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A Robust Indoor Positioning and Auto-Localisation Algorithm

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Abstract. Sensor networks that use wireless technology (IEEE standards) to measure distances between network nodes allow 3D positioning and real-time tracking of devices in environments where Global Navigation Satellite Systems (GNSS) have no coverage. Such a system requires three key capabilities: extraction of ranges between sensor nodes, appropriate supporting network communications and positioning. Recent research has shown that the first two of these capabilities are feasible. This paper builds on this and develops an automatic and robust 3D positioning capability. A strategy is presented that enables high integrity positioning even in the presence of large mean errors in the range measurements. This is achieved by an algorithm that generates a tight, high-confidence upper bound on the error in a position estimate, given the noisy range measurements from the radio devices in view. As a core feature, we present a novel network auto-localisation algorithm that fully automatically determines the positions of all nearby fixed nodes. Results from a real network using the Cricket Indoor Location System show how all sensor nodes can be determined based on only one dynamic node. Simulations of static networks with 100 nodes demonstrate the importance of solving folding ambiguities. Studies from networks with imprecise range measurements have shown that it is possible to theoretically achieve a position deviation that is of the size of the ranging error.

Keywords. auto-localisation, positioning algorithm, wireless sensor positioning, multilateration

1 Introduction

1.1 Background

Despite Global Navigation Satellite Systems (GNSS) being the most pervasive positioning systems, alternative and complementary systems are essential because GNSS are unsuitable for some ad-hoc sensor network operational environments. In particular, they cannot work indoors or in the presence of obstacles that block the signals from the GNSS satellites. This is commonly addressed by combining or integrating GPS with deduced reckoning (DR) sensors including inertial navigation systems (INS). DR, with the aid of a gyroscope and odometer, is commonly used to bridge any gaps in GPS positioning, but its positioning error grows rapidly if not controlled by other sensors or systems such as GPS. The use of cellular communications networks to assist GPS receivers in difficult environments is referred to as Assisted Global Positioning Services (A-GPS), where GPS is integrated in a mobile network and the processing is partly taken over by the network. According to Darnell and Wilczoch (2002) positioning accuracy of 50m indoors can be reached with A-GPS. The system proposed in this paper however is designed to reach a decimetre to centimetre accuracy (2σ) indoors.

The limitations of GNSS have motivated the search for complementary methods in addition to those above. Recently, a large number of wireless positioning systems has been proposed and evaluated, e.g. Niculescu and Nath (2001), Savarese et al. (2002), Savvides et al. (2003) and Smith et al. (2004). Network positioning based on graph theory has been investigated extensively using a set of range measurements between network nodes, e.g. by Eren et al. (2004) and Goldenberg et al. (2005). Wireless devices enjoy widespread use in numerous diverse applications including sensor networks. The exciting new field of wireless sensor networks breaks away from the traditional end-to-end communication of voice and data systems, and introduces a new form of distributed information exchange. The near future scenario consists of countless tiny embedded devices, equipped with sensing capabilities, deployed in all environments and organising themselves in an ad-hoc fashion.

Knowing the correct positions of network nodes is essential to many applications in future pervasive sensor networks. Examples include usage in crime prevention, emergency and incidence respond management, product tracking at industrial sites, wildlife habitat monitoring and home control. Further applications are user guidance, efficient routing in communication networks, detection of unauthorised removal of assets and geofencing.

However, for many applications, the integrity of the location information yielded from such a wireless sensor network is vital. The research focus has been on the determination of positions, effectively ignoring measurement noise. Little attention has been given to the fact that range observations are corrupted by gross errors and also affected by measurement noise. Additionally, the correctness of the coordinate positions of anchor nodes, which 'know' their positions cannot be taken for granted for real world scenarios. All these different error sources can lead to inaccurate position information. This paper takes these errors into account. A wireless positioning system which is used for Safety of Life (SoL) or liability critical applications is required to be of high reliability and integrity. It is not sufficient to deliver a coordinate output, even with corresponding figures of the uncertainties (in terms of a variance-covariance matrix). In fact, a rigorous validation process must provide the user with reliable and complete integrity information for the positional data. Any partial or complete system failure needs to be forwarded immediately to the user, who is then able to rely on the system status as indicated by the system itself.

