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Sensor placement determination for range-difference positioning using evolutionary multi-objective optimization

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ABSTRACT

This paper focuses on the application of a decision support system based on evolutionary multi-objective optimization for deploying sensors in an indoor localization system. Our methods aim to provide the human expert who works as the sensor resource manager with a full set of Pareto efficient solutions of the sensor placement problem. In our analysis, we use five scalar performance measures as objective functions derived from the covariance matrix of the estimation, namely the trace, determinant, maximum eigenvalue, ratio of maximum and minimum eigenvalues, and the uncertainty in a given direction. We run the multi-objective genetic algorithm to optimize these objectives and obtain the Pareto fronts. The paper includes a detailed explanation of every aspect of the system and an application of the proposed decision support system to an indoor infrared positioning system. Final results show the different placement alternatives according to the objectives and the trade-off between different accuracy performance measures can be clearly seen. This approach contributes to the current state-of-the art in the fact that we point out the problems of optimizing a single accuracy measure and propose using a decision support system that provides the resource manager with a full overview of the set of Pareto efficient solutions considering several accuracy metrics. Since the manager will know all the Pareto optimal solutions before deciding the final sensor placement scheme, this method provides more information than dealing with a single function of the weighted objectives. Additionally, we are able to use this system to optimize objectives obtained from fairly complex functions. On the contrary, recent works that are referenced in this paper need to simplify the localization process to obtain tractable problem formulations.

1. Introduction

Range-based localization systems use anchor nodes (nodes with fixed and known position) and measurements like received signal strength, time of arrival or time-difference of arrival to estimate the position of a target. These measurements can be converted to geometric distances or distance-differences. Exploiting the geometry of triangles, circles or hyperbolae the actual position can then be estimated. Liu, Darabi, Banerjee, and Liu (2007) provide a review of wireless indoor positioning with a comprehensive comparison of different technologies. We will subsequently consider a range-difference based positioning system using modulated infrared light (Gorostiza et al., 2011) as an example, and assume that the measurements are taken at the anchor nodes and those are the sensors. However, the methods we present in this paper can be applied to any positioning technology. The concrete choice of technology is taken into account by selecting an appropriate functional and stochastic measurement model.

It is well known that the position estimation error is affected by the measurement errors, by the geometry relating sensors and target, and by the estimation algorithm. Particularly the angle of intersection of the geometric loci corresponding to the observables (e.g., of the hyperbolae in case of range-differences) affects how the measurement uncertainties propagate to uncertainties of the estimated coordinates (e.g., Ho & Chan, 1993; Kaune, 2012). All these influences are contained in the covariance matrix of the estimated coordinates which is therefore a useful starting point to assess the predicted quality or to optimize sensor placement.

The Fisher information matrix (FIM) is used to compute the covariance of maximum-likelihood estimates. The Cramér-Rao lower

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bound (CRLB) is computed from the inverse of FIM and provides a lower bound of the covariance that is asymptotically achievable by any unbiased estimator (Kay, 1993). Bishop, Fidan, Anderson, Doğançay, and Pathirana (2010) use FIM to analyze the sensor emitter geometry and establish which sensor configurations minimize the achievable variance by an efficient estimator. Further research was focused on generalizing this work for sensor networks comprising different types of sensors (Meng, Xie, & Xiao, 2013) and considering additionally distance-dependent ranging errors (Perez-Ramirez, Borah, & Voelz, 2013). Accuracy will improve with increasing number of sensors according to the additive property of FIM, assuming that the contribution of each sensor is properly weighted during the estimation and the measurement errors are dominated by random rather than by systematic effects. Chen, Francisco, Trappe, and Martin (2006) minimize an error bound of the linear least squares estimation and conclude that optimal sensor placements are those distributions that form simple regular shapes (triangles, squares, etc.). This is a useful indication for positioning within open areas without line-of-sight (LOS) restrictions. Optimizing sensor placement for coverage and accuracy within real indoor environments with irregularly shaped floor plans and LOS obstructions requires more advanced tools and will generally lead to different optimum network geometry for different environmental restrictions and requirements.

So far, most authors applied single-objective optimization for optimum sensor placement in relation with localization. Chaudhry, Hung, Guha, and Stanley (2011) present a multi-objective evolutionary algorithm for solving the sensor placement problem while coping with multiple, possibly contradicting, criteria (maximize coverage and connectivity, minimize energy cost). Their approach is even applicable to situations where the number of sensors is not known beforehand.

