing of random measuring errors. To reduce the filters inertia in case of fast changes in heading a 'causal model' is introduced which directly uses the compass information as actuating variable (see Section 3.)

At the end of the paper first test results from WiKaF are presented. The position module is investigated both in outdoor and in indoor scenarios. Further ideas for improvement are discussed.

2. KNOWLEDGE-BASED PRE-FILTERING

The central element of the position module is represented by the Kalman filter. Using the system and measuring equations it is possible to estimate an optimal position of the pedestrian to each epoch t_{k+1}. Incorrect measuring data or an insufficient kinematic / dynamic model leads to unsatisfactory results (strong deviations from the reference trajectory). In the ideal case the filter corrects the trajectory by itself after some epochs or in the worst case it leads to the failure (diverge) of the filter. The knowledge-based component contributes to the decision making in the surrounding of the Kalman filter, in which e.g. roughly incorrect measuring data will be already excluded. Thereby the component supports the pre-filtering of the sensors' outputs which is done parallel to the data acquisition.

The pre-filtering has the task to provide adapted error models for the sensors (stochastical models which depend on the current environmental conditions) and to eliminate disturbances and outliers. Besides the evaluation of the measuring data this process also contains the selection of a priori determined case-based correction and scale factors, e.g. the declination for magnetic heading measurements or the step length under the current conditions. This process will be a 'knowledge-based calibration'. Essential precondition for the implementation of this process chain is an extensive knowledge engineering which is represented in Thienelt et al. (2005a). Some basics and examples are described in the next paragraphs.

2.1 Basics for implementation of outlier detection

A knowledge-based system consists of the following major components: a knowledge base, an inference engine, a user interface, a knowledge acquisition tool and an explanation tool. The knowledge base is the most important component of the system and contains the relevant domain-knowledge which is implemented by an expert (knowledge engineer). Knowledge engineering means the interaction between the knowledge engineer and the particular domain specialists to acquire all relevant knowledge from the domain and to implement this knowledge into the knowledge base. Special knowledge acquisition tools assist the knowledge engineer in this difficult work. The following process of finding the solution for a problem can be simplistically viewed as finding a connection between the available input factors and the conclusion. This is done by the inference engine. The user interface serves to establish the communication between the system and the end user. The explanation component helps the user to understand the reasoning strategy of the system. In the meantime knowledge-based systems are common in the field of diverse industrial and scientific applications (see Gottlob et al. 1990 and Steifik 1998).

Common knowledge representation schemes are: predicate logic, production rules, semantic nets, frames and others. In WiKaF the knowledge base is realised as a rule based / object oriented approach. Rule based programming is one of the most common techniques for the implementation of knowledge. Rules can be used to represent heuristic expert knowledge. A rule based approach consists of two parts: a set of rules and a working memory. The following example is part of the used working memory and is implemented by means of the knowledge-based system shell CLIPS (see CLIPS, 2007):

```
(deftemplate Epoche
      (slot ID (type INTEGER))
      (slot Schritt and (type INTEGER))
      (slot DRMHoch (type FLOAT))
      (slot DRMRechts (type FLOAT))
      (slot eTrexHoch (type FLOAT))
      (slot eTrexRechts (type FLOAT))
      ... )
```

In the example the cut-out of the template `Epoche` contains the multi-sensor data from the current measurement epoch and consists of 6 slots: `ID` (epoch), `Schritt` (number of steps), `DRMHoch` (*X*-coordinate of DRM III), `DRMRechts` (*Y*-coordinate of DRM III), `eTrexHoch` (*X*-coordinate of eTrex), `eTrexRechts` (*Y*-coordinate of eTrex). Each slot is identified by its name and type. So e.g. the first slots has the name `ID` and the type `INTEGER`.