1.2 The used wireless sensor platform

The system that has been used for the experiments in this paper in order to obtain ranging data for positioning and tracking is called Cricket. The Cricket nodes are tiny devices developed by the MIT Laboratory for Computer Science as part of the Project Oxygen, details are given in Priyantha (2005). A Cricket board is shown in Fig. 1. A deployed Cricket location sensing infrastructure enables people or devices to determine their position while indoors. The Cricket unit can be programmed as either as a beacon or listener. The beacons are typically static units that are mounted on the ceiling above the mobile listeners. The beacon unit broadcasts periodically an ultrasonic (US) pulse and at the same time a radio frequency (RF) message with its unique ID number. Using the time-of-flight information from different beacons and the temperature corrected speed of sound

measurement; the listener calculates its distance from the beacons. Because RF travels about 10^6 times faster than ultrasound, the listener can use the time difference of arrival between the start of the RF message from a beacon and the corresponding ultrasonic pulse to infer its distance from the beacon. The position of the listener can then be determined based on the beacon node positions and the measured ranges.



Fig. 1. Cricket unit / RS232 cable assembly

One reason to choose the Cricket system as a test bed for the novel positioning algorithm was its flexibility and programmability. For example, Cricket listeners and beacons consist of identical hardware. Even the software that is running on listeners and beacons can be the same a simple command from the host can change a Cricket node from a listener into a beacon and vice versa. The embedded software that is running on a Cricket device can be replaced simply by uploading the flash memory with modified or self-developed programs. The open architecture of Crickets has inspired researchers all over the world to use Cricket as a platform to develop new wireless positioning strategies and for algorithm testing. There is plenty of literature on Crickets and applications available. The thesis of Priyantha (2005) describes the design and implementation of the Cricket indoor location system in detail. Haggag and Mehraei (2006) document their modification of the default architecture that enables coordinated robot interaction. Wang (2004) lays the foundations for leveraging the Cricket indoor location system to supply orientation information. He also demonstrates end-to-end functionality of a Cricket Compass.

However, there are several disadvantages when choosing Cricket as a platform for ranging and positioning. In order to obtain ranges between motes, the time of flight between an ultrasonic pulse and a radio signal needs to be measured. Both, the US pulse and the RF signal sometimes suffer from multipath effects, in particular indoors due to reflections at walls, windows, tables or the floor. When a listener receives a reflected signal instead of the direct signal along the line-of-sight, a too long range is determined. A multipath signal is particularly likely to occur when a beacon node is not orientated towards the listener. Typically a listener unit can detect ultrasonic signals from a beacon within a 40 degree cone. If the beacon node is not orientated directly towards a listener, the listener receives a reflected signal instead of the direct signal. Fig. 2 shows such a scenario, where a multipath signal is received. In order to eliminate a gross error due to multipath, a high redundancy of range measurements (i.e. more than 5 ranges to each node) is necessary.



Fig. 2. Multipath scenario where the signal is reflected at the ceiling

There are several more disadvantages associated with the use of ultrasound. The speed of ultrasound is highly correlated to the temperature. Although cricket units carry temperature sensors on their chip sets, it is hard to obtain an accurate temperature along the path between sender and receiver. The speed of ultrasound depends tightly on the speed of wind, which doesn't allow for accurate positioning outdoors. With the ultrasound sender not transmitting omni-directionally, it is almost impossible to set up a dense ad-hoc network with a large number of Cricket units. In a large ad-hoc sensor network the condition that the nodes face each other is normally not fulfilled. Taylor (2005) and Taylor et al. (2006) modified a mobile cricket by attaching two additional ultrasound transducers. These transducers more closely simulate an omni-directional acoustic pulse than the conic emanation of the standard cricket transducer. His positioning algorithm uses range measurements between sensors and a moving target to simultaneously localize the sensors, calibrate sensing hardware, and recover the target's trajectory. In his experiments he used up to 55 sensors to cover a 7 x 10 meter room. Our autolocalisation algorithm however uses a lower number of beacon nodes to perform localisation and tracking.

