# Pedestrian Dead Reckoning: A Basis for Personal Positioning

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**Abstract - Generic indoor personal positioning with an accuracy better than 10m error is still a challenging research issue. It is well known that the key to solving this problem is the combination of different positioning techniques. In this paper, a combined approach of pedestrian dead reckoning (PDR) and GPS positioning is followed. An acceleration sensor provides signals with which a neural network is trained in order to make step length predictions for relative indoor positioning. An experimental system is developed and the obtained results show that the accumulated error over a 4km walk is approximately only 2%. Indoor PDR positioning results are also described.**

## 1 Introduction

Accurate relative as well as absolute personal positioning can be considered a primary factor for service differentiation and personalisation in future mobile communications. Accurate positioning is an important and emerging technology for commercial, public-safety and military applications [1]. Benefiting from accurate positioning are services for tracking people with special needs, (e.g. children, the elderly, prison inmates, the blind [2]), policemen, and firemen as well as the regulatory '911/112' emergency response systems. The innumerable commercial Location Based Services that have proposed would also benefit. In terms of service adaptability and reconfigurability in wireless networks and systems, personal positioning services could be used to improve indoor Radio Resource Management by providing location-assisted handover, dynamically identifying traffic hot-spots and allocating resources on demand, for example, using adaptive/steerable antennas, and adaptive network topology configuration and intelligent routing in ad-hoc networks. Another ad-hoc network application that could benefit from the use of location information is in virtual antenna array management, where virtual arrays implement antenna arrays by the cooperation among spatially separated single antenna terminals.

Several viable techniques currently exist for accurate outdoor positioning, the most notable being the US NAVSTAR Global Positioning System (GPS) and its new European equivalent, Galileo. The combined GPS/Galileo satellite constellation and signals will provide very much improved performance over the current GPS system, in terms of positioning accuracy and availability. Significant performance gains will be likely even in challenging environments, such as urban canyons. Consequently, standard commercial GPS/Galileo-based positioning will be an integral part of mobile positioning solutions.

In situations where GPS/Galileo signals are not reliable, ground vehicle navigation systems can make very effective use of odometry, steering direction (i.e. heading), vehicle dynamic models [4] and map matching [5] for positioning. When an end user is a passenger in such a vehicle, e.g. car, train, or subway, the passenger's cell phone could simply get its position (and

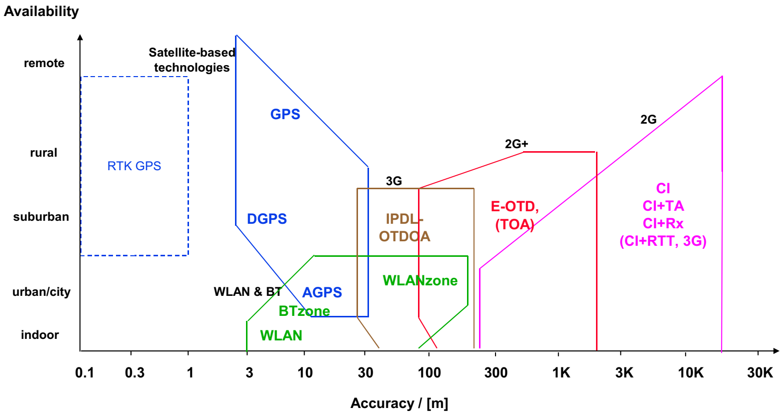


Figure 1: Comparison of Positioning Technologies (taken from [3])

velocity) from the navigation system via a Bluetooth connection, for example. It has also been demonstrated how one might detect when a user enters or exits a vehicle by comparing to known transportation routines [6].

With regards to indoor positioning, however, the situation is not nearly as clear cut. Even when fully deployed and even with so-called "high-sensitivity" receiver technology, the GPS and Galileo systems might not provide reliable, precise indoor coverage. Fortunately, other technologies exist for positioning indoor. Many depend on the presence of indoor data network base stations, such wireless WLAN access points or Bluetooth (BT) nodes. Others depend on specialized transponders with a signal structure designed specifically for positioning, such as GPS "pseudolites" [7] or Ultra-Wideband (UWB) beacons. However, the availability of such hot spot systems cannot be guaranteed in all application scenarios. Consequently, a ubiquitous indoor positioning solution will have to rely on existing outdoor systems (i.e. GSM and/or UMTS networks) and opportunistically take advantage of indoor wireless infrastructure when it is available.