As mentioned above the second part of such a system is a set of rules. A rule is divided into two parts: the left-hand side (LHS) and the right-hand side (RHS). In the LHS the preconditions of a rule are defined and in the RHS the actions. The rule will be applied if all preconditions are fulfilled. In this case the actions specified in the RHS are executed. More details can be found in Gottlob (1990), Steifik (1998) and Thienelt et al. (2005a). The following example is the CLIPS representation of a very simple rule:

```
(defrule AbfrageDruck
   (Epoche(ID ?index&: (= ?index? *aktuelle _Epoche*)))
   (DruckPTB ?DruckPTB&: (< ?DruckPTB *Schranke_Druck*))
  =>
   (bind ?*DruckPTB* 1)
  )
```

The rule `AbfrageDruck` checks if a value for the pressure is stored in the current measurement epoch. The header contains the keyword `defrule` followed from the rule name. Two preconditions follow:

Precondition 1: reads the current epoch (no precondition in the actual sense).
Precondition 2: tests if the measurement value for the pressure (`DruckPTP`) is more than a given level (global variable `*Schranke_Druck*`).

If both preconditions are fulfilled the global variable `DruckPTP` is assigned with the value `1`.

2.2 Knowledge acquisition results for sensor calibration

In this section some first results from knowledge preparation for the case-based determination of correction and scale factors of the position sensors are presented. At the present time this knowledge is not yet implemented in the pre-filtering process.

Some calibration elements of position sensors strongly depend on the current human and environmental boundary conditions. As an example the step length of the pedestrian (which is required for the calculation of a metric quantity Δs from the step counter pulses) is correlated with its physiology, velocity and the current topography. A real-time calibration of the step counter can principally be performed by GPS measurements. Nevertheless in inner urban areas the quality of the signals is often poor and in indoor scenarios there's no GPS available. This often leads to the use of out-of-date calibration information and to increasing systematic errors in the trajectory especially in dead reckoning scenarios.

Figure 2 shows the basic MISO (= Multiple Input and Single Output) concept for a GPS-independent calibration of the step counter. It shall not fully replace the GPS method but stand in dead reckoning. On the left site of the knowledge-based calibration component static (e.g. sex and size of the pedestrian) and dynamic (e.g. current heart rate) biometric and available environmental data is used as input. After the decision process (evaluation of system immanent rules modelling the complex relation between the input parameters, see Section 2.1) the current step length is provided at the output. It must be stated that the creation of such a system requires an extensive training phase and must be kept up-to-date during its operating phase.

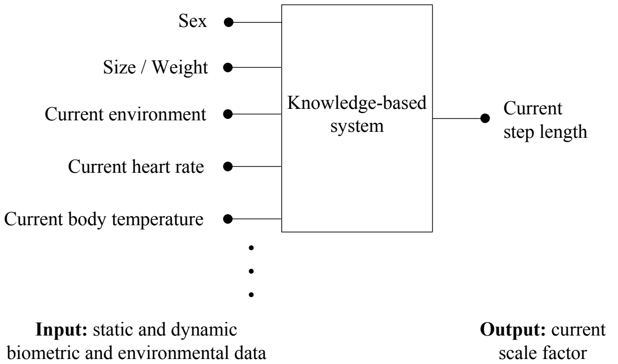

Figure 2. MISO-example for the knowledge-based calibration of the step counter.

Table 1 shows some results from knowledge acquisition for modelling the relationship between sex and step length in different states of walking.

	Women		Men	
	Step length [m]	**Mean velocity [m/s]**	**Step length [m]**	**Mean velocity [m/s]**
Slow	0,63-0,69	0,9	0,64-0,71	1,0
Normal	0,73-0,78	1,3	0,76-0,82	1,4
Fast	0,83-0,90	1,8	0,83-1,00	1,9

Table 1. Step length vs. velocity on horizontal and solid soil.

The tests were performed on a horizontal and solid soil. A clear assignment of a certain step length to a sex is complicated because of overlapping intervals and no significant difference in the velocities. But it is obvious that there is a significant increasing step length from 'slow' to 'fast walking' for both, women and men which allows a first (simple) classification. Consequently the determination of the current state of walking is an essential task. Biometric sensors shall be used to complete the multi-sensor system and deliver relevant input for calibration. In Figure 3 the measured progress of a pedestrian's pulse rate is exemplarily shown for three states of walking. The example shows significant pulse levels which can be correlated with 'slow' to 'fast walking'. This result is very promising for further investigations but requires further input data because of its dependence from the physiological and psychological state (trained or not, angry or in a good temper etc.) of the pedestrian.