Our local 3D positioning algorithm takes into account the weaknesses of current wireless ad-hoc positioning methods and algorithms, including the absence of quality and integrity indicators for the positioning results, existence of high variances and outliers in range measurements, errors in anchor nodes (or even their absence) as well as a coarse positioning mode for poorly conditioned networks.

2 Positioning

Our contribution to positioning addresses two different network computation methods. While the first section

describes a method to obtain the node positions with one mobile node the second section uses inter-beacon range measurements to create a geodetic network that allows position determination.

2 Obtaining beacon coordinates by auto-localisation

Auto-localisation is also known as Mobile Assisted Positioning or SLAT (Simultaneous Localization and Tracking) and refers to the problem to obtain the coordinate positions of fixed anchor nodes which are required to enable tracking of mobile devices. Without the use of an auto-localisation algorithm the coordinates of the fixed beacon node positions would have to be determined with another positioning system. Because GNSS is not available indoors and because the quality of the beacon nodes should be at least as good as the wireless positioning system (if not a magnitude better), time-consuming manual positioning methods are usually required to obtain beacon coordinates. Typically tachymeter measurements are carried out with a positioning accuracy of 5-10 mm (1 sigma). However, it is not practical to use a second positioning system to calibrate the beacon nodes because that increases time and effort.

The auto-location strategy used for positioning of the beacon nodes is shown in Fig. 3. A dynamic listener is slowly moved at different locations in a room thereby collecting ranging data to 4 (or more) beacon nodes that are mounted at the ceiling. Both, the mobile and the static node positions are unknown. Even the inter-beacon ranges are not available. This is the most challenging scenario for an auto-localisation task, but nevertheless the most likely scenario to occur after the nodes have been deployed in a room. The described scenario still allows creating a rigid network based on local coordinates. The deployment of static nodes in the four corners of a room allows the set up of a meaningful local coordinate system orientated along the four orthogonal walls.



Fig. 3. Auto-localisation of beacon nodes by a mobile node

Generally, the redundancy of the auto-localisation problem in 3D is given by

$$redundancy = R - 3(B + P) + 6, \tag{1}$$

where *R* is the number of observed ranges, *B* the number of fixed beacons and P the number of listener positions. If the direct line of sight conditions allow to obtain all combinations of ranges, then R = B P holds. In Fig. 3, the mobile listener has collected 4 ranges to 4 beacons at 6 different locations. Assuming the 3D case, there are 3(B)(+ P) = 30 unknown coordinates and B P = 24 range measurements. Taking into account the 6 degrees of freedom for a free 3D network, a solution would theoretically be possible without any redundancy. However, our results show that a zero or a low redundancy of the network causes the auto-localisation algorithm to fail under real field conditions. Due to the existence of outlier observations, bad geometric constraints and linearization errors of the objective function large errors in the position estimation are likely to occur. This is particularly the case in scenarios with a small redundancy, large mean or gross errors in the range measurements. In order to obtain the beacon coordinates the following procedure had been carried out:

- a) Stepwise movement of the listener in a room while collecting range measurements.
- b) Grouping of the ranges into *P* listener positions according to their time stamps.
- c) Detection of gross errors by comparing timely nearby ranges and testing triangle conditions.
- d) Setting up a distance matrix R between all nodes of the network with size (B + P) by (B + P), see Fig. 4.
- e) Filling the gaps of the distance-matrix using a simple interpolation scheme. This step establishes rough approximation of all inter-nodal ranges.
- f) Setting up a local coordinate system based on the inter-nodal ranges of four nodes (preferably beacon nodes).
- g) Computation of all coordinate positions based on multidimensional scaling (MDS), a localisation method that transforms proximity information into geometric embedding. Details of the algorithm can be found in Shang et al. (2004). Alternatively, the positions can be determined by multilateration from four locally defined nodes. Our experiments have shown that this alternative has better performance than MDS.
- h) Refinement of the coordinates by geodetic network adjustment. In application on real data this step can usually not be carried out straight away. The reason is that network adjustment involves linearization of the objective function, which is eligible only if of good approximate values of the unknowns are available. Here, the initial approximate positions are not precise enough to directly apply network adjustment using the Gauss-Newton iteration. In order to avoid a failure of the network adjustment, a heuristic optimisation method is carried out that directly uses the non-linear objective function. Using trial and error the coordinate positions are shifted in order to fit the range