Our approach differs from the others in that we use a multi-objective optimization that considers multiple accuracy measures instead of focusing on a single measure. We consider the problem of finding a distribution of anchor nodes which optimizes the performance of the positioning system within the entire, desired coverage area (region of interest, ROI) and takes into account various scalar performance measures derived from the CRLB. This is practically relevant when planning the installation of a positioning system e.g. in an existing building or when assessing a proposed technical solution, whose performance depends on the number and spatial distribution of the sensor nodes. Each of the performance measures, which we will introduce in Section 3, has a clear physical meaning. Employing multi-objective evolutionary optimization then allows finding a sensor placement configuration which is optimal in a practically relevant sense combining the objectives. For example, we can automatically find configurations such that the worst position error within the entire ROI is a minimum while at the same time the uncertainties of the estimated positions are as isotropic as possible (i.e., at location, the uncertainties are almost equal in all directions). The associated objective functions are usually in conflict with each other so the solution of the optimization problem is initially the so-called Pareto front, i.e., a surface in the M-dimensional domain of the performance measures where each point corresponds to the optimum constrained on the values of $M-1$ criteria. Numerical optimization yields a point cloud approximating the Pareto front. The final solution of the optimization problem is then extracted from this point cloud using additional selection criteria.

The last issue we discussed above means that the evolutionary optimization process we carry out assists us in solving a decision making problem by providing a decision support system (Grasso, Cococcioni, Mourre, Osler, & Chiggiato, 2013). The human expert who takes the role of the sensor resource manager receives a set of distributions of sensors which are Pareto efficient according to some objectives. There is no need of dealing with such an intractable optimization problem that involves several cost functions which depend on many parameters or deciding a priori weight coefficients for computing a single cost function that merges all the objectives. Finally, the expert has a total overview of the Pareto optimal solutions and can apply his own criteria to select a desired solution according to the current needs. Our approach can also contribute to other expert and intelligent applications that suggest focusing on sensor placement to improve a poor position estimation (Seewald, Gonzaga, Veronez, Minotto, & Jung, 2014).

The rest of the paper continues as follows. We provide an overview of recent publications within the field of sensor placement in Section 2. Section 2.1 lists the problems we found in literature and states the contributions of this work. Section 3 introduces the performance measures that we propose for sensor management. Fundamentals of multi-objective optimization and its approach by evolutionary algorithms are discussed in Section 4; Section 4.1 gives a detailed explanation of the genetic algorithm we use. Positioning with range-difference measurements and the evaluation of position estimates are briefly recalled in Section 5, including the range-difference error modeling of the infrared link. Section 6 shows the sensor placement solutions for specific examples, obtained using the evolutionary optimization.

2. Related works

We aim not only to give a survey of recent literature, but also provide a comparison to our work in order to highlight and clarify its significance.

Chiu and Lin (2011) deal with sensor placement to optimize quality of service for target positioning. They apply Lagrangean relaxation to solve a nonlinear integer programming problem that minimizes the maximum weighted error distance. Their approach introduces good and novel ideas that we have also included in our work such as considering weights for different zones of the area of interest in order to give more importance to a zone with a larger weight. They present the ROI as a set of 2D grid points which serve as candidate locations for sensors and targets. We also use grid points as candidate locations for targets. However, our approach differs in the fact that we use real numbers for the locations of sensors as decision variables, and hence we do not need to restrict their positions to a grid. Additionally, their framework uses 0/1 detection model for sensors, whereas we consider the influence of the geometry relating sensors and targets.

The work presented in Moreno-Salinas, Pascoal, and Aranda (2013) focuses on finding optimal sensor arrangements for target localization with range measurements by computing an analytical solution or using techniques from estimation theory or convex optimization. Authors maximize the logarithm of the determinant of the FIM and also find solutions for multiple targets. They assume that the noise of the measurements is white Gaussian and equal for all sensors. On the contrary, we avoid that simplification and focus on a more realistic scenario where the noise varies according to the position of sensors and target. In addition, since we use an evolutionary optimization algorithm, we avoid computing the derivatives of the objectives. The same optimality criterion was used in Nguyen and Doğançay (2015) to derive optimal sensor placement strategies and flight patterns for the Doppler-shift localization problem for a stationary target. The noise model they use is a function of the sensor-target distance and they find optimal angular separation for sensors. They show that the determinant of FIM increases with the reduction of the noise (sensors move towards the target) and the increase of the angular velocity of the sensors. Their analysis focuses only on localizing a single and stationary target, whereas we aim to find placement solutions for a whole area.

Chepuri and Leus (2015b) discuss the use of several performance measures of the CRLB. They formulate the sensor placement problem as a sensor selection problem using sparse sensing, thus they have candidate locations for sensors and minimize the number of 1 entries