Reduction of Location Estimation Error using Neural Networks

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ABSTRACT

The objective of this work is to estimate the locations of Bluetooth enabled devices. Collecting received signal strength from a device may help with estimating its location. However, for indoor environments, the signal attenuation model becomes complex and difficult to represent concisely due to multi-path and small-scale fading effects. The flexible modeling and learning capabilities of neural networks provide lower errors in determining the position even in the presence of these destructive effects. A standard backpropagation learning algorithm was employed to minimize the error between target and estimated locations in order to find the weights of the links of the neural network. Simulation results show that a neural network with three input units and 8 hidden layer units and two output units can provide 75cm root mean square (RMS) error.

Categories and Subject Descriptors

C.2.1 [**Network Architecture and Design**]: Wireless communication; C.2.3 [**Network Operations**]: Network monitoring; C.4 [**Performance of Systems**]: Measurement techniques, Performance attributes

General Terms

Experimentation, Measurement, Performance

Keywords

Indoor location estimation, neural networks

1. INTRODUCTION

The locations of devices in a building can be used to provide location-based services to users, such as asset tracking, location-sensitive billing and locational advertising. Additionally, the location of a wireless device may be used as a proxy for a user's location for emergency services. In the last decade, Global Positioning System (GPS) technology has been used for outdoor localization of an arbitrary object with increasing accuracy. However, insufficient resolution and signal strength inside buildings cause GPS not to perform accurately indoors due to multi-path effects, interference, obstacles, mobility, etc. Also, GPS requires considerable cost, complexity, and battery consumption in mobile devices. Therefore, a complementary method of localization that can give similar results is needed. There are several indoor location techniques available such as Active Badge [11] using infrared signals, Active Bat [12], [6], Cricket [9], using a combination of RF and ultrasound, PinPoint 3D-iD [13], RADAR [1], Nibble [4] and SpotON [7], using RF-based location determination. However, the purpose of this work is to determine the locations of people in a building, such as the rooms in which someone is present, and the actual location of a person in a room, when there is a security concern. As Bluetooth devices become more widespread it may be possible to use them to estimate the location of people in a building. The received signal strength information (RSSI) may be used to determine the position of Bluetooth enabled devices inside a working area. The RSSI is collected from mobile Bluetooth devices by multiple Bluetooth USB adapters (BUAs) connected to a PC.

MELT'08, September 19, 2008, San Francisco, California, USA.

2. NODE IDENTIFICATION

Bluetooth (IEEE 802.15) is a communications protocol primarily designed for low power consumption, low cost and short range [3]. Bluetooth supports a variety of applications including cell phone to headset, PC to printer or Local Area Network (LAN) Access Point (AP) connections, and PC to input devices such as mouse and keyboard. The Bluetooth standard is defined over the Physical and Data link layers of the OSI model with four sub-layers: radio frequency (RF) layer, baseband layer, link manager, logical link control and adaptation protocol (L2CAP). The Bluetooth RF layer is a short-range radio standard with three power classes having nominal ranges of 1m, 10m, and 100m. The devices employ radio communications in the 2.4GHz spectrum, so they do not need to be in line of sight. The baseband layer establishes the physical link between devices forming a piconet. A piconet has a master device and each master can connect to at most 7 slave devices. A scatternet is created by combining multiple piconets.

Bluetooth devices are uniquely identified by their Media Access Control (MAC) addresses. Observation of the MAC may be accomplished via two general approaches. The first approach is to use a network management protocol. The Simple Network Management Protocol (SNMP) is a widely used application layer protocol that facilitates the exchange of network management information between network devices. SNMP can be used to poll a LAN AP device to collect information regarding the Bluetooth devices that are in range of the AP. The advantage of using a network management protocol is that it allows access to the information from any networked computer. However, the SNMP approach requires pairing, i.e., a mobile device must register with the AP. Finding the locations of devices that do not or cannot pair with the AP requires a second approach to accessing information. A Bluetooth USB adapter may be configured as a master Bluetooth device, which can scan and detect mobile Bluetooth devices. One advantage of this approach is that it does not require pairing but only that slave devices respond to an inquiry coming from a BUA. While this is more reliable than the first approach, it does not guarantee all devices will be found.