measurements. The heuristic step improves approximate positions for the network adjustment – typically from meter to cm level. The disadvantage of using heuristic methods is the high computational cost. However, taking into account that the auto-localisation is executed only once and not processed in real-time, the usage of timely expensive heuristic methods is not critical. An insight into heuristic methods is given in Mautz (2002).



Fig. 4. Distance matrix of the example with 4 beacons and 6 listener positions

After the auto-localisation procedure has been completed, the coordinates of the static beacon nodes are available in a local system. An over-determined auto-location setup allows determining quality indicators of the coordinates. A numerical example based on mobile assisted positioning is given in the experimental results section.

2.2 Instant coordinate determination in a sense network

In case the network has an inter-nodal connectivity of c > 4 (or c > 3 in 2D), the network can be initialised without a multi-epochal auto-localisation procedure. Once the ranges between the beacons have been obtained and collected at a central processing unit, the sensor position coordinates can be determined based on only a single epoch. Thereby it does not matter, whether the nodes are static or dynamic. The positioning strategy is based on the creation of a rigid structure: The key issue for an anchor free positioning is to find a globally rigid graph, or in other words, a structure of nodes and ranges which has only one unique embedding, but still can be rotated, translated and reflected. In 3D, the smallest graph consists of five fully connected nodes in general position. If such an initial cluster passes statistical tests, additional vertices are added consecutively using a verified

multilateration technique. Nodes that have not been able to take part in the rigid cluster are positioned using a more error prone method and thereafter added to the cluster. The process flow of our positioning strategy is illustrated in Fig. 5.

The creation of a cluster aims to compute unique positions of vertices in a local coordinate system that can be transformed into a higher spatial reference system by translations, rotations and a reflection. A straightforward method to determine the position of an object based on simultaneous range measurements from three stations located at known sites is called trilateration. Manolakis (1996) and Thomas and Ros (2005) provide fast algebraic and numeric algorithms for trilateration in robotics. Coope (2000) shows that the effect of errors in the range measurements can be particularly severe when the trilaterated point is located close the base plane or the three known stations are nearly aligned. Moore et al. (2004) show that there is a high probability of incorrect realisations of a 2D-graph when the measurements are noisy.

The coordinate system of the cluster is conveniently defined in local coordinates based on the three ranges r_{12} , r_{13} , r_{23} between the nodes P_1 , P_2 , P_3 . The coordinates read

$$P_{1}:(0,0,0), P_{2}:(r_{12},0,0),$$

$$P_{3}:\left(\frac{r_{12}^{2}+r_{13}^{2}-r_{23}^{2}}{2r_{12}},\sqrt{r_{13}^{2}-\left(\frac{r_{12}^{2}+r_{13}^{2}-r_{23}^{2}}{2r_{12}}\right)^{2}},0\right).$$
(2)

A forth point is added to the network by 3D-tilateration thereby arbitrarily choosing one of the two folding ambiguities and discarding the other. However, as long as there are only 4 points involved, the flip ambiguity does not affect the inner structure of the general tetrahedron which is spanned by the base plane and the trilaterated point. As soon as a 5th node is added to the cluster by trilateration from the points in the base plane 1, 2 and 3, the ambiguity problem does matter, as there are two different embeddings. As shown in Fig. 6, nodes 4 and 5 could be on either the same side of the base plane or on opposite sides. If the distance between nodes 4 and 5 is also measured, we call this graph a 'quintilateral' or in short a 'quint' since all 5 nodes are fully linked by range measurements to each other. Only the additional range measurement r_{45} between nodes 4 and 5 can disambiguate between these two embeddings. As can be seen in the example in Fig. 6, r_{45} is significantly longer than the reflected case $r_{45'}$, which means that if r_{45} is available, the correct embedding can be selected. Consequently, such a quint is rigid in 3D, assuming the nodes are not in a singular position.



