Data-Driven Modeling of Signal Strength Distributions for Localization in Cellular Radio Networks

Datengetriebene Modellierung von Feldstärkeverteilungen für die Ortung in zellulären Funknetzen

Marian Grigoraş, Olga Feiermann and Uwe D. Hanebeck

In this article, we propose a novel approach to solving the localization problem in cellular networks, with a focus on indoor environments. The goal is to estimate a mobile user's position, based on measurements of signals received from different base stations. Our solution uses the Progressive Bayes estimation framework to model the distribution of signal measurements, as obtained in a series of calibration measurements. In the localization step, we compute the full probability density over the user position. We also show that user motion models can be easily integrated in our solution.

In diesem Artikel wird ein neuer Ansatz für die Lokalisierung in Innenräumen in zellulären Funknetzen vorgeschlagen. Das Ziel ist die Schätzung der Position eines Benutzers basierend auf den Feldstärkemessungen von verschiedenen Basisstationen. Unsere Lösung benutzt das Progressive-Bayes-Schätzverfahren, um die Wahrscheinlichkeitsdichte der Feldstärkemessungen bei gegebenen Kalibrierungsmessungen zu modellieren. Im Lokalisierungsschritt wird eine volle Wahrscheinlichkeitsdichte über die Benutzerpositionen berechnet. Des Weiteren zeigen wir, dass die Benutzerbewegungsmodelle leicht in unsere Lösung integrierbar sind.

Keywords: Location estimation, probabilistic modeling, Gaussian mixtures

Schlagwörter: Ortungssysteme, Stochastische Modellierung, Gauss-Mischverteilungen

1 Introduction

The problem of location based services is of growing importance in all types of modern cellular networks, be it GSM or UMTS for mobile phones, wireless LAN (WLAN) for mobile computing devices or DECT for cordless telephony. Examples of such services include locating the origin of an emergency call, guiding a user through a city, campus or building, delivering information about nearby points of interest, identifying the technician closest to a disturbance in an industrial campus or simply enabling a user to see its own position on a map. All such applications rely on methods that can accurately estimate the position of a mobile user inside the network ("localization", "positioning").

Various positioning technologies can be considered for such a system. We are interested in systems that require no additional infrastructure, in order to minimize the overall installation cost. In indoor environments, due to complex propagation effects, specific problems need to be addressed. Furthermore, we consider the additional problem of tracking a mobile user and getting position estimates based on his previous positions and behavior ("tracking"). Also for cost reasons, this paper does not cover the case when digital map information is available, because such information is usually expensive to collect and maintain.

Throughout this presentation we encounter arbitrary functions for which an analytic parametric representation is required. We use the Progressive Bayes estimation framework [3] to solve this problem.

We proceed by introducing the localization problem in detail in Sect. 2, where we also give a brief overview of previous approaches. Section 3 follows with the description of the Progressive Bayes positioning system, while Sect. 4 discusses the implementation of the tracking algorithm. Section 5 presents a set of simulation results for a simple implementation case. The advantages and disadvantages of the proposed method, as well as points to be addressed in the future are given in Sect. 6.

2 Problem Description

The main goal of the localization problem is to provide an accurate estimate of the position of a mobile user in a designated area. In a cellular network, the existing infrastructure consists of a number of base stations placed at such positions, so as to facilitate a good radio connection to the network at every point inside the target area. This means that a mobile device always has a good connection to at least one base station, but usually the mobile device receives signals from several base stations, as depicted in Fig. 1. A cellular network positioning system tries to use this additional information to improve the accuracy of the position estimate.

Technologies for Positioning Systems To minimize the installation cost, we are interested in a system that requires no additional hardware, using the already available *standard* infrastructure.

Based on the underlying electromagnetic propagation laws, several positioning technologies can be used. They are based on different characteristics of the radio signal received by a mobile device, like propagation time [2], incoming angle or signal amplitude. For an introductory survey of these technologies, see [5]. Angle based and propagation time based systems require special hardware on the network or the mobile device, e. g. the latter requires high precision clocks and synchronization. These methods can achieve a high positioning accuracy, at the cost of high system cost. Meanwhile, signal strength information is easily available in all cellular networks, as the communication network uses it for its own handover protocols. The drawback in this case is that signal strength is strongly affected by noise, typically leading to worse positioning accuracy.

For many consumer, industrial and logistic applications the accuracy demands can be fulfilled by signal strength based systems [7]. We focus on this approach to provide an integrated positioning system that is affordable to many customers.