For many envisioned positioning-dependent applications, a maximal positioning error of 5-10m (i.e. room scale) is required. Fig. 1 gives an overview of the coverage of a wide range of positioning technologies and techniques. As can be seen from the figure, if we discount wireless LAN and Bluetooth technologies, the estimated indoor accuracy is 30-50m using IPDL-OTDOA (Observed time difference of arrival with Idle Period on the Downlink) in 3G networks. Therefore, improvement to the left boundary of the 3G zone will be needed. Higher accuracy is of course desirable but it is technically very difficult to attain. Furthermore, seamless indoor and outdoor operation is essential. Given the constraints and requirements outlined above, it is clear that no single technology will solve the positioning problem.

Many application contexts that are not currently well-served are those where the end user is moving around on foot, typically indoors. Fortunately, just like for vehicles, we can take advantage of the known 'platform dynamics' and do relative position estimation using a Dead Reckoning approach. The Pedestrian Dead Reckoning (PDR) has been shown to yield positioning accuracy adequate for many end applications. As part of research collaboration with MobilTec GmbH, a working PDR test bed was created for developing, validating and demonstrating new positioning techniques and approaches for indoor applications. In the remainder of this paper, we discuss our improvements to existing PDR approaches. The PDR technique itself is described in Section 2. Results obtained from an experimental system are presented in Section 3, and conclusions are drawn in Section 4.

# 2 Pedestrian Dead Reckoning approach

Dead reckoning is a relative navigation technique. Starting from a known position, successive position displacements are added up. The displacement estimates can be in the form of changes in Cartesian coordinates (i.e. x and y coordinates) or, more typically, in heading and speed or distance. With sufficiently frequent absolute position updates, dead reckoning's linearly growing position errors can be contained within pre-defined bounds.

Pedestrian Dead Reckoning is simply the estimation of a step length (or walking speed) and a course over ground (or direction of walking). There is an extensive body of research on this subject [8–11]. The PDR technique has been applied to the problem of navigation in a number of projects [2, 12, 13]. The PDR technique is effective if a hard mounting point on the pedestrian is used. The device must be worn by the same user since the step model is trained with a particular individual's walking patterns.

## 2.1 Algorithm details

The PDR technique is naturally decomposed into the step detection and estimation part and the heading estimation part. Each of these is discussed in turn.

### 2.1.1 Step Model

We have based our step length estimation algorithm on the method described in [14] and [15]. Other authors have proposed minor variations to this same basic idea. First an acceleration magnitude signal is calculated from the three orthogonal accelerometer signals. Step boundaries are defined by the positive-going zero crossings of a low-pass filtered version of this signal. See Fig. 2 for details. Next, numerical step features are created. The acceleration magnitude's maximum value, minimum value and variance are determined for each step (i.e. time between zero crossings). These are depicted in Fig. 3. The integral of the acceleration magnitude between footfalls is also calculated.

The numerical features calculated above are then used in a feed-forward neural network [16] as input training patterns. The output training patterns are the step lengths estimated from GPS position fixes, interpolated to footfall occurrences. The network is then optimized using a standard non-linear optimization technique (e.g. scaled conjugated gradients). As is standard practice, in evaluating this approach and in tuning the neural network, we used one portion of our recorded experimental data for training the network and a different, independent held-out portion of data for verifying the neural network predictions. It was found that less than 10 hidden layer neurons was required to get good cross-validated results, in part because the neural network was configured with direct (linear) connections in addition to the usual (non-linear) links through the hidden layers. Fig. 4 shows a typical fit of the model to training data and Fig. 5 demonstrates that the model is effective at rejecting outliers in the training data.

Other researchers have used thresholding rules to reject false step occurrences based on the time interval between footfalls [10] and on the magnitudes of the numerical step features [17]. We have made no attempt to do so because the neural network, once optimized using correct training data, will predict a step length very close to zero for these cases.

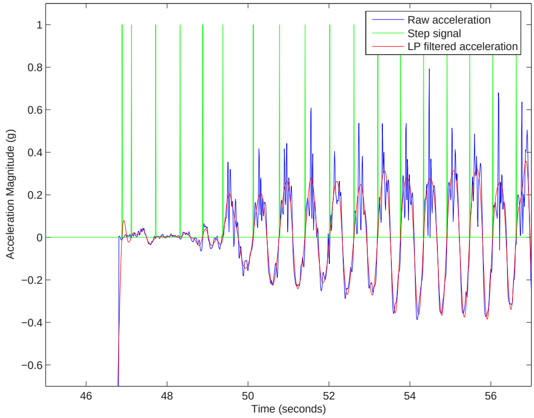


Figure 2: Step Acceleration during Start: This figure shows the behaviour of the step detection algorithm at start from standstill.

