A Helmet-Mounted Pedestrian Dead Reckoning System

Stéphane Beauregard

TZI Technologie-Zentrum Informatik
Universität Bremen, Bremen, Germany
stephane.beauregard@tzi.de

Abstract. Since most persons in emergency service wear some sort of headgear, we investigate how basic navigation sensors could be incorporated into a safety helmet and thereby be made truly wearable. It is well known that the key to solving the generic ubiquitous localization problem is the combination of different positioning techniques and sensor modalities. In this paper, a combined approach of pedestrian dead reckoning (PDR) and GPS positioning is followed. An novel combination of neural-network step length predictions and helmet-mounted sensors is presented. The experimental system shows low accumulated error over an extended walk and indoor/outdoor navigation is demonstrated.

1 Introduction

Relative as well as absolute positioning can be considered primary factors for service differentiation and personalisation in the future mobile communications, as well as a catalyst for a variety of envisioned Location-Based Services. Applications include tracking of people with special needs, children, the elderly and prison inmates, and navigation aids for the blind [1]. However, accurate positioning is also an important and emerging technology for public safety and military applications [2], i.e. for policemen, firemen, rescue workers and soldiers. Since most persons on public safety or military service wear some sort of headgear, in this paper, we investigate how basic navigation sensors could be incorporated into this headgear and thereby be made truly wearable. The goal of this research is to enable infrastructure-less indoor positioning with an accuracy better than room scale, a performance requirement for many emergency and "tactical" scenarios.

2 Background

Several viable techniques currently exist for accurate outdoor positioning, many of which rely on existing public wireless infrastructure [3]. When GPS signals are available, absolute positions to within a few meters of ground truth can be attained. With regards to indoor positioning, however, the situation is not nearly as simple. Even when fully deployed and with so-called "high-sensitivity" receiver technology, the GPS/Galileo system 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" [4] or Ultra-Wideband (UWB) beacons. However, the availability of such hot spot systems cannot be guaranteed in all application scenarios. If existing outdoor (i.e. GSM and/or UMTS networks) or indoor (WLAN) infrastructure can be detected, they could be used opportunistically for indoor positioning [5], but technically, it has proven to be very difficult to do so. For example, positioning errors in cellular systems are often on the order of the cell radius outdoors and much worse indoors. For many envisioned indoor positioning applications, a maximal positioning error of 5-10m (i.e. room scale) is required. 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 generic, ubiquitous positioning problem.

3 Wearable, Helmet-Mounted Sensors

Since mobile end users will often be moving around on foot[1], we can take advantage of the known 'platform dynamics' and do position estimation using the Pedestrian Dead Reckoning approach. PDR has been shown to yield positioning accuracy adequate for many end applications. We use GPS as a means to calibrate and validate (at least outdoors) the PDR technology. GPS can of course also be the basis for outdoor positioning *per se*.

The PDR technique is effective if a hard mounting point for the sensor is used. In previous research, belt (waist), lower back and torso mounts have been used successfully. In one project, the motion sensors were carried in a loose-fitting backpack, however this was found to give less than satisfactory results [6]. As far as the author knows, the helmet-mounted PDR sensors described here are novel. See Figure 1 for an illustration of possible sensor placement. The initial impetus for this mounting choice was actually the GPS antenna which has to have a clear view of the sky. This is difficult to do at any other point on the body[2]. The choice was fortuitous, as there are many other small active and passive context sensors that could be mounted on helmets, such as small video cameras or range sensors. Also, the motion sensors themselves could be used for coarse activity recognition (e.g. walking, running, loitering, visually scanning surroundings, crawling).

[1] When end users are in a vehicle, e.g. car, train, or subway, it would make sense to tap into the vehicle's navigation system for positioning purposes. For example, a cell phone could get its position from a car's navigation system.

[2] In [7], a special antenna was used to partially overcome this problem for shoulder mounting.

Fig. 1. Helmet-mounted Sensor: The orange box on the helmet brim is the XSens motion sensor and the smaller device on the top is the GPS antenna.