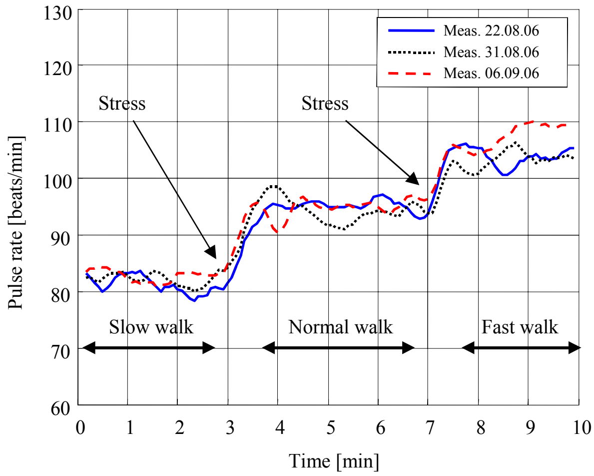

Figure 3. Reproducable pulse rate during different walking scenarios of a male, trained proband.

2.3 Further applications for a knowledge-based component

According to Thienelt et al. (2006b) the following additional applications could be also managed by a knowledge-based component.

- Choice of the motion model:

  Based on current geometry and kinematic of the pedestrian's trajectory the knowledge-based component determines the required motion model for the system equations of the Kalman filter. This may be a constant straight or circular motion without or with actuating variables (see Sections 3.1 and 3.2). The aim of this differentiation is to minimize overshooting effects of the Kalman filter in the case of fast turns of the pedestrian. Integrating an actuating variable (changes of heading) into the motion model this is achieved in Eichhorn (2005) for vehicle positioning with gyro data.

  One possible input for decision making could be magnetic heading data from the digital compass which allows the determination of temporal changes in orientation and thus a certain conclusion about the current kinematic progress. One big problem are the magnetic disturbances which may suggest a wrong motion.

- Sensor administration:

  The acceptance of a mobile application strongly depends on its operating characteristics. This is closely linked with its available energy. The simplest way to save energy is to switch off all sensors which are currently not used. Another possibility is an individual variation of the sensors measuring frequencies depending on the current walking scenario. For example an activated GPS receiver in an indoor environment is a waste of energy and substantially affects the run time of the whole system. Therefore the knowledge-based system should be also used for energy management.

3. CENTRAL KALMAN-FILTER

The combination of the pre-filtered raw data from the multi-sensor system to a position is realised by a position module with central Kalman filter (see Thienelt et al., 2005a). The theoretical assumptions concerning the current motion of the pedestrian are represented by the system equations. Fundamentals of Kalman filtering are described e.g. in Gelb (1974) and Schrick (1977).

Two different 2-D motion models are implemented in the WiKaF prototype. Both models are derived from a non-accelerated, constant circular motion (assumption for one sampling interval). The second model contains an additional measured actuating variable (change of orientation $\Delta\alpha$ of the pedestrian) which reduces the filter's inertia in case of sudden changes of the pedestrian's orientation. Positive and negative accelerations of the pedestrian are assumed to be stochastic influences and considered in the disturbance variables of the filter.

The 'motion model without actuating variable' is a constant circular motion in the sampling interval $[t_k, t_{k+1})$. Referring to Wang (1997) the undisturbed model can be quantified by the following non-linear kinematic equations.

$$\begin{aligned}
Y(t_k) &= Y(t_k) + v_t(t_k)\sin(\alpha(t_k))\,(t_{k+1}-t_k) \\
&\quad + \frac{1}{2} a_r(t_k)\cos(\alpha(t_k))\,(t_{k+1}-t_k)^2 \\
X(t_{k+1}) &= X(t_k) + v_t(t_k)\cos(\alpha(t_k))\,(t_{k+1}-t_k) \\
&\quad - \frac{1}{2} a_r(t_k)\cos(\alpha(t_k))\,(t_{k+1}-t_k)^2 \\
\alpha(t_{k+1}) &= \alpha(t_k) + \frac{a_r(t_k)}{v_t(t_k)}(t_{k+1}-t_k) \\
v_t(t_{k+1}) &= v_t(t_k) \\
a_r(t_{k+1}) &= a_r(t_k)
\end{aligned} \tag{1}$$

In (1) the five state quantities are represented by

$Y(t_k), X(t_k)$	=	absolute position of the pedestrian in the reference frame at t_k,
$\alpha(t_k)$	=	azimuth of the motion at t_k,
$v_t(t_k)$	=	tangential velocity of the motion in $[t_k, t_{k+1})$,
$a_r(t_k)$	=	radial acceleration of the motion in $[t_k, t_{k+1})$.