Indoor Environment While for the unobstructed outdoor environment the localization problem can be solved in many applications by GPS based systems, the indoor environment proves more complex and time variant. The increased *complexity* is largely due to multiple propagation effects (like reflection, refraction, scattering) introduced by the building structures (walls, corridors), all of which distort the transmitted signal [4]. Noise and co-channel interference also add to the unpredictability of signal propagation laws in indoor environments. *Time variation* is usually due to people walking around, robots near assembly lines or even changes in the building structure. There are reports [1] indicating that in a WLAN environment a single person can attenuate the signal by up to 3.5 dBm. Our own measurements in a DECT indoor environment indicate body attenuation values of up to 10 dBm. This means that people in the vicinity of a measurement device have a significant impact on the received signal strength values, that is, the time variation of the system is not negligible.

Fig. 2 shows a set of measurements in a WLAN environment. We notice that the inherent noise level of 2 dBm increases to about 10 dBm when people are located close in the vicinity of the measurement device. Because of the practical difficulties of recording any information about attenuation effects introduced by people, we include this kind of noise in the measurement noise. With this assumption the system remains time invariant, but with an increased noise level.

Another time-dependent nonlinearity is introduced by doors, which can be considered as having two discrete states: open and closed. We will show in Sect. 3.1.1 that, given a large enough number of calibration points, the different effects introduced by a door can be captured by our general calibration model.

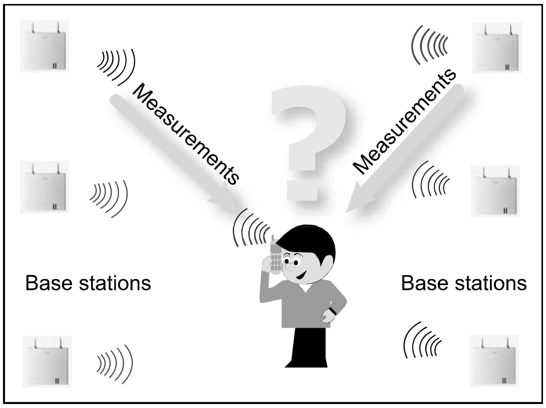

Figure 1: System layout: A mobile device measures the signal strength levels of surrounding base stations.

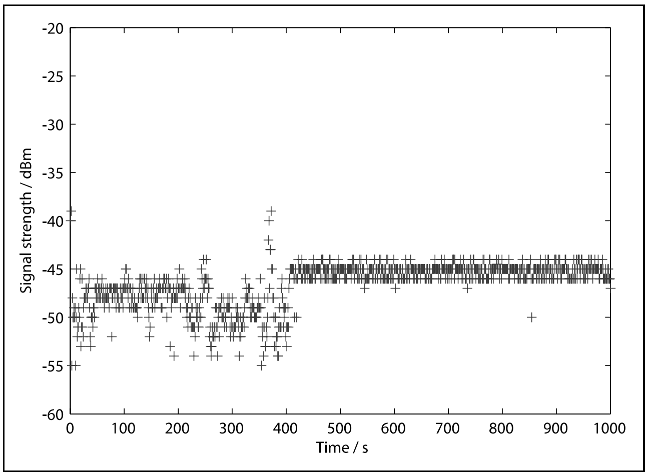

Figure 2: In the first 430 seconds, several persons were in the vicinity of the measurement device. For the remaining measurements, the room was empty. The signal noise of a WLAN base station drops from about 10 dBm, when persons are in the room, to 2 dBm , when the room is empty.

Indoor Position Representation In the general case, the user position must be represented as a three-dimensional variable. However, the indoor environment has a discrete vertical nature, that is, the only relevant vertical information is the floor on which the person is located. Usually, the concrete separation between floors makes it easy to identify the correct floor, thus reducing the problem to a two-dimensional case. In this paper we represent a two-dimensional user position at time t with: $\underline{x}_t = [x, y]$.

Calibration Measurements Due to the high complexity of the indoor propagation environment, many implementations of positioning systems make use of a set of *calibration* measurements. These consist of signal strength reference values, measured at known positions. Typically, better equipment as well as repeated measurements can be used during the calibration step, to reduce the measurement noise as much as possible.

Systems differ in the way they make use of the calibration data. Some systems [6; 8; 9; 11] use it to build models of the environment ("forward modeling"), which they later use in the *localization* step to estimate the user position by maximizing a likelihood function relative to the position. Other systems [1] build a direct mapping of signal strength measurements into the position space ("inverse modeling"). We will use a *forward modeling* approach.

Gathering the calibration data can be tediously for large networks, but a solution has been proposed in [10] to automatize this process, by using a robot with an independent navigation system.

One-shot Positioning The most direct way to implement a positioning system is to make successive positioning instances independent from one another. Such a system receives measurements from a mobile device and computes a position estimate with no prior knowledge of the user's position, that is, it uses in no way previously recorded measurements. While this approach is straightforward, it also comes with a major drawback, in the form of information loss. As information gained through previous measurements is not used, successive position estimates for a given user ("tracking") have large noise. The solution we propose to this problem is to create a user motion model and implement it in the *system update* step of the Progressive Bayes estimation method.

