# Real-Time Error in Location Modeling for Ubiquitous Computing

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**Abstract**

No matter which technologies or techniques a ubiquitous location system uses, its measurements will have some amount of quantifiable error. Unfortunately, error information is often conveyed arbitrarily or simply for performance evaluation instead of as an online characteristic of system behavior. Terms such as accuracy, precision, granularity, and resolution are overloaded with various meanings. In this short paper, we argue that *real-time error distributions* provide a concise quantitative summarization of system accuracy and are useful in applications, simulation, and sensor fusion.

## 1 Introduction

As we have previously advocated to the ubiquitous location-sensing community, an error distribution can summarize a location system's accuracy and precision well [8]. An example is: "Using 5 basestations per $300m^2$ of indoor factory floor space, location-sensing system $X$ can locate 10 tagged objects per second to within error margins defined by a Gaussian distribution centered at the objects' true location and with $\sigma = 3.5m$." Such a summarization is most likely a *minimum performance level* (MPL) built from empirical studies of the location system. An MPL has 3 fundamental components but may look quite different for location systems built using different technologies:

1. **Infrastructure Density** – The number of necessary infrastructure elements per area or volume of space.
2. **Location Rate** – The number of objects per second that can be located. The rate may be limited by the protocol overhead or the amount of available wireless spectrum.

3. **Error Characteristics** – A gross summary function of the maximum location error that may occur when locating objects.

An MPL summarizes overall system behavior more concisely than values assigned to often ambiguous terms such as accuracy, precision, granularity, and resolution. However, an MPL still says little about the real-time behavior of the location system. A standard method is needed to capture and communicate *real-time error distributions*. Section 2 explores several types of real-time errors and how they can be related in a common framework. In Section 3, we illustrate the value of real-time error information. Finally, Section 4 suggests a path to adopting a standard for real-time error information in ubiquitous computing applications and Section 5 concludes.

# 2 Real-Time Error

There are many sources of real-time location errors – errors that vary dynamically from moment to moment depending on the state of the infrastructure, environment, and mobile objects. We identify 3 real-time measurement errors encountered by ubiquitous location systems.

## 2.1 Signal Propagation

Location systems often use wireless technology for detecting proximity or measuring distances. Wireless transmissions are subject to the reflection and absorption factors of different physical materials. For example, infrared is attenuated 100% by any brick or plaster wall, but only 5% by glass; depending on frequency, radio emissions are attenuated $\approx 10\%$ by plaster walls. Reflective properties can be similarly enumerated.

Location systems account for these dynamic signal propagation errors using an environment model. This model may be empirical such as the prebuilt signal-strength measurement dataset used in the Microsoft Research RADAR location system [2], or parametric such as Seidel and Rapport's indoor propagation equations modeling the effects of floors and ceilings on 900MHz radio signals [12].

The result of environment propagation modeling, although representable in a variety of ways, is a way to assign probabilistic uncertainty to individual measurements, such as distances and angles, which are combined to compute objects' locations. This measurement uncertainty is often represented as a statistical distribution such as a Gaussian with the expected value, $\mu$, equal to the measured quantity and $\sigma$ derived from the propagation model.

## 2.2 Time Variations

Time-of-flight distance measurements or time-stamped proximity readings require a certain precision and agreement about time. Since perfect synchronization is impossible, time variations will introduce error into measurements used to compute objects' locations. Fortunately, time variation errors can be modeled with a distribution much the same way as signal propagation.

For example, in GPS, receivers are not synchronized with the satellite transmitters and thus cannot precisely measure the time it took the signal to reach the ground from space. Therefore, GPS satellites are precisely synchronized with each other and transmit their local time in the signal allowing receivers to compute the difference in time-of-flight – a quantity called a *pseudorange* measurement. Four satellite pseudoranges allow the receiver to use linear least-squares to solve a system of four equations (4 pseudoranges) and four unknowns (X, Y, Z, and time) thereby incorporating timing errors directly into the total error model. Refer to [5] for a summary of GPS theory and Misra et al. [10] for a theoretical discussion of how errors combine to effect overall location accuracy in the GPS system.