Two disturbance variables quantify deviations between reality and model assumptions. In (1) the tangential velocity v_t is disturbed by a stochastic tangential acceleration $w_{a,t}$ and the radial acceleration a_r by a stochastic radial jerk $w_{\dot{a},r}$.

The linearised and disturbed system equations of the kinematic Kalman filter result are represented by the following equation

$$\boldsymbol{x}_{k+1} = \boldsymbol{T}_{k+1,k}\,\boldsymbol{x}_k + \boldsymbol{S}_{k+1,k}\,\boldsymbol{w}_k \tag{2}$$

with $\boldsymbol{x}$ representing the vector of the state quantities, $\boldsymbol{T}$ the transition matrix, $\boldsymbol{S}$ the disturbance matrix and $\boldsymbol{w}$ the vector of the disturbance variables.

The 'motion model with actuating variable' is a constant circular motion in the sampling interval $[t_k, t_{k+1})$ which is 'causally modified' (see Eichhorn, 2005). The modification is realised by the integration of a measured actuating variable and results in the non-linear equations (3).

$$\begin{aligned}
Y(t_{k+1}) &= Y(t_k) + \frac{v_t(t_k)(t_{k+1}-t_k)}{\Delta\alpha(t_{k+1})} \\
&\cdot \Big[\cos(\alpha(t_k))\,(1-\cos(\Delta\alpha(t_{k+1}))) + \sin(\alpha(t_k))\,\sin(\Delta\alpha(t_{k+1}))\Big] \\
X(t_{k+1}) &= X(t_k) + \frac{v_t(t_k)(t_{k+1}-t_k)}{\Delta\alpha(t_{k+1})} \\
&\cdot \Big[-\sin(\alpha(t_k))\,(1-\cos(\Delta\alpha(t_{k+1}))) + \cos(\alpha(t_k))\,\sin(\Delta\alpha(t_{k+1}))\Big] \\
\alpha(t_{k+1}) &= \alpha(t_k) + \Delta\alpha(t_{k+1}) \\
v_t(t_{k+1}) &= v_t(t_k)
\end{aligned} \tag{3}$$

The four state quantities are represented by

$Y(t_k), X(t_k)$	=	absolute position of the pedestrian in the reference frame at t_k,
$\alpha(t_k)$	=	azimuth of the motion at t_k,
$v_t(t_k)$	=	tangential velocity of the motion in $[t_k, t_{k+1})$.

The disturbance is realised by a stochastic tangential acceleration $w_{a,t}$ disturbing v_t. The linearised and disturbed system equations of the filter result in the following equation.

$$\boldsymbol{x}_{k+1} = \boldsymbol{T}_{k+1,k}\,\boldsymbol{x}_k + \boldsymbol{B}_{k+1,k}\,u_k + \boldsymbol{S}_{k+1,k}\,w_k \tag{4}$$

In comparison to the pure kinematic model (2) this model is extented by an actuating variable $u(t_k)$ and its associated coefficient matrix $\boldsymbol{B}$.

In (4) the change of the azimuth of the motion $\Delta\alpha(t_{k+1})$ is introduced as actuating variable u and is obtained from measurements (e.g. from the digital compass HMR, see Section 1). Sudden changes in the pedestrian's orientation can be already considered in the prediction of the filter which leads to a significant damping of overshooting effects in the filtered trajectory. The application of (4) requires the consideration of only one disturbance variable: the disturbance of the tangential velocity.

If the actuating variable $\Delta\alpha(t_{k+1})$ is only superposed by typical measuring noise model (4) leads to good filter results. In practise the use of a digital compass is affected by various magnetic disturbances which lead to outliers or systematic errors. In most cases these effects cannot be completely eliminated during the pre-filtering process and lead to bad predictions and an unstable progress of the filter. In comparison with (4) model (2) is more inert but also more stable.