Tracking Basically, any tracking algorithm makes some assumptions about the user motion, to be able to impose some restrictions on a new position estimate, based on previous estimates. In the case of robots, we receive input(control) signals from various sensors (speed, direction or even the robot's own position estimate given by internal sensor-fusion algorithms). But when it comes to locating mobile devices carried by people, no such input is available. A limitation that one can reasonably impose is the user's speed. Normally, people do not walk faster than 1.5 m/s, and this can be used to limit the area they could have drifted away from the last known position. More complex user models might try to estimate the user's speed and direction of movement.

An important parameter for the tracking problem is the measurement sample rate. This usually depends on the underlying technology. For WLAN we were able to receive a new measurement each 200 ms, while in DECT, using standard measurement equipment, the interval is 1.2 seconds. The long refresh interval leads to specific problems to be addressed in a DECT network. First, if the user is moving at normal speed (1.5 m/s), a measurement taking 1.2 seconds means that different base stations are being received and measured at different user positions, as much as 1.8 meters apart from one another. To add even more difficulties to a DECT implementation, the interval between two successive signal strength measurements from the same base stations cannot be precisely determined, due to internal system measurement jitter. Thus, apart from being large, the measurement interval is also not constant. Theoretically, for a nominal measurement interval of 1.2 seconds, the real time interval for a particular base station could take values between 0 and 2.4 seconds.

In this paper, for simplicity reasons, we ignore the effects of user motion on the measurement process. This can be achieved in practice by not moving while performing a measurement. As for the time uncertainty of the measurement, this does not affect our solution, as we already said that we consider our environment to be time invariant.

3 The Progressive Bayes Positioning System

In a cellular network environment, the area where the positioning system is to be implemented is already covered by a number of N_{BS} base stations. In this paper we assume that the existing infrastructure is constant in time, that is, base stations' positions do not change and no additional base stations are installed while the system is running. Any such change requires, in the present implementation of the positioning system, a re-calibration of the affected area.

As mentioned in Sect. 2, our approach to the user position estimation takes place in two steps. First, in the *calibration step*, we use a set of calibration measurements (samples) to build a full statistical model of the environment. Second, in the *localization step*, we use the previously created model and a set of measurements taken by a mobile device to estimate its position.

The calibration step can also be seen as the system training phase, while the localization step describes the usage phase of the positioning system.

Building a full statistical model of the environment is a task that involves an exact representation of a non-linear, multidimensional function. An exact analytic representation of such a function may be impossible to obtain. Even when available, it may be too complex or not practical for recursive applications. Hence, approximations are generally inevitable. We will use the Progressive Bayes estimation framework [3] to approximate arbitrary probability density functions with Gaussian mixtures.

The flexibility of the Progressive Bayes estimation algorithm is particularly valuable in this context, because we have the possibility to define either a maximum approximation error or a maximum number of approximation components.

A general disadvantage of approximation methods is that they are computationally expensive. While this is certainly true for our non-linear, multidimensional environment model, we note that this approximation is an offline process, that has to be performed only once.

3.1 The Calibration Step

To create a model of our environment we first perform a series of calibration measurements, consisting of signal strength measurements taken at known positions. At each position $[x_i, y_i]$ we measure the signal strength values for all received base stations (identified by their unique IDs)

$$\underline{m}_i = \left[m_i^{(1)}, \ldots, m_i^{(N_{BS})} \right],$$

where $m_i^{(k)}$ is the measured value corresponding to base station k at calibration point i, and N_{BS} is the total number of base stations. In real applications it is often the case that only a subset of the total number of base stations is received. This is either due to attenuation effects, preventing the reception of base stations that are too far away, or to technological limitations of the measurement device.

Based on both theoretical and experimental grounds, we can safely assume that measurements from different base stations are *independent*. Therefore, we build a separate model for each base station. Afterwards, in the localization step, we have to merge the estimates corresponding to each base station into a global position estimate.

It is enough to describe the building of an environment model for only one base station. Thus, a calibration point i for base station k is described by the variable

$$\underline{c}_i^{(k)} = \left[x_i, y_i, m_i^{(k)} \right].$$

The full set of calibration measurements for the chosen base station is then given by

$$\underline{C}^{(k)} = \left[\underline{c}_1^{(k)}, \ldots, \underline{c}_{Np}^{(k)} \right],$$

where N_p is the total number of sample points.

The main goal of the calibration step is to find the density function $\mathcal{D}$ over the $\underline{C}$ space, that is most probable to have generated our input samples: $\mathcal{D}^{(k)}(x, y, m)$.

It is important to note here, that this is a stochastic model, that is, for a given measurement $\hat{m}$ it stores a *probability density* over the position space $\mathcal{D}^{(k)}(x, y|\hat{m})$, as opposed to functional models, that only store a single position $[\hat{x}, \hat{y}]$.