As we have seen, individual signal and time measurements each have a degree of uncertainty and, assuming the proper models, it is possible to assess each measurement's uncertainty in real-time. Assuming a Gaussian error model, the uncertainty for $n$ measurements, $\sigma_m$, is computed as per Equation 1.

$$\sigma_m = \sqrt{\sum_{i=1}^{n} \sigma_{m_i}^2} \tag{1}$$

## 2.3 Dilution of Precision

If location is computed using geometric quantities,[1] the final location measurement uncertainty $\sigma_m$ derived from the propagation and timing models will be magnified by a dilution of precision (DOP) factor, $rms(location\ error) = DOP * \sigma_m$.

DOP is a standard, unit-less quantity summarizing the quality of aggregate geometric measurements. The most general form of DOP is Geometric DOP (GDOP). GDOP is the proportional root mean square of the horizontal, vertical, and time uncertainty as computed in Equation 2.

$$GDOP = \frac{\sqrt{\sigma_x^2 + \sigma_y^2 + \sigma_z^2 + \sigma_t^2}}{\sigma_m} \tag{2}$$

Assuming the measurements $m_1 \ldots m_n$ are uncorrelated and have a common variance (as would be the case for a least-squares location solution), it can be shown that DOP is a function only of the spatial arrangement of the mobile units and sensors. The volume of the shape formed by the unit-vectors from the object to the measurement points is inversely proportional to the magnitude of the DOP and higher DOP implies more uncertainty in the computed location. Figures 1 and 2 illustrate low and high DOP situations using a hypothetical 2D

[1]Not all location systems operate geometrically. One incarnation of RADAR [2], and various vision systems employ abstract scene analysis (for RADAR, in the RF rather than visible spectrum) against a prebuilt dataset of non-geometric quantities.

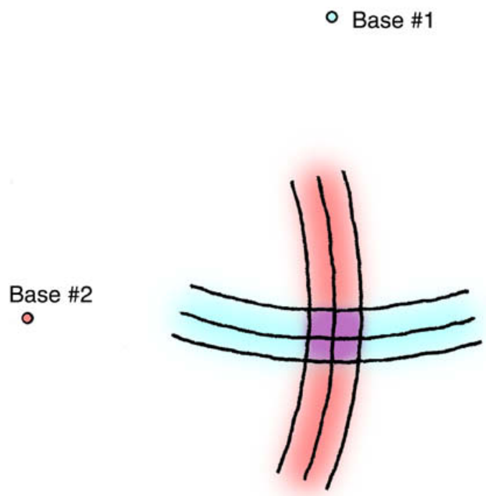


Figure 1: In this hypothetical 2D distance-measurement location system, low dilution of precision occurs because the measurement points have good separation from each other relative to the object being located – conceptually, the area of uncertainty in the intersection is small.

location system based on distance measurements to 2 basestations. Again, [5] and [10] contain a more detailed discussion of the computation and use of DOP values.

We now have a formal method of computing the MPL mentioned in Section 1. Given an arrangement of fixed sensors, a GDOP probability distribution can be estimated by computing the GDOP of mobile units at regular locations in the environment. Finding the configuration with the highest GDOP and $\sigma_m$ yields the location system's MPL.

# 3 Applying Real-time Error Information

Real-time error distribution information is valuable in several ways.

## 3.1 Applications

Context aware applications can benefit from real-time error information. For example, an application routing phone calls to handsets near a user may behave very differently if it knows the user's location is uncertain to 60m ($\sigma_m = 20m$ and $GDOP = 3.0$) then if the uncertainty is only 18cm ($\sigma_m = 10cm$ and $GDOP = 1.8$). The second case is probably close enough to choose a phone to ring, while in the first case, the system may just take a message.