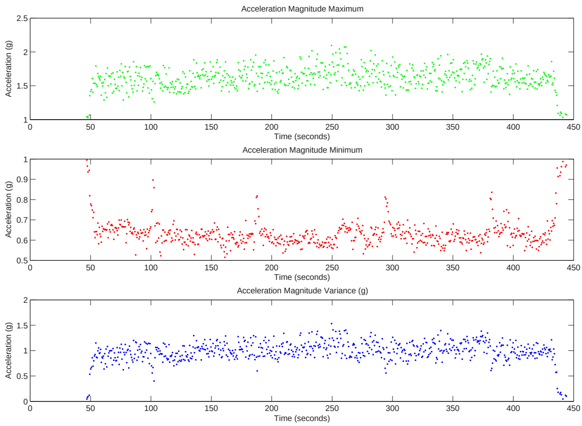


Figure 3: Step Acceleration Analysis: Three of the four numerical features calculated for each step are shown. Notice that both the acceleration maxima and minima are 1g at standstill at the beginning and end of the walk and that the variance drops to zero as well. The spikes in the acceleration magnitude minima are caused by additional radial accelerations during turning manoevres at 102, 188, 294 and 382 seconds.

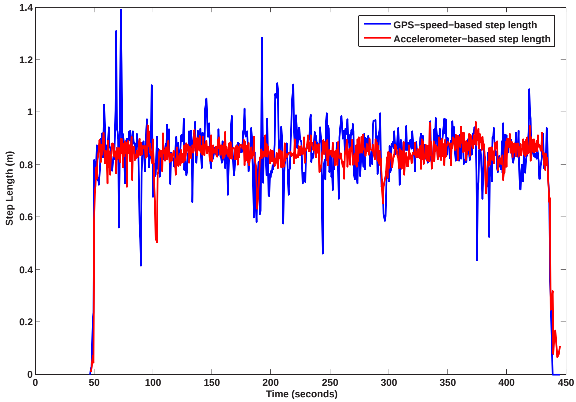


Figure 4: Step Length Model Calibration: The model fit to the training data (first half of the data) and the model estimates for the held out testing data (second half of the experiment) are excellent. The model is clearly not giving a simple average of the data as it correctly predicts the stopping dynamics. It even fits the fictitious step length reduction during turns. These reductions are side-effects of the GPS receiver's position and speed filter.

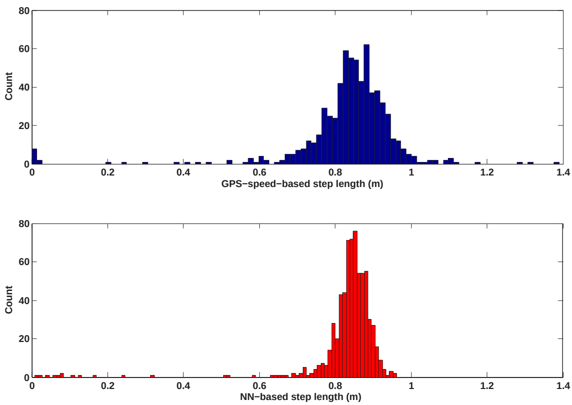


Figure 5: Step Length Model Histograms: Step lengths from the GPS training data and the fitted model estimates are compared. There is a significant variance reduction from the fitting process and the largest deviations in the training data ("outliers") are effectively rejected.

Figure 6: Equipment used for PDR Tests.

#### 2.1.2 Heading Estimation

A combination of magnetic compass measurements and GPS course over ground were used. These signals were used individually when available and no attempt was made to systematically fuse them. Note that a compass gives orientation and not necessarily the direction of travel, because pedestrian could be side stepping, for example. We assume that the compass is mounted in a fixed orientation relative to the user's body.