To be able to use $\mathcal{D}^{(k)}(x, y, m)$ in a recursive filtering technique, we want to have an approximate analytic representation. Using the Progressive Bayes estimation framework, we define the approximation as a Gaussian mixture with three-dimensional, axis-aligned components

$$\mathcal{D}^{(k)}(x, y, m) \approx \sum_{j=1}^{N^{(k)}} w_j^{(k)} \mathcal{N}\left(x - \mu_{x,j}^{(k)}, \sigma_{x,j}^{(k)}\right) \mathcal{N}\left(y - \mu_{y,j}^{(k)}, \sigma_{y,j}^{(k)}\right) \mathcal{N}\left(m - \mu_{m,j}^{(k)}, \sigma_{m,j}^{(k)}\right). \quad (1)$$

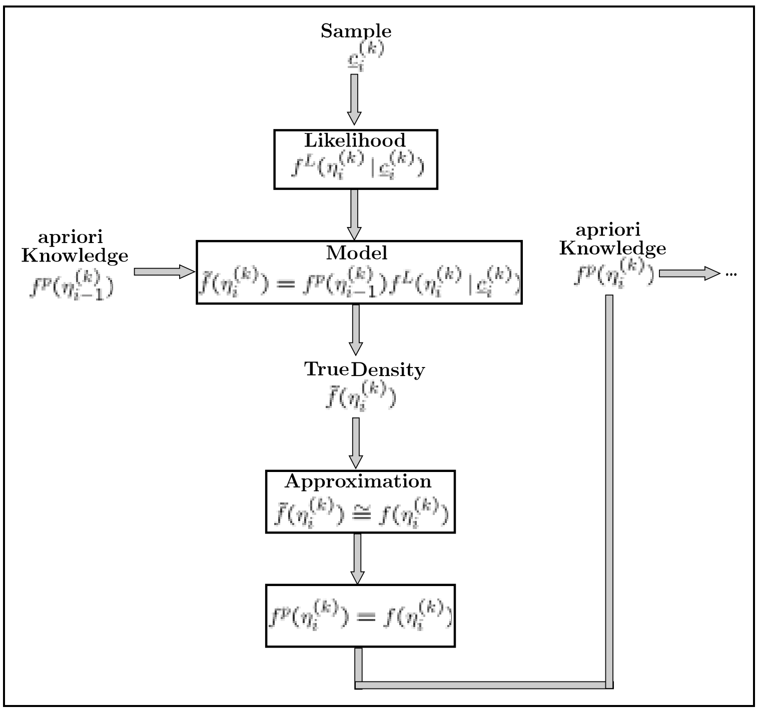

Figure 3: Computing the density function in the parameter space: New samples are used to update an existing parameter model.

We note that the approximation is fully described by the parameter vector

$$\underline{\eta}^{(k)} = \Big[w_1^{(k)}, \mu_{x,1}^{(k)}, \sigma_{x,1}^{(k)}, \mu_{y,1}^{(k)}, \sigma_{y,1}^{(k)}, \cdots \\ w_{N^{(k)}}^{(k)}, \mu_{x,N^{(k)}}^{(k)}, \sigma_{x,N^{(k)}}^{(k)}, \mu_{y,N^{(k)}}^{(k)}, \sigma_{y,N^{(k)}}^{(k)} \Big] .$$

We define a new, sample based version of Progressive Bayes, that translates the optimization problem over the discrete space $\underline{C}$ into a classical, continuously defined optimization problem in the *parameter space* $\underline{\eta}^{(k)}$.

We start from a uniform a prior density $f^p(\eta_0^{(k)})$ in the parameter space and subsequently insert calibration points into it, according to Fig. 3.

Considering a new sample, a corresponding model $f^L(\eta_i^{(k)}|\underline{c}_i^{(k)})$ for this sample is first generated in the parameter space, which is then used to update the existing model by multiplying the two densities together: $\tilde{f}(\eta_i^{(k)}) = f^p(\eta_i^{(k)})\, f^L(\eta_i^{(k)}|\underline{c}_i^{(k)})$. Because we want to have an analytic representation of the updated model, at each step we perform an additional Gaussian mixture approximation, using the Progressive Bayes estimation. As more samples are inserted into it, the parameter model will form a more distinct maximum, corresponding to the optimal values of the parameter vector $\underline{\eta}^{(k)}$.

3.1.1 Modeling of Time Variant Environment Changes

As previously mentioned in Sect. 2, a typical indoor environment has a number of time-dependent nonlinearities, introduced for example by people walking around or by doors (particularly metallic ones) getting opened and closed. For the former case, we already showed that, due to the lack of information on the positions of people influencing a particular measurement, we include the corresponding noise into the measurement noise. Thus, we can further consider that our system is time invariant, by increasing the measurement noise level.