In WiKaF a suitable solution is applied using model (2) in the long sequences with nearly constant kinematics (low curvature of the trajectory, e.g. walking along a street) and model (4) in highly kinematic scenarios (changing and strong curvatures, e.g. fast turns of the pedestrian). The indicator for model changing is provided by compass and step counter.

4. RESULTS

4.1 Tests in an outdoor scenario

The presented results are obtained from a scenario in a test area which is located in the center of Vienna. The main characteristics of this area are narrow streets and buildings with 5-6 floors (height of 15-20 m). The topography causes bad GPS quality (complete loss of signal or multipath) and consequently extensive dead reckoning scenarios. In Figure 4 it is shown that a 70 m section in the 'Gußhausstraße' and a 200 m section in the 'Karlsgasse' must principally be passed in dead reckoning.

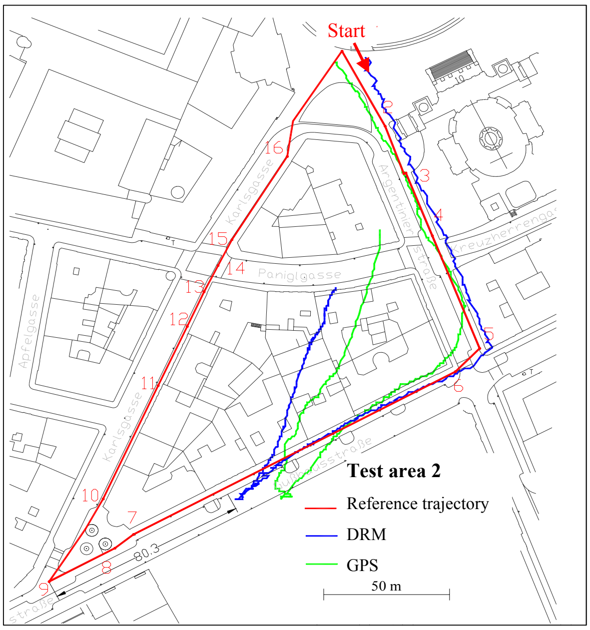

Figure 4. Results from test area 2 without WiKaF.

In comparison with the reference trajectory (red line) the results of the GPS solution (green line) are track stable in 'Argentinier Straße' but become very poor in 'Gußhausstraße' and are not available in 'Karlsgasse'. The trajectory was also determined with the commercial Dead Reckoning Module DRM III (see Section 1, blue line). It shows a similar behaviour like GPS. It can be recognized what happens if the GPS signal is too strongly weighted in an urban environment. The influence of GPS errors is extremely high and the guidance of a pedestrian becomes impossible. Consequently the quality evaluation of the GPS signals is of substantial importance. In WiKaF this is done by the knowledge-based component and the innovation test of the Kalman filter.

The blue line in Figure 5 shows the filtered trajectory when the WiKaF position modul is used. I contains the motion models of Wang (1997) and Eichhorn (2005). It is shown that the shape of the reference trajectory is in most parts well reconstructed. In some sections even a track troth filtering is achieved ('track troth' means the correct allocation of the roadside and / or the sidewalk to the pedestrian).

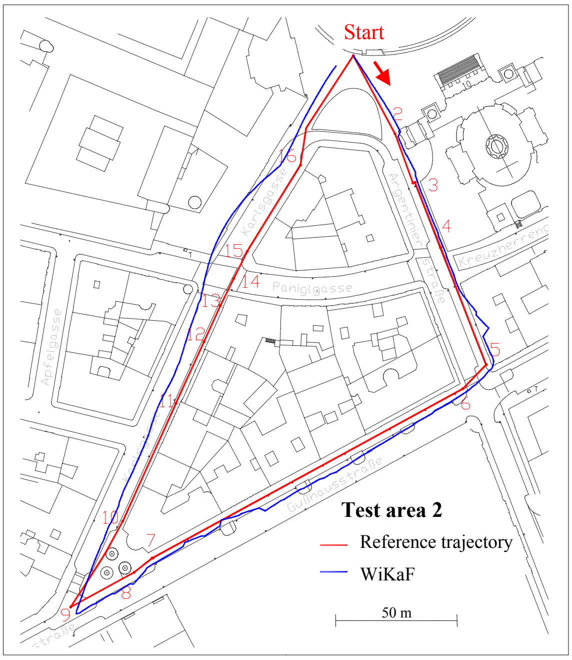

Figure 5. Results from test area 2 with WiKaF.