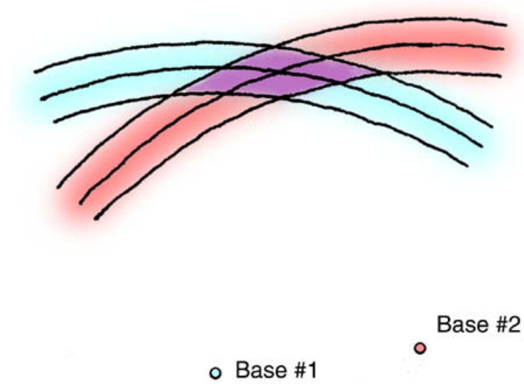


Figure 2: In this hypothetical 2D distance-measurement location system, high dilution of precision occurs because the measurement points have poor separation from each other relative to the object being ranged. The *distance* measurement error is the same as in Figure 1, but the location uncertainty will be larger.

### 3.2 Simulation

Trace logs of real-time error distributions can be used as part of a simulator's input. Prototyping location-aware ubiquitous applications using a location system simulator provides a rigorous testing environment and potentially avoids the monetary cost of purchasing, deploying, and configuring hardware infrastructure when the goal is simply to evaluate the suitability of a certain location-sensing system in building the application. Preliminary work on this idea has begun. For example, Byland and Espinoza have built a simulator for a campus-sized location-sensing system using a Quake III gaming arena [4].

### 3.3 Sensor Fusion

Sensor fusion is the use of multiple location systems simultaneously to form hierarchical and overlapping levels of sensing to increase accuracy beyond what is possible using any individual system. Real-time error information provides the necessary pieces for fusing information by convolution of error distributions. This approach is similar to the multi-sensor collaborative robot localization technique of Fox et al. [6].

## 4 A Path to Implementation

We believe it is possible to adopt a method of conveying real-time error information that is beneficial in a variety of location-aware ubiquitous applications. Several issues deserve consideration.

## 4.1 Standards

Communicating real-time error information is already a feature in navigation system protocols such as the National Marine Electronics Association (NMEA) standard 0183. NMEA 0183 is a voluntary standard adopted by device manufacturers for interfacing navigation devices such as radars, chart plotters, autopilots, compasses, GPS units, and other such equipment. Modern GPS units including hand-held units support NMEA 0183. NMEA 0183 is a serial message passing protocol consisting of asynchronous "sentences" communicating a variety of navigation information and control instructions. Several of these sentences contain location error information such as timing drift and dilution of precision.

It is quite reasonable to believe that similar voluntary communication standards could be adopted for the small-scale, indoor domain of location systems for ubiquitous computing. Indeed, much like the data protocol of NMEA 0183, ubiquitous computing systems such as one.world [7] and ICrafter [11] are often built using asynchronous message passing architectures to allow for decentralized operation and scalability.

## 4.2 Frames of Reference

A location system must adopt a frame of reference. GPS and marine navigation devices employ the World Geodetic System 1984 (WGS84) model of the earth's shape and coordinate system whereas many ubiquitous computing applications have their own ad hoc reference frames defined by a campus, building, room, or other administrative boundary. Ubiquitous location systems could adopt WGS84 or standardize a more complex method of referencing and converting different reference frames.

## 4.3 Symbolic Locations

Ubiquitous computing applications are often interested in symbolic locations (e.g. in the kitchen, near a wall display) instead of exact physical positions. Symbolic information allows events to be generated when certain physical arrangements or proximity situations occur. Yet symbolic location needs are sometimes at odds with describing computed locations using geometric properties and real-time error distributions. For example, the Xerox ParcTab infrared beacons [13] have relatively high location uncertainty but are great for "find the room"-style operations.

One solution used by the EasyLiving team at Microsoft Research is an abstraction layer merging the real-time error distributions with an external database of room volumes and geometric service regions of objects to obtain relevant symbolic information [3]. In the distillation process, much of the error may be eliminated or deemed irrelevant.

## 5 Conclusion

We have shown how *real-time error distributions* can be an effective summarization of location system accuracy and are useful in applications, simulation, and sensor fusion. Our current work involves incorporating real-time error information to fuse several location systems including proximity sensors, RFID tags, GPS, infrared beacons, and the SpotON Ad Hoc Location System [9]. In addition, we are working on a method of querying the fused location model for spatial and temporal object arrangements. Application areas we are investigating include artistic expression, experiment capture in a biology laboratory [1], and undersea exploration with large numbers of stationary and autonomous robot sensors.

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