Doors, on the other hand, present a different situation, in that they introduce a more regular non-linearity in the system. We show that, given a large enough number of calibration measurements, the resulting time invariant model will include information on various states of metallic doors. For simplification, we consider the case of a one-dimensional user position (for example, user walks along a corridor). Let a metallic door be located in the middle of the corridor, and let it only have two states: completely open, or completely closed. Fig. 4 depicts a simple scenario, where two base stations are situated at both ends of a 60 m long corridor.

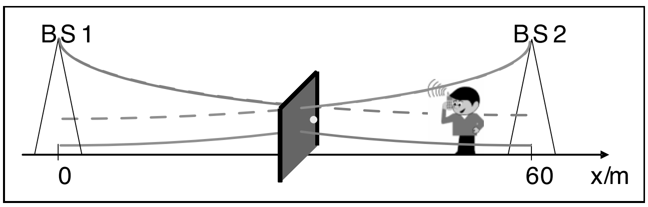

Figure 4: Sample scenario: user walks along a corridor. The dotted line indicates the signal strength, if the metallic door were open. The solid line depicts the signal strength propagation when the door is closed.

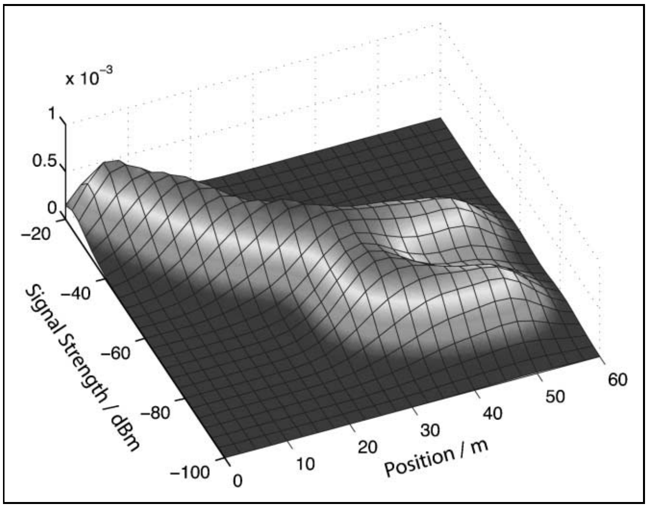

Figure 5: Full propagation model, given as a probability density function over the one-dimensional user position and the signal strength measurement.

It is clear that the signal strength received at the user's position depends on the state of the metallic door (a closed door additionally attenuates the transmitted signal). Lacking independent information on the door's state, we perform several calibration measurements at the user's position. It is important that the calibration measurements are taken both when the door is closed, and when it is open. The resulting *time invariant* model is shown in Fig. 5.

We notice that the probability density of the signal strength distribution at the user's current position is given by the following section in the full model: $\mathcal{D}(m|x)$, where m is the measurement variable and x the current position. An example is given in Fig. 6.

Thus, even though information from independent sensors is not available, our model incorporates probabilistic information about various system states, which, along with measurements from other received base station, leads to a better global position estimate.

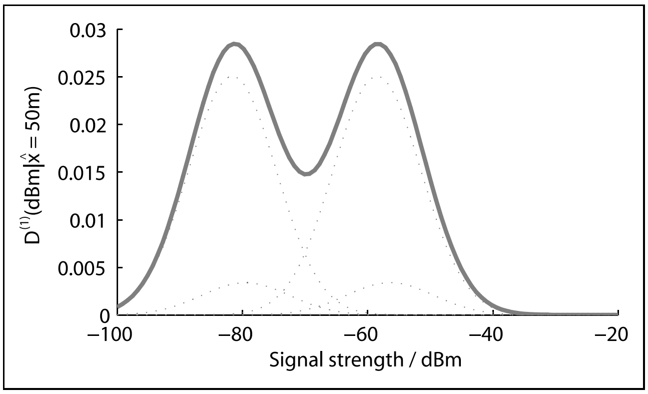

Figure 6: Distribution of expected signal strength measurements at a given user position: $\hat{x} = 50$ m.

3.2 The Localization Step

In the localization step, a mobile device at an unknown position measures the signal strengths received from all available base stations. Let N_r be the number of base stations received during this measurement ($N_r \leq N_{BS}$). We only take into consideration the models of these N_r base stations, ignoring the ones that were not received. Based on the measurement vector and on the models generated in the calibration step, for each base station we compute an estimate of the user's position. For base station k, the position estimate can be directly derived from 1 as $\mathcal{D}^{(k)}(x, y|m^{(k)})$.

The resulting N_r position estimates can now be merged into a global estimate, using the formula

$$\mathcal{D}(x, y|\underline{m}) = c \prod_{k=1}^{N_r} \mathcal{D}^{(k)}\left(x, y|m^{(k)}\right), \tag{2}$$

where c is a normalizing constant.

As the individual position estimates $\mathcal{D}^{(k)}(x, y|m^{(k)})$ are obtained as Gaussian mixtures from the full probabilistic models, the resulting global estimate is in itself also a Gaussian mixture. The number of components in the resulting global estimate is the product of the number of components in each individual calibration model. In this case we employ the Progressive Bayes estimation method to reduce the complexity of the resulting estimator, by approximating it with a new Gaussian mixture of limited complexity.

4 Tracking

Implementing a solution to the tracking problem using the Progressive Bayes estimation approach is conceptually straightforward. We note that new measurements become available at discrete time steps. Fig. 7 shows the processing steps needed at a generic time step t.

A signal strength measurement vector from the mobile device is used to obtain a position estimate according to 2. This estimate is now considered as a new measurement input for the *filter step*, where it is combined with a previously predicted position estimate $f^p(\underline{x}_t)$. The resulting "true" function $\tilde{f}^e(\underline{x}_t)$ is an arbitrary probability density,

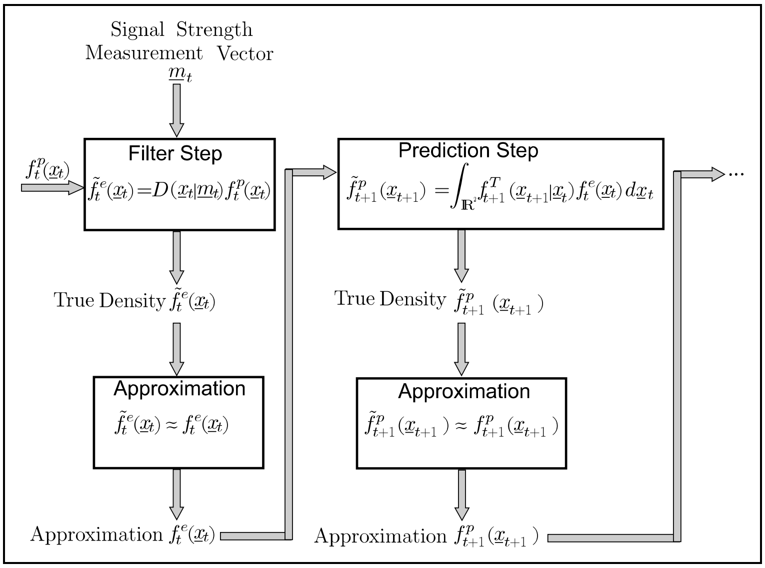

Figure 7: Tracking diagram: processing at time step t.

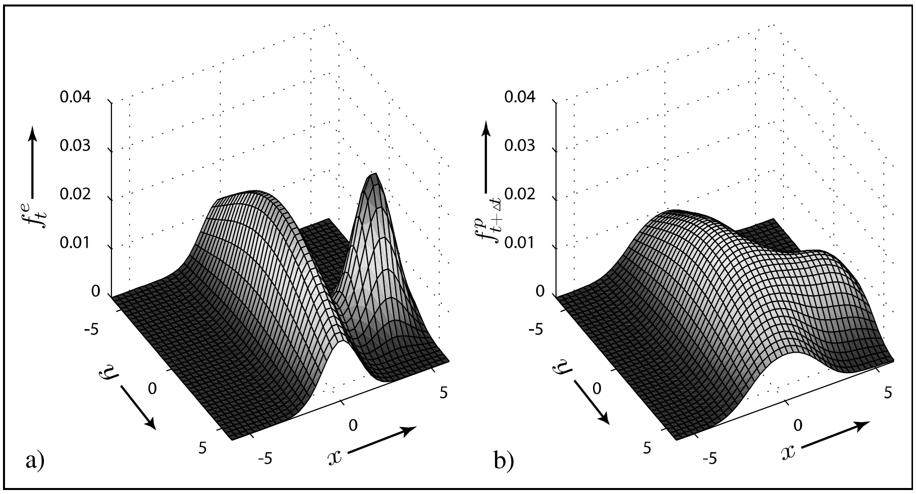

Figure 8: Sample prediction step: Position density function before (a) and after (b) the prediction step. The estimate in (b) has lower, broader peaks, corresponding to an increase in the position uncertainty.

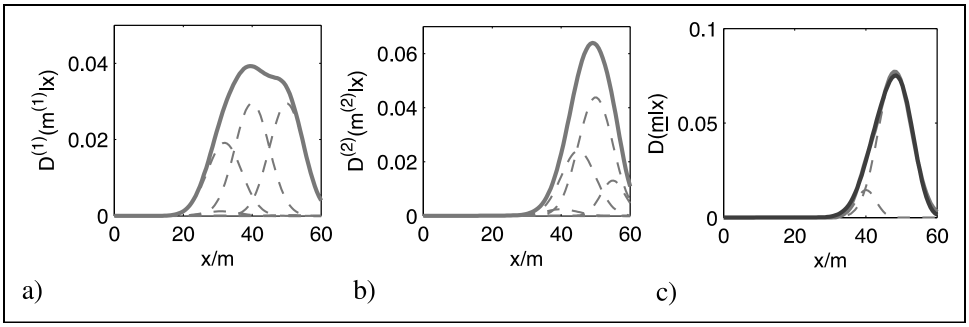

Figure 9: (a) and (b) show the individual position estimates relative to the 2 base stations. (c) shows the global estimate. The more imprecise estimate corresponding to the first base station is improved by the second estimate, which is much more accurate as the user is very close to the second base station.

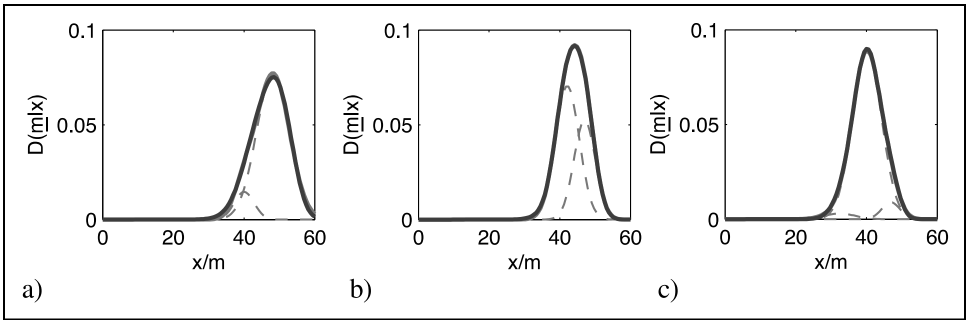

Figure 10: Position estimate after (a) 1, (b) 2, and (c) 8 measurement update steps for a static user.

which needs to be approximated with a Gaussian mixture $f^e(\underline{x}_t)$.

This approximation is further used in the *system update step* as input for a human motion model that helps us to predict the estimate of the user position at the next time step.

We choose a simple motion model, where the user is assigned a certain maximum speed v_{max}. Given a user position $\underline{x}_t$ at time t, we assume that at time $t+1$ the position will have a uniform probability density around $\underline{x}_t(f^T_{t+1}(\underline{x}_{t+1}|\underline{x}_t))$, in a circular region of radius $r = \Delta t \cdot v_{max}$, where Δt is the difference between the two time steps.

The predicted position estimate is then given by the following equation

$$\tilde{f}^p_{t+1}(\underline{x}_{t+1}) = \int_{\mathbb{R}^2} f^T_{t+1}(\underline{x}_{t+1}|\underline{x}_t)\ f^e_t(\underline{x}_t)\ d\underline{x}_t\ .$$

A sample result of the system update step is given in Fig. 8.

We employ again the Progressive Bayes estimation method to approximate $\tilde{f}^p_{t+1}(\underline{x}_{t+1})$ with a Gaussian mixture $f^p_{t+1}(\underline{x}_{t+1})$, which becomes the prior estimate for the next filter step.

5 Simulation Results

We present a set of simulation results for the measurement update step in the simple scenario introduced in Sect. 3.1.1. We consider the mobile user to be taking several measurement at the same position, that is at coordinate $\hat{x} = 45\,\mathrm{m}$. For simplicity of presentation we consider the user to be static, such that we can omit the prediction step and only show the results of the measurement update step. At each measurement time the mobile device receives two scalar signal strength values, corresponding to the two base stations at the ends of the corridor. Based on each measurement, we obtain a position estimate relative to each base station, by sectioning the full calibration model for the corresponding signal strength value. A global position estimate, given all measurement values, is then computed as the product of the individual position estimates, according to 2. Fig. 9 shows both the two individual estimates and the resulting global estimate for a particular measurement step. If prior information on the user position is available from a previous prediction step, we combine it with the newly computed global estimate.

The whole processing is repeated for each set of measurements taken by the user. Fig. 10 shows the corresponding position estimates after several processing steps.

6 Conclusions and Future Work

In this article we proposed a novel approach to solving the localization and tracking problems in cellular networks, by employing the Progressive Bayes estimation algorithm in both the calibration and the localization step.

Apart from the usual advantages of Progressive Bayes estimation (error control, complexity control), applying the method in the positioning context is particularly valuable, as it creates a full probabilistic description of the indoor propagation environment and allows for the natural integration of user motion models. Convergence and complexity of the proposed algorithm has to be further investigated. Getting an estimate of the computation time is also very important for any practical implementation.

The proposed approach is also suited for further development, in the sense of using measurements from the localization step to simultaneously update the propagation field models. This resembles the Simultaneous Localization and Mapping (SLAM) problem from the robotics field.

References

[1] P. Bahl and V.N. Padmanabhan. A Software System for Locating Mobile Users: Design, Evaluation, and Lessons, 2000. Revised Version of Microsoft Research Technical Report MSRTR-2000-12, available from the authors webpages.

[2] C. Kee, D. Yun, H. Jun, B. Parkinson, S. Pullen, and T. Lagenstein. Centimeter-Accuracy Indoor Navigation. *GPS World*, pages 14–22, November 2001.

[3] U.D. Hanebeck, K. Briechle, and A. Rauh. Progressive Bayes: A New Framework for Nonlinear State Estimation. In *Proceedings of SPIE*, volume 5099, pages 256–267, Orlando, Florida, 2003.

[4] H. Hashemi. The Indoor Radio Propagation Channel. In *Proceedings of the IEEE*, volume 81, pages 943–968, 1993.

[5] J. Hightower and G. Boriello. A Survey and Taxonomy of Location Systems for Ubiquitous Computing. Technical Report UW-CSE 01-08-03, University of Washington, Computer Science and Engineering, Box 352350, Seattle, WA 98195, August 2001.

[6] A.M. Ladd, K.E. Bekris, A. Rudys, L.E. Kavraki, D.S. Wallach, and G. Marceau. Robotics-Based Location Sensing Using Wireless Ethernet. In *Proceedings of the 8th annual international conference on Mobile computing and networking*, pages 227–238. ACM Press, 2002.

[7] A.M. Ladd, K.E. Bekris, A.P. Rudys, D.S. Wallach, and L.E. Kavraki. On the Feasibility of Using Wireless Ethernet for Indoor Localization. *IEEE Transactions on Robotics and Automation*, 20(3):555–559, June 2004.

[8] A. Rauh, K. Briechle, U.D. Hanebeck, C. Hoffmann, J. Bamberger, and M. Grigoraş. Localization of DECT Mobile Phones Based on a New Nonlinear Filtering Technique. In *Proceedings of SPIE*, volume 5084 of AeroSense Symposium, pages 39–50, Orlando, Florida, 2003.

[9] T. Roos, P. Myllymaki, H. Tirri, P. Misikangas, and J. Sievanen. A Probabilistic Approach to WLAN User Location Estimation. *International Journal of Wireless Information Networks*, 9(3), July 2002.

[10] P. Rößler, U.D. Hanebeck, M. Grigoraş, P.T. Pilgram, J. Bamberger, and C. Hoffmann. Automatische Kartographierung der Signalcharakteristik in Funknetzwerken. In R. Dillmann, T. Gockel, and H. Wörn, editors, *Autonome Mobile Systeme 2003 (AMS 03)*, Karlsruhe, 2003. Springer.

[11] A. Schwaighofer, M. Grigoraş, V. Tresp, and C. Hoffmann. GPPS: A Gaussian Process Positioning System for Cellular Networks. In S. Thrun, L. Saul, and B. Schölkopf, editors, *Advances in Neural Information Processing Systems 16*. MIT Press, 2004.

Manuscript received: 17th October 2004.

Dipl.-Ing. (University "Politehnica" Bucharest) Marian Grigoraş is with Siemens AG, Corporate Technology, Information & Communications, Neural Computation Department. His current research interests are primarily in positioning technologies for indoor environments and nonlinear estimation.

Address: Siemens, Corporate Technology, Information & Communications 4, 81730 München, Tel.: +49-89-63640995, Fax: +49-89-63649767,
E-Mail: grigoras@ira.uka.de

Dipl.-Math. (St. Petersburg State University) Olga Feiermann works at the Intelligent Sensor-Actuator-Systems Chair at the Universität Karlsruhe (TH), mainly in the area of nonlinear estimation methods and their applications to a variety of practical applications.

Address: Universität Karlsruhe (TH), Chair of Intelligent Sensor-Actuator-Systems (ISAS), Kaiserstraße 12, 76128 Karlsruhe, Tel.: +49-721-6086797, Fax: +49-721-6083962,
E-Mail: feiermann@ira.uka.de

Prof. Dr.-Ing. Uwe D. Hanebeck is a full professor at the Universität Karlsruhe (TH) and holds the Chair of Intelligent Sensor-Actuator-Systems. Main research areas: Nonlinear estimation, sensor-actuator-networks, robotics, telepresence systems.

Address: Universität Karlsruhe (TH), Chair of Intelligent Sensor-Actuator-Systems (ISAS), Kaiserstraße 12, 76128 Karlsruhe, Tel.: +49-721-6083909, Fax: +49-721-6083962,
E-Mail: hanebeck@ira.uka.de