Accessing Bluetooth hardware is arranged by the Host Controller Interface (HCI), which provides a standard command interface to the Bluetooth baseband controller and link manager, and access to hardware status and control registers. For each physical bus (USB, RS232, UART etc.) HCI specification defines the interface functions based on the physical bus used. Using Bluetooth Protocol Stack and HCI a trigger command called *inquiry* can be sent from a master device to a slave device and gather information such as MAC address, clock offset and class. Given these capabilities, using the Bluetooth Protocol Stack for identifying Bluetooth devices inside the range of a master Bluetooth device is the best approach for maximizing the chance of detecting a device.

3. APPROACHES TO LOCATION ESTIMATION

After identifying the devices in range of a master Bluetooth device, the second step is to determine the location of those devices relative to the master.

Lateration is a commonly used location estimation technique in which the distance measurements are acquired from $(k+1)$ neighbors in a k-dimensional plane. The example of lateration in a 2-dimensional plane is called triangulation, in which a node needs to know the distances from at least three neighboring nodes to estimate its location.

Several approaches exist for estimating distance from a neighbor, including signal attenuation and time of arrival (TOA) and time difference of arrival (TDOA). In signal attenuation, the power of the received signal is measured by the sensor node and is reported as the Received Signal Strength Indication (RSSI). Knowing the signal strength emitted by the source node and the attenuation relationship with distance (such as $1/r^2$, where r is the separation distance), the relative distance can be calculated. If the RSSI measurement were deterministic one could find the distance between a sensor and a location exactly. Then, in a two-dimensional plane, using three sensors we could locate a node at any location exactly. Figure 1 shows three sensors s_i placed at (x_i, y_i) and a location L. (x, y) coordinates for location L can be calculated using equations $d_i^2 = (x_i - x)^2 + (y_i - y)^2, i = 1, 2, 3$, since there are three equations and two unknowns.

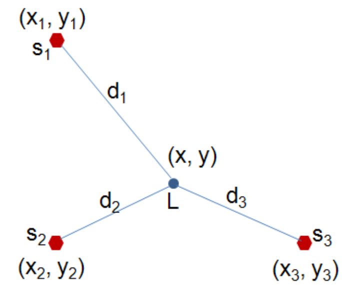

Figure 1: Lateration in 2-dimensional plane

However, for indoor environments or large distances, the attenuation relationship becomes complex and difficult to represent concisely due to multi-path effects and reflection of the radio waves [10]. Multi-path reflections occur when the signal bounces off surfaces near the transmitter. Because the reflected signal arrive with nearly the same amplitude as the direct path signal, the actual received signal is the vector sum of all the signals incident from any direction or the angle of arrival. The reflections combine destructively or constructively at the receiver. As environment conditions vary the RSSI information fluctuates over time and is not deterministic. Since the RSSI is always greater than the white noise floor, the multipath reflections can cause in much larger estimation errors.

Measuring the RSSI value without establishing a connection (pairing Bluetooth devices) is possible using the *inquiry* command. However, the RSSI is quantized in steps of 1dB over the range, -128 < RSSI < 127, which leads to errors. Assuming a free space path loss model with a path loss exponent of 2, a best case resolution of $\pm$11cm is achieved, and with a path loss exponent of 4, then the best case resolution is $\pm$6cm.

A free space propagation model assumes that radio signals emitted from a point source of energy travel in all directions in a straight line, and fill the entire spherical volume of space with energy strength varying with $1/r^2$ rule. However, real-world signal propagation cannot be modeled accurately by this model. Three phenomena, reflection, diffraction and scattering cause signal distortions and increase signal fades and propagation losses. Multi-path reflections, shadowing effects, diffraction around sharp corners or scattering from wall, ceiling, or floor surfaces make it difficult to simulate the large-scale and small-scale effects on signals inside a building using a basic model, and also degrades the link performance.