Fig. 5. Positioning algorithm, which does not require any initial approximate coordinates

However, there are geometric constellations where the ambiguity cannot be solved by the redundant range r_{45} , because the difference between the distances d_{45} and d_{45} ' is of the same magnitude as the ranging error. In order to decide which of the two embeddings is correct, we compare the computed distances d_{45} and d_{45} ' with the measured distance r_{45} . In some cases the differences between the measured and the calculated distances $\Delta_{45} = |r_{45} - d_{45}|$ and $\Delta_{45'} = |r_{45} - d_{45'}|$ may both be very small. Assuming a mean error of the range measurement r_{45} , say 5%, both differences Δ_{45} and $\Delta_{45'}$ are likely to pass the statistical test of their null hypotheses, which means that both could be a result of noise. Consequently, the range r_{45} does not disambiguate between both embeddings.

The best way to deal with this problem is to reject such unstable point formations. It is better not to use a nonrobust quint than rely on a structure with incorrect internal flips. In our point of view it is crucial to ensure a correct embedding for several reasons. Firstly, the displacement caused by an incorrect flip can be large. Secondly, these errors have a negative affect on the expansion of the structure when additional vertices are added later. Thirdly, and most importantly, once a folding error has been introduced in a network it is hard to detect and eliminate it later.



Fig. 6. (a) Quintilateral, (b) a version where node 5 has been mirrored at the base plane

After the quint is verified to be robust and not affected by a false flip, the next task is the expansion of the minimal rigid structure. The remaining nodes are added to the quintilateral individually using 3D-multilateration from four or more stations at a time. 'Multilateration' is basically a trilateration technique, where the new node is initially determined from three stations at a time. The redundant distance measurements are used to disambiguate between two different embeddings and to verify the initial computation. Multilateration allows redundant determination of the nodes. The resulting coordinate differences provide essential information to detect false range measurements, e.g. due to multipath effects.

However, there is again a high probability of incorrect folding of a graph when the measurements are noisy. For instance, if a new node is multilaterated from points located closely to one plane and the ranges are affected by errors, a flip ambiguity may occur due to the mirroring effect of that plane. These incorrect graph realisations need to be avoided by identifying weak tetrahedrons with volumes smaller than a threshold which is driven by the estimated noise in the ranges. Only tetrahedrons that have passed the test on robustness are further considered or otherwise discarded. This step again eliminates the mirroring ambiguity of nodes added to a rigid structure and improves the accuracy measures. Once a node's position is determined, it serves as an anchor point for the determination of further unknown nodes. This way, starting from the initial quintilateral the position

information iteratively spreads through the whole network.

The trilateration and multilateration problem considered so far solves for one single unknown point at a time. The sequential accumulation of nodes by multilateration is known as iterative multilateration (Savvides, 2001). However, this technique is very sensitive to measurement noise. Initially, small errors accumulate quickly while expanding the network. The propagation of errors in a large network must be minimised as much as possible. Geodetic network adjustment is an essential tool to evenly distribute the errors that have been accumulated by iterative multilateration. Network adjustment provides coordinate estimates of several unknown nodes thereby improving the reliability of the quality indicators as determined a posteriori, see Grafarend and Sanso (1985). The theory of linear Least-Squares (LS) adjustment can be found in Grafarend and Schaffrin (1993).

Outlier observations distort the network but they cannot be isolated by performing a least-squares adjustment and analysing the residuals. Thus, outliers need to be removed in a separate analysis before the network is adjusted. While performing simulations on the anchor free start-up, results show that only a fraction of vertices can become a member of one single cluster. The remaining vertices are likely to make up their own clusters which may or may not be connected to neighbouring clusters. In case two clusters share a sufficient number of vertices and/or range observations between them, they can be merged using an over-determined 3 dimensional 6-parameter transformation.

The outcome of clusterisation is a cluster of nodes with their coordinates and variances in a local system. As this step is concluded by a free minimally-constrained leastsquares adjustment it is possible to assess the internal consistency of the measurements.

A more elaborate discussion of the positioning algorithm and details of the mathematical background are presented in Mautz et al. (2007).