The *r.m.s.* (= root mean square) values of the filtered trajectory are presented in Table 2 and quantify the absolute position errors. In sections with available GPS and good quality ('Resselpark' and 'Argentinier Straße') the *r.m.s.* values are ≤ 3 m and the trajectory is track troth. In sections with poor or no GPS ('Gußhausstraße' and 'Karlsgasse') the *r.m.s.* values are in an interval of 3-5 m.

Section	GPS-availability	Error (*r.m.s.*)
Start at 'Resselpark'	very well	2 m
'Argentinier Straße'	well	3 m
'Gußhausstraße'	no	3-5 m
Part I 'Karlsgasse'	poor	3-5
Part II 'Karlsgasse'	no	9 m

Table 2. *R.m.s.* values of outdoor test with WiKaF.

With *r.m.s.* = 9 m the worst case can be detected at the end of 'Karlsgasse' after more than 200 m dead reckoning in total. The reason for this is a simultaneous drift of the magnetic heading sensor caused by magnetic disturbances (see Thienelt et al., 2006a), e.g. parking cars etc.

4.2 Tests in an indoor scenario

The indoor tests were realized at the institute building of research Group Engineering Geodesy in Vienna. Start and stop of the trajectory are the main entrances of staircases 1 and 2. The route follows staircase 1 up to the third floor, crosses the floor and goes down again by staircase 2. GPS is only available at the beginning of the trajectory. Figure 6 shows the progress of the reference trajectory (red line) and the results of WiKaF (blue line).

The good results in the height profile are achieved by air-pressure measurements which are transformed by an empirical linear characteristic line determined by calibration (see Thienelt et al., 2006a). In comparison to the height the determination of the horizontal position is much more challenging. Especially the spiraled structure of the staircases leads to drift errors up to 8 m at the end. This is not sufficient for indoor positioning which aims at room detection and requires further improvement.

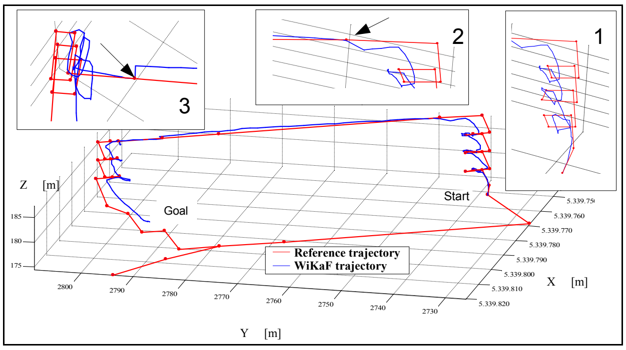

Figure 6. Some results from the indoor tests.

The 'bad guy' in the dead reckoning scenario is the digital compass which induces serious errors in heading. At the beginning of the third floor these errors are nearly random. Various test measurements show quantities between 15 to 60 gon. For a successful indoor guidance it is necessary to provide good initial values for absolute position and heading at the beginning of the scenario and to provide possibilities for a system update during dead reckoning. In Figure 6 this is realised in the third floor where the heading is updated by the information of two reference points which are situated at the beginning and at the end. Using this additional information the east deviation of the trajectory reaches only 3 m and the north deviation 5 m. These errors are preliminarily caused by scale errors in the step length. Its real-time knowledge-based calibration (see Section 2.2) will be subject of further investigations.

5. CONCLUSIONS AND OUTLOOK

In comparison with standard modules for pedestrian positioning (like DRM III) the presented WiKaF results show a significant improvement. The position module was successfully implemented and tested in out- and indoor scenarios with promising results. But it must be stated that extensive dead reckoning and consequently indoor scenarios are still a problem and require further investigations and improvement. Our future work will mainly focus on the combination of out- and indoor scenarios and the further reduction of outliers and systematic effects of position sensors like the digital compass.

A possible support of the autonomous multi-sensor system in indoor sections could be achieved by the preparation of the infrastructure, e.g with WirelessLAN positioning (IMST, 2007) or RFID tags (RFID = radio frequency identification, see Finkenzeller, 2000). Investigations are documented e.g. in Retscher et al. (2006).

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