### 2.2 Tools

The main instruments for these experiments were the Xsens MT9 IMU and the UBlox GPS receiver. The IMU sensor head and GPS antenna were mounted on a styrofoam bicycle helmet. Data was logged using a tablet computer and the various batteries, cables, connectors and adapters (e.g. RS-232 to USB cables) were carried in a small backpack, see Fig. 6. (The UMTS phone shown in the figure was used to connect to an Internet-based DGPS service called NTRIP. Unfortunately, the versions of the RTCM messages from the NTRIP streams could not be parsed by our UBlox receiver.) The XSens and UBlox application software was used for data logging. Measurements were reprocessed off-line to convert the raw binary log files to ASCII. These were then reformatted and cleaned-up using Perl before import to the analysis package. Matlab and a Machine Learning package [16] was used in the analysis and plotting of results.

## 3 Results

The results of the neural network prediction is shown in Fig. 7. The difference between the cumulated model step lengths and the true surveyed distance is only a few percent. This compares very favorably with step length estimation results reported in [15], where errors were as large as 5.4% of the total distance traveled.

Using the magnetic heading information available from the motion sensor, it is possible to calculate an estimated track on the ground. Figure 8 shows this estimated track in comparison to the GPS track ground truth for an outdoor / indoor test. The starting point is at the path

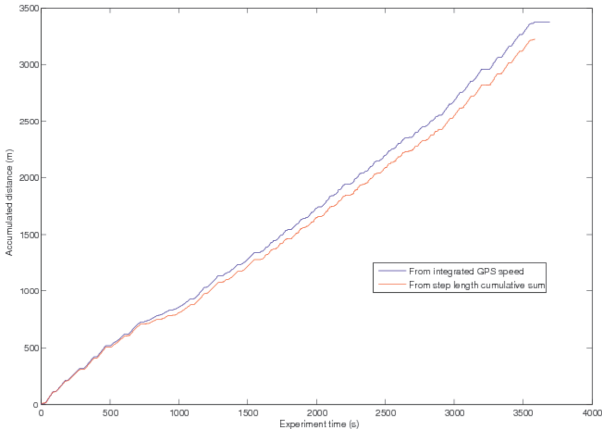


Figure 7: Cumulated Step and GPS Distances

intersection just below the chapel and for an idea of the scale, the sides of the rhombus track are exactly 100m. The position offset after the 1 km walk is only about 10 m. If we had fused the PDR and GPS measurements up to the entry of the building, the path offsets seen in the figure would be absent.

# 4 Conclusion

The attained accuracy of the PDR positioning approach is within 10m when assuming that the distance between absolute GPS location fixes is less than about 500m. The step length estimation results are superior to those published elsewhere. This can be attributed to the developed neural-network-based step-length estimation technique. Many avenues to PDR performance improvements, such as the detailed modeling of stops and starts, loitering, steering and stair climbing, are still open for future research.

The mounting of the PDR motion sensors on a helmet is, to our knowledge, novel and performs well, as we have seen. This configuration, as well as the waist and torso mounts, may be appropriate for some end users. However, for most commercially acceptable mounting options, such as loosely carrying the sensor cluster in a coat pocket or handbag, we can expect PDR-only positioning results to be distinctly worse than what we have shown here. This has in fact already been shown in experiments where the motion sensors were placed in a soft backpack and on a piece of everyday clothing [10]. Nonetheless, the loose-mounted PDR approach may provide useful, coarse measurements as long as these are fused with RF based techniques, such as state-of-the-art RF signature matching or conventional cellular positioning methods. Consequently, the PDR technique can be considered a basis for future, high-performance personal positioning systems.

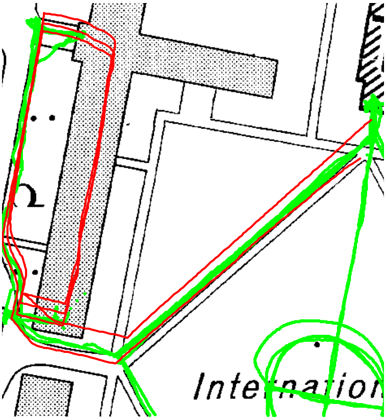


Figure 8: Comparison of GPS and PDR Tracks for Outdoor and Indoor Test: red, PDR-estimated track; green, GPS ground truth.

## 5 Acknowledgements

This research was conducted in cooperation with MobilTec GmbH as part of the Mobile Discovering System (MDS) project, funded by the BIS (Bremerhavener Gesellschaft für Innovationsförderung und Stadtentwicklung mbH) within the T.i.M.E. program of the State of Bremen/Bremerhaven. Stéphane Beauregard is currently affiliated with TZI Technologie-Zentrum Informatik, Universität Bremen, Germany (stephane.beauregard@tzi.de).

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