2.3 Transformation into a reference coordinate system

Most applications require the network nodes to be tied in a coordinate system of higher order. With a minimum availability of four anchor nodes, the local coordinates can be transformed unambiguously into the relevant target system. This can be achieved by a 3D-Cartesian coordinate transformation. A closed form solution for the determination of transformation parameters using the 3D-Helmert transformation is given by Horn (1987). Subsequent to the transformation, a fully constraint LS network adjustment is performed that permits all of the available anchor nodes and all range measurements to be processed together in order to refine all position approximates simultaneously. Additionally, the mean error in the coordinates is reported by the point confidence ellipse for each node.

3 Experimental Results

In section 3.1 the performance of the localisation algorithm proposed in chapter 2 is evaluated on real sensor data obtained from Cricket nodes. In order to asses the performance of a large and dense network simulated ranging data are used in section 3.2.

3.1 Initialisation of a dynamic network

In order to assess the performance of network initialisation with the support of a mobile node (with unknown positions!), the following measurement setup was chosen: four stationary nodes (= beacon nodes) were deployed at the office ceiling. Due to the system architecture of crickets the inter-beacon range signals could be obtained. One dynamic node was carried through the room and range measurements taken at an interval of 1s between the mobile node and the static nodes located in the corners. Within a time span of 5 minutes, 1000 range measurements had been obtained with *a priori* noise level of $\sigma_r = 0.01$ m. Now the task for the positioning algorithm was to recover the 3D network geometry without adding any supplementary information, e.g. geometric constraints or approximate positional information. The main difficulty in recovering the relative node positions for this configuration is that the connectivity graph does not contain five nodes making up a quint. Consequently, the strategy described in section 2.2 could not be followed and the post-processing method described in 2.1 was used instead. This method included: setting up a rough distance matrix, global optimisation of the objective function and network adjustment.

In a first step, the range measurements are grouped into 34 epochs of 2.5 second intervals each by an implemented algorithm. Multiple range observations within one group are averaged if there is a difference of less than 2 cm, or discarded otherwise. 120 range measurements are finally taken into account to determine 30 virtual node positions of the dynamic node and 4 beacon node positions. Consequently, the number of unknowns is 3 * 34 = 102. According to (1) the redundancy of the system can be computed as 120 - 102+ 6 = 24. The redundant distance constraints in the network could be used to determine the system inconsistency and the empiric mean error of the node positions. After step g) in section 2.1 had been carried out, the empiric mean error was 1.52m. With application of the refinement step (global optimisation) the error could be further reduced to 0.05m and finally down to

0.0096m by network adjustment. This mean error is within the magnitude of the observational noise level. Thus, the inner network geometry could be recovered successfully. Fig. 7 shows the location of the recovered node positions.



Fig.7. X-Y view with 4 stationary cricket node positions in the corners of a room (black dots) and 30 virtual positions of a mobile node (red dots).

This example shows that it is feasible to establish a local network in a room without surveyed anchor nodes, any presumptions on the node locations or any inter-node range measurements between the static devices. After the mobile positioning algorithm has been carried out, all distances between the static nodes are determined. The graph between the static nodes is a rigid structure that can be used for further navigation of mobile nodes.

3.2 Initialisation of a dense network

In order to assess the performance of the proposed positioning algorithm, a simulated network consisting of 100 nodes was set up randomly in a $10 \text{ m} \times 10 \text{ m} \times 10 \text{ m}$ test cube. Assuming a maximum communication range of 3.5 m between the radios, only the inter-node distances of less than 3.5 m have been recorded into an observation file. After execution, the file contained 570 range measurements. Based on these 570 ranges, the positioning algorithm was used to recover the node positions. As detailed in the section 2.2, the algorithm created quints, then larger clusters by lateration and cluster merging. 10 points were chosen randomly to serve as anchor nodes for a 3D-transformation of the local cluster into the original geodetic datum.