For these reasons, in realistic situations, deriving location from signal strengths is not trivial. One method for incorporating the effects of a complex fading environment is to use neural network models and automated learning techniques for location estimation of wireless devices [2]. The flexible modeling and learning capabilities of neural networks achieve lower errors in determining the position. A previous study considers a high-speed wireless LAN environment using the IEEE 802.11b standard [2]. This research considers a low cost, low power and low signaling rate environment using Bluetooth technology. Three class-2 version 2.1 BUAs used as master Bluetooth devices provide RSSI information collected from mobile Bluetooth enabled devices. The RSSI

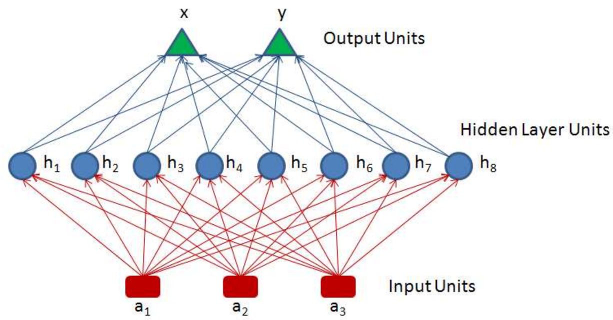

Figure 2: Multi-layer perceptron configuration

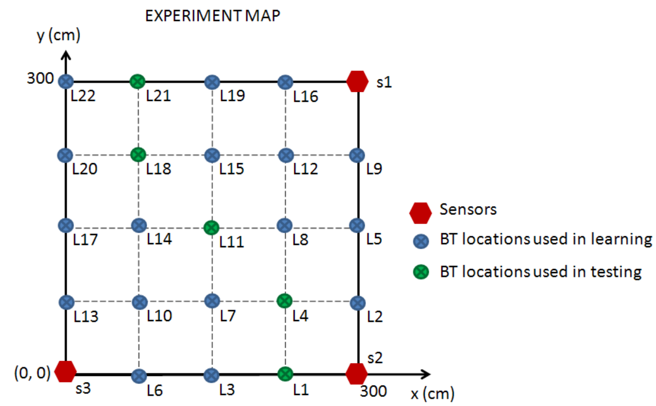

Figure 3: Physical topology

information and precisely measured training locations train the neural network.

4. LOCATION ESTIMATION WITH NEURAL NETWORK

Using neural networks (NN) with automated learning techniques represents a method for reducing the positioning error for location estimation problems. RSSI measurements by themselves result in poor estimates of location due to multipath interference [5]. Neural networks are capable of modeling the relationship between signal strengths coming from a terminal whose location is to be estimated, and the position of that terminal. NNs employ a non-linear transformation of each unit and a if a sufficiently large number of weights are employed a NN can model the RSSI fluctuations. In order to specify the weights, a learning strategy is required. The learning strategy starts from a set of labeled examples to construct a model that will then generalize.

In the standard multi-layer perceptron (MLP) architecture shown in Figure 2, the RSSI values are applied to the input layer, and this information flows sequentially through the hidden layer to the output layer. In each layer, each unit first calculates a scalar product between a vector of weights and the vector given by the outputs of the previous layer. A transfer function is then applied to the result to produce the input for the next layer. The transfer function for the hidden layer is the sigmoidal function, and each unit at the output layer is a linear unit with real outputs. Weight parameters between input layer and hidden layer, and hidden layer and output layer are denoted as v_i and w_j, respectively. s_i and h_j are input and hidden layer stimuli. The transfer functions are

$$f(x) = 1/(1+e^{-x}),\ where\ x = \textstyle\sum_{i=1}^{i=I} v_i s_i, \quad (1)$$

$$f(x) = x = \textstyle\sum_{j=1}^{j=H} w_j h_j, \quad (2)$$

where I and H are the number of input and hidden layer units, respectively.

A network with a single hidden layer is sufficient to approximate any continuous function to any desired accuracy, provided the number of hidden neurons is sufficiently large [8].

4.1 Backpropagation Learning Method

[2] employed a learning technique that uses second-derivative information: one-step-secant (OSS). This research employs a back propagation learning algorithm because the neural network convergence time occurs quickly. The objective is defined as minimizing the difference between target output and estimated output for each training data point. The error function, where (x, y) pair determines the target output and (x', y') pair determines the estimated output, used to estimate the weights of the network is

$$E = \sqrt{(x-x')^2 + (y-y')^2}. \quad (3)$$

5. EXPERIMENT RESULTS AND DISCUSSION

The experiments employed three class-2 Bluetooth USB adapters and Bluetooth ID badges with equivalent specifications. Figure 3 shows the experimental space. It has dimensions of 300cm×300cm with 75cm×75cm grids. The locations of Bluetooth USB adapters (BUAs) are denoted by s_i, $i = 1, 2, 3$, and the (x, y) coordinates of the BUAs are as follows: $s_1 = (300, 300)$, $s_2 = (300, 0)$ and $s_3 = (0, 0)$. In Figure 3, $L1, L4, L11, L18$ and $L21$ are test locations and $L2, L3, L5 - L10, L12 - L17, L19, L20$ and $L22$ are training locations.

The experiments involve three different test areas depending on the triangle defined by three BUAs located on three corners of the experiment area. The area inside this triangle is denoted by A_1, the virtual line that connects s_1 and s_3 is denoted by A_2, and the area outside the triangle is denoted by A_3.

5.1 Training

The NN was trained to learn between 1 and 17 locations, shown as blue dots in Figure 3. Adding training locations one by one to the training set shows the effect of the training sets inside and outside of the triangle formed by the three Bluetooth USB adapters. The experiment began with the locations inside of the triangle and continued through the locations outside of the triangle.

Figure 4 shows the average root mean square (RMS) error for training locations at the first and 300th iterations with respect to location indices. According to this figure, adding locations outside the triangle to the training set causes an increase in average RMS error. Figure 4 also shows that the RMS error after the 300th learning iteration is less than the RMS error after the first learning iteration.

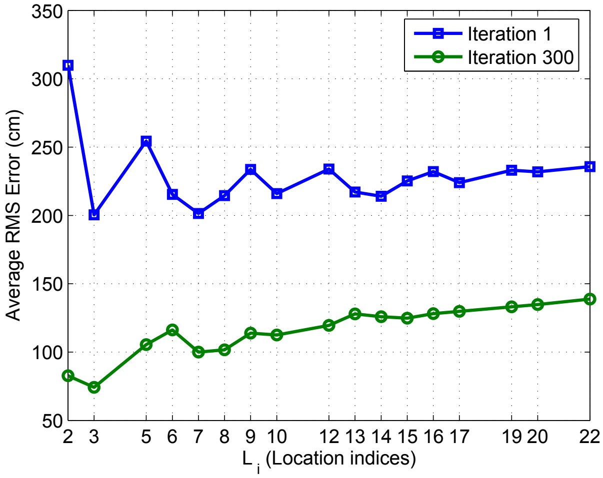

Figure 4: Average error vs. trained locations

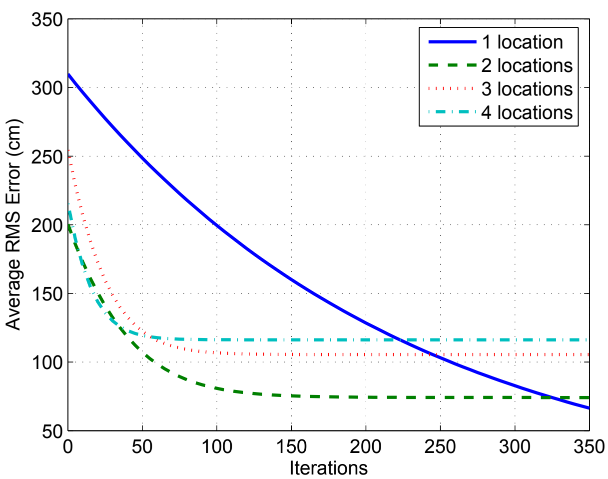

Figure 5: Average error vs. training iterations

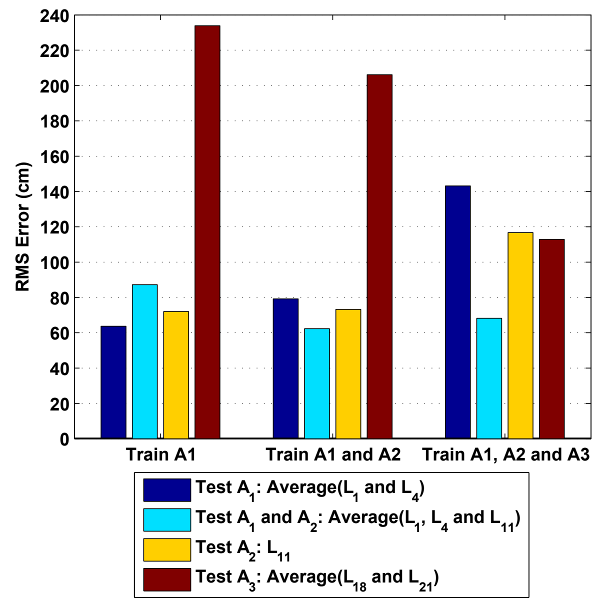

Figure 6: Testing errors under different training conditions

Figure 5 shows the behavior of the RMS error with respect to the number of iterations in the training process. According to this figure, as iterations increase, RMS converges to a horizontal asymptote that increases as a function of the number of training locations used. This increase is also a result of adding training locations one by one as explained above.