4 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 [6–9]. The PDR technique has been applied to the problem of navigation in a number of projects [1, 10, 11]. Note that once configured, PDR systems are not transferable between users since step models are trained with a particular individual's walking pattern.

4.1 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.

Step Model Many papers on PDR simply rely on a fixed average step length for each specific user. This naïve approach gives relatively good navigation results for typical speeds but performs less well with walking patterns far outside of normal range. We have based our step length estimation algorithm on the method described in [12] and [13]. 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. Notice that at standstill, both the acceleration maxima and minima are 1g and the variance is zero. The integral of the acceleration magnitude between footfalls is also calculated. Hand-tuned thresholding rules, based on the distributions of step frequency and of step acceleration features, are created to reject false step detections.

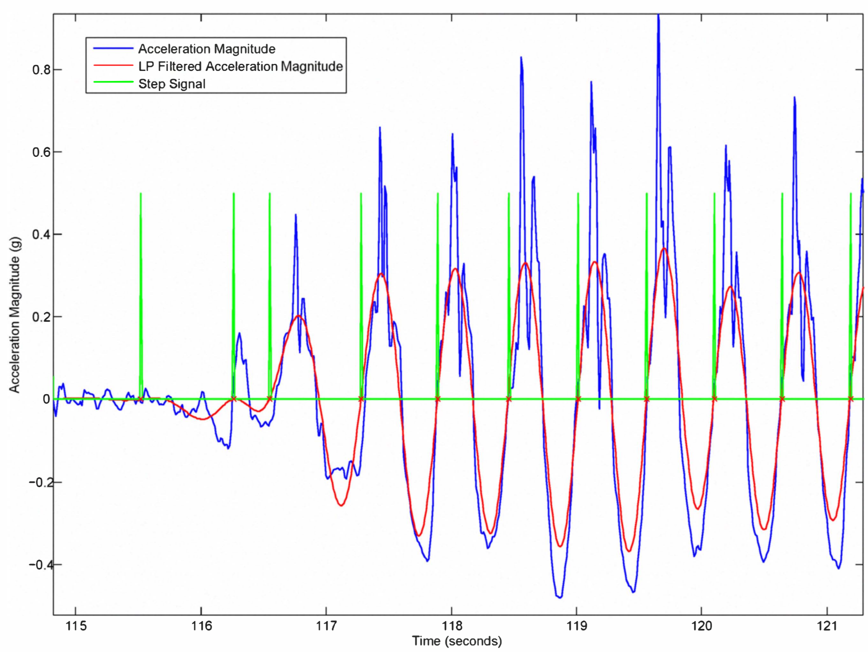

Fig. 2. Step Acceleration during Start: This figure shows the behaviour of the step detection algorithm at start from standstill.

The numerical features calculated above are then used in a feed-forward neural network [14] as input training patterns. The output training patterns are the

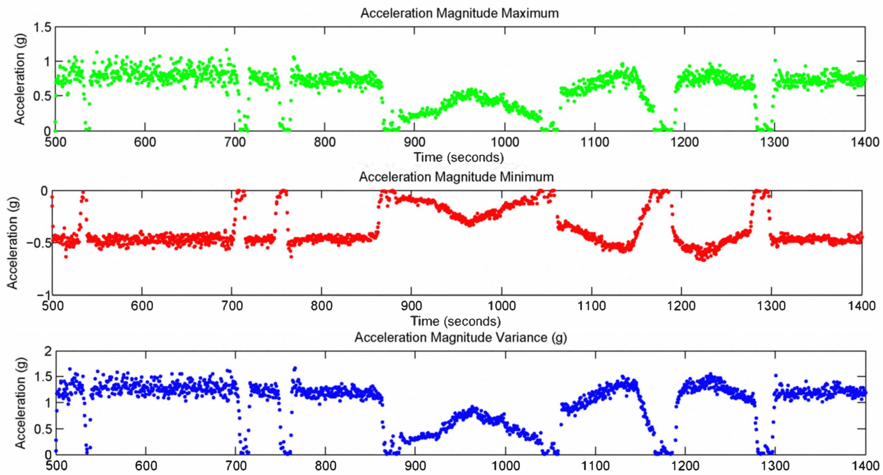

Fig. 3. Step Acceleration Analysis: Intermediate features calculated for each step are shown.

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)[3]. 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.

Figure 4 shows a typical fit of the model to training data. For the time window between 900 and 1050 seconds (experiment time), the experimenter walked in a very wide range of speeds, from barely advancing (0.5 m/s) to an Olympic race walk clip (2.0 m/s). The model handles this wide range of speeds very well. Note that for the period around 900 seconds, the GPS position and speed fixes were erroneous. This did not aversely effect the fit of the neural network to the data. The model fit for the held out testing data is typically very good.

Heading Estimation The motion sensor's yaw output (rotated from the sensor-fixed frame to the earth-fixed frame) was used for deriving a heading. Details on the calibration of the heading estimation (i.e. magnetometer gain and scale factors as well as sensor fusion filter tuning) can be found in [15].

For the experiments, we ensured that the motion sensors were mounted in a fixed orientation relative to the user's body, i.e. that the helmet was worn tightly. Also, the subject kept the helmet pointed in the direction of motion at all times. Future research will aim at relaxing this restriction. Estimating a direction of motion simultaneously with arbitrary gaze orientation and walking style, e.g.

[3] Note that the neural network was configured with direct (linear) connections in addition to the usual (non-linear) links through the hidden layers.

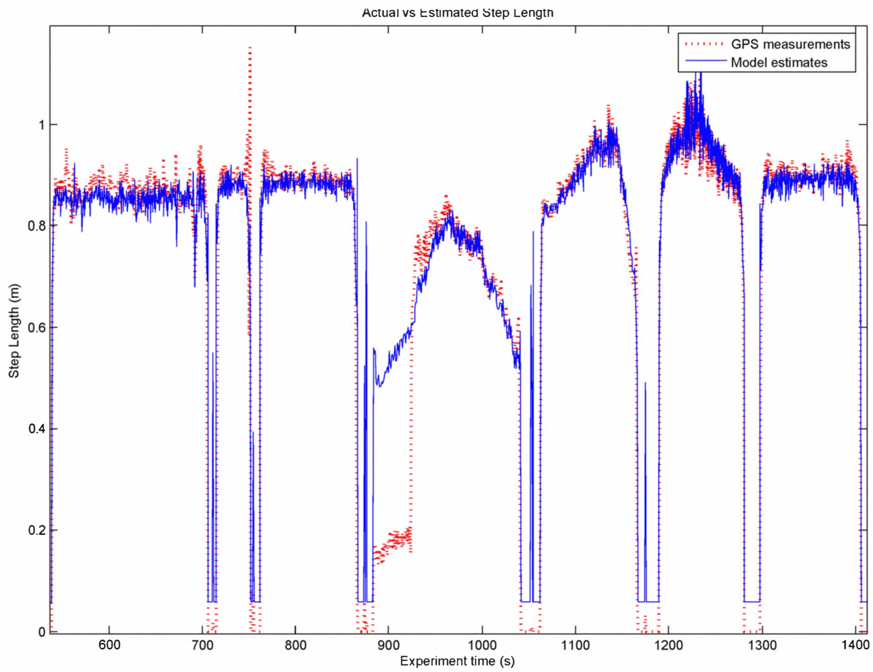

Fig. 4. Step Length Model Calibration

side-stepping, is not simple with this sensor setup. Very accurate rotation matrices and non-trivial inertial calculations are required to derive a direction of travel under these circumstances.

4.2 Tools

The main instrument for these experiments was the Xsens MT9 IMU and the UBlox GPS receiver. The IMU sensor head and GPS antenna were taped to a construction helmet for easy of use by one person. Data was logged using a laptop computer and the USB cabling and GPS receiver were carried in a small backpack. 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 [14] was used in the analysis and plotting of results.

5 Results

The results of the neural network prediction for one typical experiment are shown in Fig. 5. The difference between the cumulated model step lengths and the true surveyed distance is only a few percent. These step length estimation results are similar to those reported in [16] and compare very favorably with [13], where errors were as large as 5.4% of the total distance travelled. The results also confirm those found in earlier work by the author [5, 15].

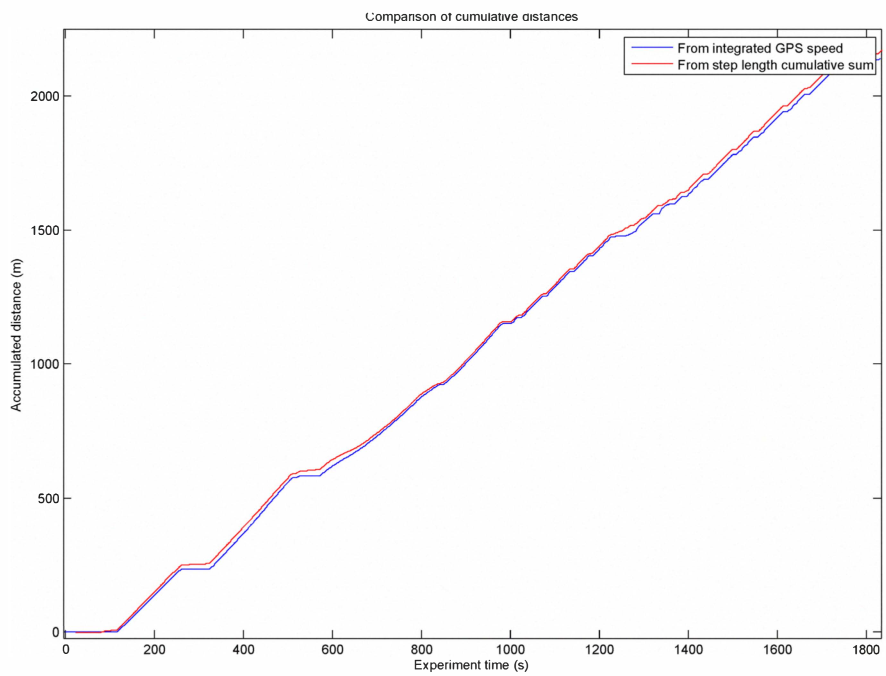

Fig. 5. Cumulated Step and GPS Distances

Using the magnetic heading information available from the motion sensor, it is possible to calcuate an estimated track on the ground. Figure 6 shows this estimated track in comparison to the GPS track ground truth for an outdoor test. The track segment lengths are comparable and the position offset after the 30 minute walk is only about 40 m. The visual diffences between the GPS and PDR tracks can be attributed to heading errors and to GPS blunders due to nearby buildings.

The experiment was continued to include outdoor / indoor transitions. Figure 7 shows the PDR estimated track in comparison to the GPS track "ground truth". Here the performance of GPS receiver is clearly very poor. There are frequent position fix blunders, on the order of 20-30m, due to satellite signal masking and distortions from the 4-story building. Along the entire south-eastern side, there is no fix at all. Our receiver features a "high-sensitivity" mode that is advertised to work in certain indoor environments but in the glass covered inner courtyard, it is giving almost useless results. New signal structures in the GPS