The criterion used for the performance assessment in positioning is the average deviation

$$a_p = \frac{1}{n} \sum_{i=1}^n \sqrt{\left(\hat{\mathbf{P}}_i - \mathbf{P}_i\right)^2},\tag{3}$$

where *n* is the number of nodes, \mathbf{P}_i the true position vector and $\hat{\mathbf{P}}_i$ the estimated position vector of the localised node *i*. The internal consistency of the free network is assessed by the square root of the estimated reference variance

$$\hat{\sigma}_r = \sqrt{\frac{1}{m-3n} \mathbf{v}^\mathsf{T} \mathbf{v}} = \sqrt{\frac{1}{m-3n} \sum_{i=1}^m (\hat{r}_i - r_i)^2} \tag{4}$$

where **v** is the vector of residuals containing the differences between the estimated distances \hat{r}_i (obtained from a LS-adjustment) and the measured distances r_i .



Fig. 8. True position deviations a_p (pluses) for measurement noise σ_r between 0m and 0.2m. For comparison, the dots show the estimated deviations $\hat{a}p$.



Fig. 9. True position deviations a_p (pluses) in comparison with the estimated reference mean errors shown as dots.

Fig. 8 shows how the noise level in the ranges σ_r influences the average position deviation a_p of the localised nodes at a maximum signal range $r_{\text{max}} = 3.5$ m. The linear dependencies on σ_r and a_p in Figs. 8 and 9 have approximately an average proportionality factor of 1. This testifies that our localisation algorithm has almost reached the best possible performance level, which has

been determined by Savvides (2003a) as the Cramer Rao Bound behaviour. This is especially true for noise levels with less than 3.5% error (0.1m level), where almost all nodes in all networks have been localised correctly. Note that a single falsely located node (e.g. due to a false folding ambiguity) causes the average position deviation to rise significantly.

4 Conclusions

The cricket sensor node system has been used to successfully apply a full 3D auto-location algorithm. Furthermore, it could be shown that a dense network of inter-beacon ranges can be used compute an instantaneous geodetic network.

Experimentation has shown that the motion of a mobile node can be exploited to automatically create the rigid topology of the network nodes. Range measurements taken at various points in time of a mobile node have enabled positioning of all nodes in a local coordinate system. However, this auto-localisation method requires a high redundancy of observations and a full elimination of outliers in the range measurements, since the computation of coordinates is extremely sensitive to errors.

A second experiment based on simulation has demonstrated the feasibility to determine dense ad-hoc distance networks with the presence of large observation errors and poor geometric conditions. In order to achieve a reliable positioning based on geodetic adjustment even in the presence of errors and sub-optimal geometry, a robust algorithm has been set up, that particularly avoids flip ambiguities in the network. We have studied networks with relatively large measurement errors of up to 7.5% of the true ranges and shown that it is possible to achieve a position deviation that is of the size of the ranging error.

Future work will focus on further moving away from laboratory conditions. The application of the algorithms for other sensor hardware (besides the Cricket System) will be the next challenge. A major challenge will be a positioning functionality for ill-conditioned networks that makes best use of available range measurements, connectivity information, temporal-spatial derivatives, travel behaviour and GIS data.

References

- Coope I (2000), Reliable computation of the points of intersection of n spheres in n-space, ANZIAM Journal, Vol. 42(E), pp. C461-477, 2000.
- Darnell, C and Wilczoch, C (2002), *Real Time Positioning; Construction and implementation of a GPS-Communicator*. Master's thesis in Control and

Communication, Report no. LITH-ISY-EX-3246-2002, Linköping University, Sweden.