5.2 Testing

Testing employed 5 locations $(L1, L4, L11, L18, L21)$ both inside and outside of the triangle to show the effect of the training set and triangulation. Figure 6 shows testing errors under three different training conditions. In the first case, the network is trained on only the locations in training area A_1. In the second case, the network was trained using the locations in training areas c and A_2. In the third case, all locations in A_i, i= 1, 2, 3, are used to train the network. Testing locations are not included in the training set for any case. For these three cases, we test for locations in A_i, i= 1, 2, 3. As expected, RMS error for testing in A_3 decreases with the addition of more locations to the training set. This is also true for test errors for A_2 due to the fact that the neural network knows the difference between the locations in A_1 and A_3, and has a better understanding of the intersection area, A_2. However, RMS error for testing the locations in A_1 increases with the addition of locations in A_2 and A_3. Increasing errors occur because with the addition of more locations the NN modifies its weights so that the estimation error on the average is less. This causes more errors for the locations in A_1, but fewer errors for the locations in A_3.

Figure 7 demonstrates that the average RMS errors for locations in A_1 and A_2, are 87cm when the training set has only locations in A_1, but 62cm when the training set has locations in both A_1 and A_2. The results obtained are fairly accurate compared to the size of a person. However, the

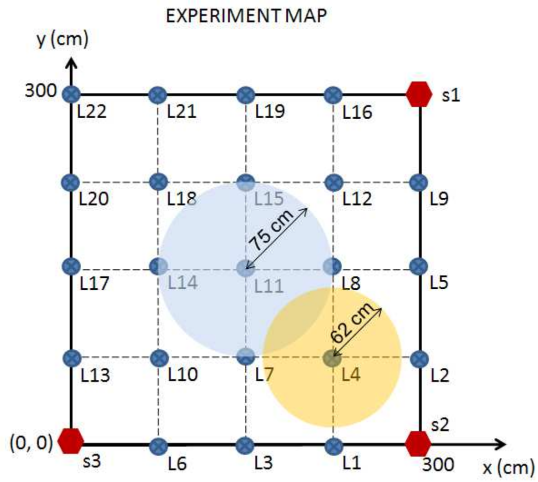

Figure 7: Errors on experiment map

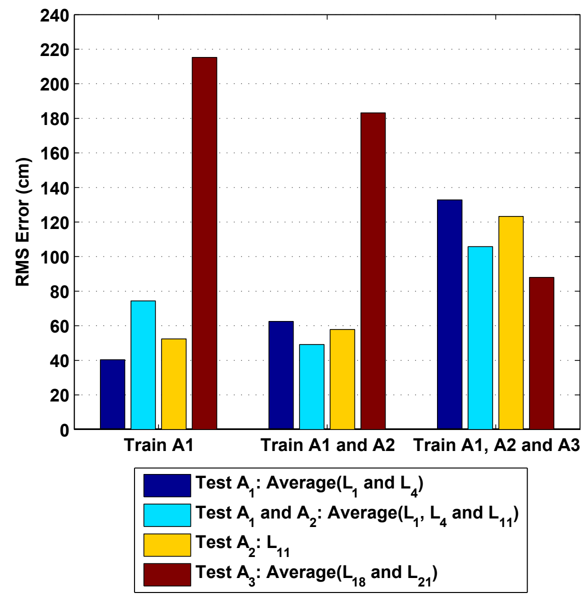

Figure 8: Testing errors with radial representation of outputs

errors are large enough that a person could be located on the opposite side of a wall. We would like to reduce the error to less than the thickness of a wall, so that a person who is standing near a wall will be located correctly. Also it is imperative that the location being detected be within the triangle. However, this requires covering a service area with multiple triangles.

In the previous experiments the RSSI information collected from the three Bluetooth USB adapters and the neural network produce a location estimate in (x, y) coordinates. Changing the output representation from Cartesian coordinates to radial coordinates can produce more accurate results. In this experiment, the neural network has again two outputs; the first output is the distance between a location L and the origin of the experiment area (0, 0), and the second output is the angle between the x-axis and the line connecting origin and L.

Figure 8 demonstrates the performance of the experiments done with Radial representation of outputs. Comparison of Figure 6 and Figure 8 shows that Radial representation performs better than Cartesian representation on the average. Observe also that the most accurate estimate has been improved from an RMS error of 62cm to 50cm for test locations in A_1 and A_2 when the neural network is trained by locations in A_1 and A_2.

6. CONCLUSION AND FUTURE WORK

Estimating the location of a Bluetooth device in an area that has two dimensions requires at least three BUAs. Because random variations due to multipath effect may be independent increasing the number of BUAs may not reduce localization error. This causes a limitation on the placement of the BUAs. Obviously, we expect less error for the localization of Bluetooth devices inside the triangle than for those outside the triangle. Therefore, BUAs must be placed so that the area inside the triangle formed by three BUAs is maximized. Alternatively, if localization depends on other objectives such as security, this argument can be changed so that BUAs must be placed so that the service area is inside the BUA triangle to maximize the estimation accuracy. Also, a denser training grid on the service area may improve the accuracy. When a larger space needs to be covered by a network, the tessellation of the space may be important. In this case, the tessellation of the service space must be arranged so that the placement of Bluetooth USB adapters minimizes the estimation and detection errors.

Future work can be organized into three parts: neural network related steps, steps related to information that can be used for location estimation, and tessellation of the service space. The effect of the number of hidden layers, representation of input and output information of the neural network, and the number of units used in a hidden layer require further exploration. We showed that the representation of outputs in the neural network affects the performance, but finding a better representation form is still an open problem. Also, increasing the number of hidden layer units, or the number of hidden layers in the neural network, may provide a better learning capacity to the neural network, which should, in turn, lead to better results. Location estimation techniques can use a map of the experiment area, such as walls, cubicles, doors, along with the location related information. Incorporation of a building diagram combined with RSSI to improve location estimation is another step for future work. Combining more than one type of location related information, such as RSSI and TOA, and employing a sequence of location estimates to better estimate the position of moving devices, are other things to be explored. Finally, we will expand our work from two-dimensional location estimation to three-dimensional location estimation to provide more realistic estimates.

7. REFERENCES

[1] P. Bahl and V. N. Padmanabhan. Radar: An in-building rf-based user location and tracking system. In *IEEE INFOCOM 2000*, pages 775–784. IEEE, March 2000.

[2] R. Battiti, A. Villani and T. L. Nhat. Neural network models for intelligent networks: deriving the location from signal patterns. 2002.

[3] Bluetooth technology.

[4] P. Castro, P. Chiu, T. Kremenek and R. Muntz. A probabilistic room location service for wireless networked environments. In *Ubicomp 2001: Ubiquitous Computing, Springer*, pages 18–34, 2001.

[5] F. Gustafsson and F. Gunnarsson. Mobile positioning using wireless networks - possibilities and fundamental limitations based on available wireless network measurements. *IEEE Signal Processing Magazine*.

[6] A. Harter, A. Hopper, P. Steggles, A. Ward and P. Webster. The anatomy of a context-aware application. In *MOBICOM 1999*, pages 59–68, August 1999.

[7] J. Hightower, G. Borriello and R. Want. Spoton: An indoor 3d location sensing technology based on rf signal strength. In *The University of Washington, Technical Report: UW-CSE*, February 2000.

[8] K. Hornik. Approximation capabilities of multilayer feedforward networks. *Neural Networks*, 4(2):251–257, 1991.

[9] N. B. Priyantha, A. Chakraborty and H. Balakrishnan. The cricket location support system. In *MOBICOM 2000*, pages 32–43, August 2000.

[10] J. Proakis and M. Salehi. *Communication Systems Engineering*. Prentice Hall, Upper Saddle River, NJ, 2002.

[11] R. Want, A. Hopper, V. Falcao and J. Gibbons. The active badge location system. *ACM Transaction on Information Systems*, 10.

[12] A. Ward, A. Jones and A. Hopper. A new location technique for the active office. *IEEE Personal Communications*, 4.

[13] J. Werb and C. Lanzl. Designing a positioning system for finding things and people indoors. *IEEE Spectrum*, 35.