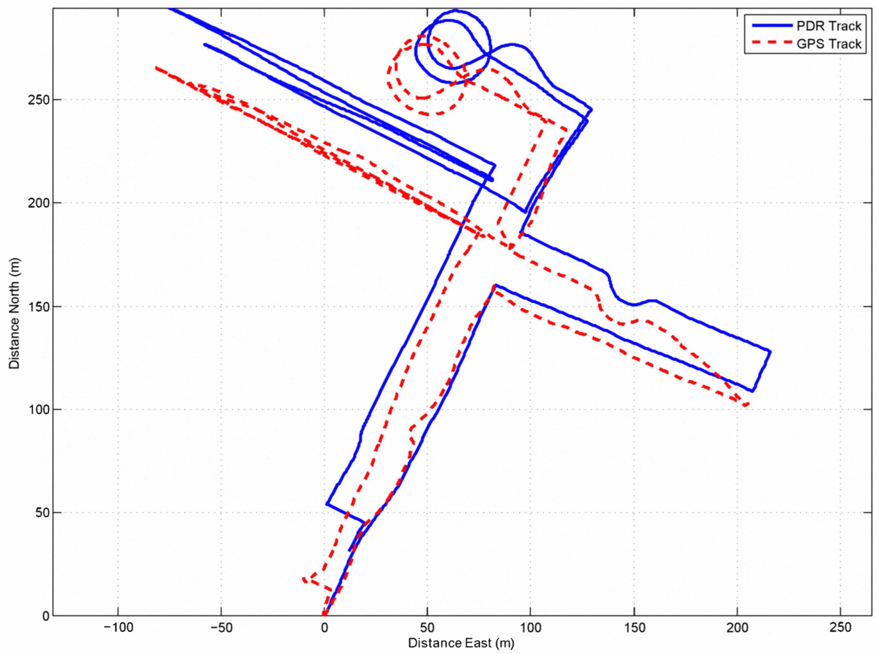

Fig. 6. GPS and PDR-estimated Tracks Outdoors

and Galileo systems and better antennas designed for weak signal acquisition could improve the reception of very weak signals, but severe multipath effects will likely remain, both indoors and in so-called "urban canyons". Consequently, alternative systems and techniques, such as PDR, will be essential for urban and "tactical" personal / personnel positioning.

6 Conclusion

The mounting of the motion sensors on a helmet in our experimental set up is 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 (e.g. firemen and police officers). The helmet can be used as a mounting platform for other useful sensors, such as video cameras or microphones.

Our 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 loitering, steering and stair climbing behaviours, are still open for future research. In the short term however, simply separating the gaze orientation from the direction of travel is a challenging research problem.

GPS and Galileo will likely be indequate for urban and "tactical" personal / personnel positioning and for enabling envisioned location based services, par-

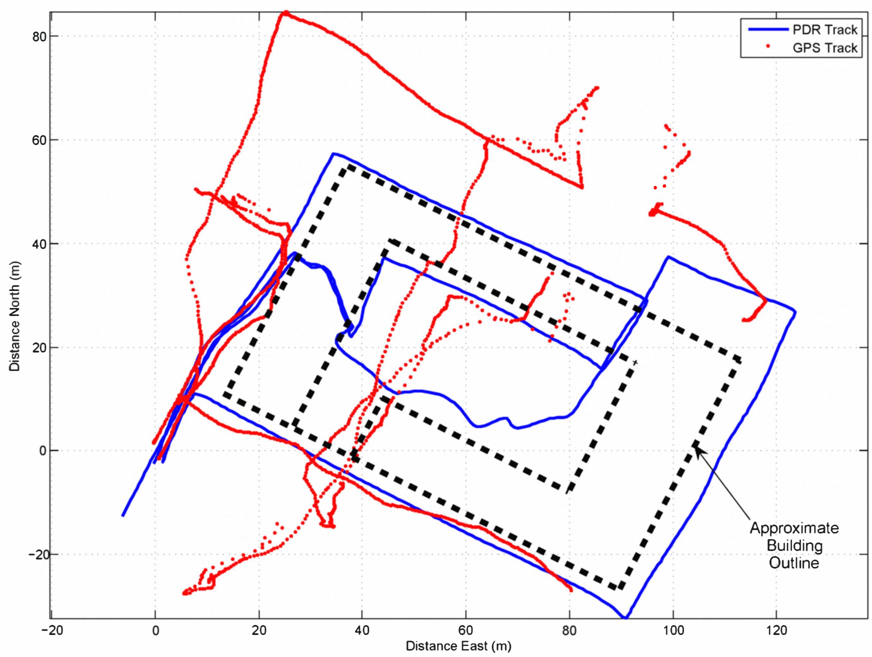

Fig. 7. GPS and PDR-estimated Tracks with Indoor / Outdoor Transitions

ticularly indoors. Alternative, robust and accurate positioning systems and techniques, such as PDR show here, will be required.

7 Acknowledgements

This research was conducted in the context of the WearIT@Work project (EC IST IP2003 0004216) and under the direction of Prof. Dr. Otthein Herzog. A preliminary version of this research was conducted at the International University Bremen under the supervision of Prof. Dr. Harald Haas with funding from the T.i.M.E. program of the State of Bremen.

References

1. Rouiller, J., Perrottet, D., Ladetto, Q., Merminod, B.: Faciliter le déplacement des aveugles avec une carte numérique et une interface vocale. MPG (2002) 517–521
2. Pahlavan, K., Xinrong, L., Makela, J.: Indoor geolocation science and technology. IEEE Communications Magazine **40**(2) (2002) 112 – 118
3. Beauregard, S., Omiyi, P.: Mobile Positioning Techniques Literature Review. Technical report, International University Bremen, Bremen, Germany (2004) (unpublished).
4. Cobb, H.S.: GPS Pseudolites: Theory, Design, and Applications. PhD thesis, Stanford University (1997)
5. Beauregard, S.: Mobile Discovering System (MDS): Navigation Algorithms and Experiments. Technical report, International University Bremen, Bremen, Germany (2005) (unpublished).
6. Cliff Randell, C.D., Muller, H.L.: Personal position measurement using dead reckoning. In Narayanaswami, C., ed.: Proceedings of the Seventh International Symposium on Wearable Computers, IEEE Computer Society (2003) 166–173
7. Ladetto, Q., van Seeters, J., Sokolowsi, S., Sagan, Z., Merminod, B.: Digital magnetic compass and gyroscope for dismounted soldier position and navigation. In: NATO-RTO Meeting: Military Capabilities enabled by Advances in Navigation Sensors, Istanbul, Turkey, NATO Research and Technology Agency, Sensors & Electronics Panel (2002)
8. Ladetto, Q., Merminod, B.: Digital magnetic compass and gyroscope integration for pedestrian navigation. In: 9th Saint Petersburg International Conference on Integrated Navigation Systems, Saint Petersburg, Russia (2002)
9. Ladetto, Q., Gabaglio, V., Merminod, B.: Two different approaches for augmented GPS pedestrian navigation. In: International Symposium on Location Based Services for Cellular Users, Locellus (2001)
10. Gartner, G., Frank, A., Retscher, G.: Pedestrian navigation systems in mixed indoor/outdoor environment - the NAVIO project. In: 9th Internation Symposium on Planning & IT (CORP 2004 & Geomultimedia04). (2004) 165–171
11. Abwerzger, G., Ott, B., Wasle, E.: Demonstrating a GPS/EGNOS/Loran-C navigation system in difficult environments as part of the ESA project SHADE. In: EURAN 2004 Conference, Munich, Germany (2004)
12. Kappi, J., Syrjarinne, J., Saarinen, J.: MEMS-IMU based pedestrian navigator for handheld devices. In: ION GPS 2001, Salt Lake City, UT (2001) 1369 – 1373

13. Leppakoski, H., Kappi, J., Syrjarinne, J., Takala, J.: Error analysis of step length estimation in pedestrian dead reckoning. In: ION GPS 2002, Portland, OR, The Institute of Navigation (2002) 1136 – 1142
14. Nabney, I.T.: Netlab: Algorithms for Pattern Recognition. Advances in Pattern Recognition. Springer-Verlag (2002)
15. Beauregard, S.: Mobile Discovering System (MDS): Final Report. Technical report, International University Bremen, Bremen, Germany (2005) (unpublished).
16. Ladetto, Q.: In Step with INS: Navigation for the Blind, Tracking Emergengy Crews. GPS World (2002) 30–38