- Eren, T; Goldenberg, D; Whiteley, W; Yang, Y; Morse, A; Anderson, B and Belhumeur, P (2004), *Rigidity, computation and randomization of network localization*. In: Proceedings of IEEE Infocom '04, Hong Kong, China, April 2004.
- Goldenberg D; Krishnamurthy, A; Maness, W; Yang, Y; Young, A; Morse, A; Savvides, A and Anderson B (2005), *Network Localization in Partially Localizable Networks*. In Proceedings of IEEE INFOCOM 2005, Miami, FL, March 13-17, 2005.
- Grafarend, E and Sanso, F (Editors) (1985), *Optimization and Design of Geodetic Networks*. Springer-Verlag.
- Grafarend, E and Schaffrin, B (1993), *Ausgleichung in linearen Modellen*, Wissenschaftsverlag, Mannheim, Leipzig, Wien Zürich
- Haggag, H and Mehraei, G (2006), *Robot Interaction Using Cricket, an Indoor Positioning System*, Technical Report of the Maryland Engineering Research Internship Teams (MERIT), University of Maryland and Virginia Commonwealth University.
- Horn, B (1987), Closed-from solution of absolute orientation using unit quaternions. Journal of Opt. Soc. Amer., vol. A-4, pp. 629–642, 1987.
- Manolakis, D (1996), Efficient Solution and Performance Analysis of 3-D Position Estimation by Trilateration, IEEE Aerospace and electronic systems, Vol 32, No. 4, Oct. 1996.
- Mautz, R., Ochieng, W.Y., Brodin, G., Kemp, A. (2007), 3D Wireless Network Localization from Inconsistent Distance Observations, Ad Hoc & Sensor Wireless Networks, Vol. 3, No. 2–3, pp. 141–170.
- Mautz, R. (2002), Solving Nonlinear Adjustment Problems by Global Optimization, Bollettino di Geodesia e Scienze Affini, Vol. 61, No.2, pp. 123 – 134.
- Moore, D; Leonard, J; Rus, D and Teller, S (2004), *Robust distributed network localization with noisy range measurements*, Proceedings of the ACM Symposium on Networked Embedded Systems, 2004.
- Niculescu, D and Nath, B (2001), *Ad-hoc positioning system*, in: IEEE GlobeCom, 2001.

- Priyantha N. B. (2005), *The Cricket Indoor Location System*, PhD Thesis, Massachusetts Institute of Technology, June 2005, 199p.
- Savarese, C; Langendoen, K and Rabaey, J (2002), Robust positioning algorithms for distributed ad-hoc wireless sensor networks, in: USENIX Technical Annual Conference, Monterey, CA, 2002, pp. 317–328.
- Savvides, A; Han, C and Strivastava, M (2001), *Dynamic Fine-Grained Localization in Ad-hoc Networks of Sensors*, Proceedings of ACM SIGMOBILE 2001, Rome, Italy, July 2001
- Savvides, A; Park, H and Srivastava, M (2003), The n-Hop Multilateration Primitive for Node Localization Problems. MONET 8(4): 443-451.
- Savvides, A; Garber, W; Adlakha, S; Moses, R and Srivastava, M (2003a), On the Error Characteristics of Multihop Node Localization in Ad-Hoc Sensor Networks, Proceedings of the Second International Workshop on Information Processing in Sensor Networks (IPSN'03), Palo Alto, California, 317-332.
- Shang, Y; Ruml, W; Zhang, Y and Fromherz, M (2004), *Localization from Connectivity in Sensor Networks*, IEEE Transactions on Parallel and Distributed Systems, vol. 15, no. 11, pp. 961–974, Nov. 2004.
- Smith, A; Balakrishnan, H; Goraczko, M and Priyantha N (2004), *Tracking Moving Devices with the Cricket Location System*, Proc. 2nd USENIX/ACM MOBISYS Conf., Boston, MA, June 2004.
- Taylor, C., Rahimi, A., Bachrach, J., Shrobe, H., and Grue, A. (2006), *Simultaneous localization, calibration, and tracking in an ad hoc sensor network.* In: Proceedings of the 5. international Conference on information Processing in Sensor Networks (Nashville, Tennessee, USA, April 19 - 21, 2006). IPSN '06. ACM Press, New York, NY, 27-33. DOI= http://doi.acm.org/10.1145/1127777.1127785
- Taylor, C J; (2005), Simultaneous Localization and Tracking in Wireless Ad-hoc Sensor Networks, Master Thesis of Engineering, Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology.
- Thomas, F and Ros, L (2005), *Revisiting Trilateration for Robot Localization*, IEEE Transactions on Robotics, Vol. 21, No. 1, pp. 93-101, February 2005.
- Wang, K J (2004), An Ultrasonic Compass for Context-Aware Mobile Applications, Master Thesis of Engineering, Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology.