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A NEURAL METHOD FOR IDENTIFYING TRANSMISSION SOURCE LOCATIONS

Thomas L. Hemminger, Penn State, Behrend, Erie, PA USA
David R. Loker, Penn State, Behrend, Erie, PA USA
Carlos Pomalaza-Raez, Indiana Univ.-Purdue Univ., Fort Wayne, IN USA

ABSTRACT

In recent years, there has been great interest in node localization within low-power communication networks. These technologies include Bluetooth, GPS, IEEE 802.11, and other transmission protocols. Most techniques are based on variations in the RF signal-to-noise ratio, but this paper introduces a new method, which employs packet statistics. In this work, packet information was collected from several stationary clients while moving a portable server and access point. Packet statistics and the corresponding server locations were subsequently used to train neural networks. Our studies have shown that the networks can determine the location of additional transmitters based on the packet histories of the stationary clients.

I. INTRODUCTION

Recent advances in wireless technology have sparked a growing interest in node localization in high speed, low-cost wireless networks [1], [2]. These may include emergency, military, and commercial transmissions. Determining the location of a transmitter can have several applications. For example, it can be used to determine the location of an autonomous vehicle, i.e., robots [3], [4], or it may be used as a security device for locating an intruder [5], [6]. The problem increases in complexity when addressed within buildings or other large structures. Infrared and ultrasonic techniques have been studied but are limited to line-of-site coverage, which severely restricts their applicability [7], [8]. Recently, the abundance of mobile communication systems and the development of high-speed low-cost wireless networks have yielded new prospects for localization schemes. Cell phone technology and GPS can be applied in outdoor applications but are not generally reliable within large buildings [9], [10]. Most techniques discussed in the open literature are based on an analysis of receiver signal-to-noise ratio but this is normally based on the RF signal strength [11]-[13]. One well-known approach is RADAR, which is an RF system (802.11) for locating and tracking users within large structures [14]. This procedure determines user location by combining signal strength measurements with signal propagation models. Several algorithms have been developed for IEEE 802.11 and/or Bluetooth technologies, which include triangulation, Hidden Markov Models, Monte Carlo, and Bayesian statistics [15]-[19]. One of the more challenging problems when relying on signal strength is its unpredictability. RF signal strength within buildings is affected by multipath propagation effects and absorption, resulting in non-linear behavior. One method of addressing multipath effects is to implement a RAKE receiver. However, this requires estimates of tap weights based on characteristics of the channel model and adds cost and complexity to the system [20], [21]. In this paper, we endeavor to determine the location of a server from the packet statistics recorded on several geographically dispersed clients. The data is then used to train a set of feedforward neural networks which can be consulted later to determine the location of other servers in the test area. For this work, we considered both the IEEE 802.11 and Bluetooth protocols because of their enormous popularity in the wireless domain, but decided on the former because of the greater fluctuations in link quality inherent in Bluetooth [16].

This paper is organized as follows. Section II presents some details on 802.11b as they relate to this project. Section III describes the experimental procedure and Section IV outlines how packet data is used to train the neural network. Section V presents our results and we conclude the paper in Section VI.

II. IEEE 802.11B STANDARD

For this experiment, a Cisco IEEE 802.11b compatible wireless local area network (WLAN) using the infrastructure mode was established with one access point and seven stations, where one station acted as the server and the other six stations as clients. A TCP network connection was created between the server and each client. A Cisco Aironet wireless LAN adapter diagnostic utility provided receive and transmit statistics for each client. Of the 42 parameters afforded by this software, we determined that 13 provided significant measures of signal quality and are listed in Table 1. It can be argued that these are not independent measures, but they do provide a diverse set of parameters that incorporate the effects of CRC checks, packet acknowledgements, and retransmissions.

Table 1: Packet statistics exhibiting sizeable variation with server movement

Receive Statistics	Transmit Statistics
Bytes Received	Bytes Transmitted
Beacons Received	Ack Packets Transmitted
Total Packets Received OK	RTS Packets Transmitted
Duplicate Packets Received	CTS Packets Transmitted
PLCP CRC Errors	Packets Deferred Energy Detect
PLCP Format Errors	Packets No Ack Received
MAC CRC Errors	

The RF signal-to-noise ratio was also recorded as the 14th datum. Trend analysis of this data revealed a considerable level of correlation and a matrix rank ≈ 6, meaning a strong

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level of dependence. Therefore, we computed the correlation coefficient matrix R to determine which of the 14 candidate functions yielded the least independent information, where $r_{ij} = C_{ij} / \sqrt{C_{ii} C_{jj}}$, and C is the covariance matrix. This is not exhaustive and there is a risk of eliminating some salient features provided in the software if further pruning is performed.

For this reason an additional avenue was exploited to help verify these results by looking at the problem from a signal subspace point of view. A signal matrix X can have the eigendecomposition

$$X = \sum_{i=0}^{p} \lambda_i \, v_i \, v_i^T \tag{1}$$

where λ_i is an eigenvalue, v_i is the associated eigenvector, and T represents the transpose. It is well known [22] that a matrix with rank $M < p$ will have p-M eigenvalues equal to zero. The eigenvectors associated with the non-zero eigenvalues are considered as principle eigenvectors and span the signal subspace. For this application we computed the singular value decomposition (SVD), retaining all M non-zero singular values.

$$X = U \Sigma V^T = \sum_{n=0}^{M} \sigma_n \, u_n v_n^T \tag{2}$$

The ratio of the largest singular value to the smallest is known as the condition number. Each of the aforementioned measurements was systematically removed, the SVD computed, and the condition number determined. There was no significant reduction in this value when reducing the number of measured parameters below eight. From (2) it is easy to see that

$$X V = U \Sigma V^T V = U \Sigma = \sum_{n=0}^{M} \sigma_n \, u_n \tag{3}$$

providing a matrix transformation of rank ≈ 6, though the extra pre-processing and merging of input data is not necessary here. The relevant parameters retained from both of the correlation tests of server-client software are listed in Table 2. Based upon the IEEE 802.11b standard, the Medium Access Control (MAC) sub-layer frames each packet with sub-layer headers (containing a frame control field and address information) and a trailer containing a CRC character. There are three types of frames: Control, Management, and Data. Several types of control frames include Request-to-Send (RTS), Clear-to-Send (CTS), and Acknowledge (ACK). The RTS/CTS mechanism reserves the medium in advance of the actual transmission of the frame. The ACK control frame is used to indicate successful reception of each frame. If the sender does not receive the ACK by an expected time, it will infer that a collision has occurred and re-send the frame. In addition, as a method of clear channel assessment, if a sender detects RF energy, it will delay sending that packet.

The receive statistical information shown in Table 2 includes the number of all packets (synonymous with frames) that were successfully received, the number of packets that contained a CRC error in the data portion of the packet, and the number of bytes of data successfully received. The transmit statistical information shown in Table 2 includes the number of bytes of data successfully transmitted, the number of acknowledge packets transmitted in response to received unicast packets, the number of packets transmitted that failed to receive a corresponding acknowledge packet, and the number of packets delayed from being sent immediately because RF energy was detected.

Table 2: Packet Statistics with Lower Interdependency. The alphabetical symbols are used later for reference. The SNR has been included here.

Receive Statistics	Transmit Statistics
(a) Bytes Received	(d) Bytes Transmitted
(b) Total Packets Received OK	(e) Ack Packets Transmitted
(c) MAC CRC Errors	(f) Packets Deferred Energy Detect
(s) SNR	(g) Packets No Ack Received

III. Experimental Procedure

This work was performed in the Engineering Complex at Penn State Erie, The Behrend College. The experiment was conducted on the upper floor, which consists of several laboratories and a large open walkway. Six Pentium-class computers were used for our experiments, all running the Cisco utility. A laptop computer was configured as a server and placed immediately adjacent to the access point. Both of these units were placed on a mobile cart, while all the clients were integrated into stationary desktops. Transmission points in the corridors are thought to be more relevant for this work rather than those restricted to isolated offices (see Fig. 1). Paper size is A4 (297 × 210 mm). The margins and other strategic information are presented in Table 1.

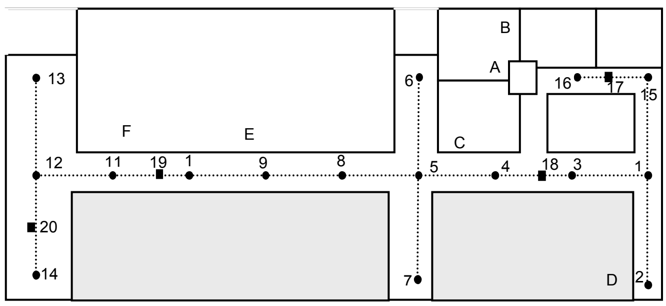

Fig. 1. Upper floor of the Engineering Complex. Shaded areas are open to both floors. The circles (1-16) represent initial transmission points equally spaced by 20 feet (6.1 m), the receivers are designated by A-F. The boxes (17-20) indicate positions of additional transmission points. Dotted lines indicate the original acquisition path; however, the acquisition order is not critical.

The building has three access points for entry to a local academic wireless network. The signals between these access points and their wireless clients share the same region of the spectrum as the wireless devices used in this experiment and as such, they cause interference. This interference has been implicitly taken into account since the data used in the analysis has not been pre-processed to filter out or decrease its influence. A more serious type of interference would be the presence of one or more mobile servers attached to the same wireless network since these would alter the statistics of the data. This unusual configuration having one mobile server/access point and six stationary clients was chosen to facilitate our experiments with the equipment at hand.

For this experiment we allowed the clients to accumulate packet information over a two-minute period to provide a statistically significant database. However, in practice it would likely be better to employ a moving average method similar in concept to FIR filters. Preliminary tests showed that plots of all relevant measurements were reasonably smooth, and well behaved, which introduces the possibility of interpolating the measurements to provide a larger training set for the neural networks. It is well known that feedforward neural networks require a sufficient number of training sets in order to provide a solution set that spans the output space. There are techniques that address this issue, e.g., cross-validation, but we have decided to enhance the number of input patterns with cubic spline interpolation. Details of this procedure are included in Section IV. We spaced our transmission points uniformly at 20-foot (6.1 m) intervals as shown in Fig. 1. The locations of the clients A-F are also shown. The server was positioned at the first transmission site, all packet statistical accumulations were reset, then the packet characteristics (Table 2) were recorded along with the signal-to-noise ratio (SNR). The noise power was approximately the same at all client locations, i.e., -92 dBm and was not recorded. The data was stored at each receiver and the procedure was repeated at all subsequent sites for a total of 16 sets of measurements. Once the experiment was complete, the information from several sample locations was downloaded to Excel and visually inspected to identify trends and similarities. Some information was unaffected by moving the server, and hence irrelevant, while others displayed significant variation. As stated in Section II, thirteen of the 42 packet statistics varied substantially during the experiment but we did expect redundancy in the sets. After adding in the SNR from the RF signal strength we analyzed these 14 parameters from each computer and determined that, at most, eight of these points should be retained.

One important factor to consider is the number and placement of clients. Many, but not all, localization techniques require three positional measurements. With our system, we were initially uncertain what the lower limit was on the number of clients. In principle, it is conceivable that one client would be sufficient to estimate the location of the mobile access point, since each coordinate in the building should have a unique "signature" due to constructive and destructive multipath propagation effects. In this regard, we feel that concentrating on packet statistics and identifying the signal patterns at the receivers is a novel approach to the localization problem. Another issue is the problem of client placement. For the greatest performance and robustness, it is appropriate to space the receivers as far as possible from each other while remaining within a reliable transmission range. However, this is not always feasible and can be highly dependent on the available facilities. For this reason, we chose to use a format that was best suited to the Ethernet access points in our building, which would more likely be representative of a real situation. The locations of the receivers are illustrated in Fig. 1. Many LANs employ one stationary access point to service several communication nodes. Unfortunately, use of a fixed access point eliminates the ability to triangulate on the server, hence each client would receive the same packet statistics and SNR from the access point and positional information would be lost.

IV. NEURAL NETWORKS

Neural networks have become popular in several engineering fields and appear to be a logical approach to this problem since they are particularly well suited in solving non-linear problems. We begin by recording packet statistics, SNR, and the x-y coordinates of the access point at N locations. We next create an 8-tuple input vector $v_i = \{a_i, b_i, c_i, d_i, e_i, f_i, g_i, s_i\}$ and output vector $o_i = \{x_i, y_i\}$, where $i \in N$ is the position index, a – g are the packet parameters described in Table 2, and s is the SNR. The next step is to train the network for all $\{v_i, o_i\}$ pairs. The locations of all N transmission points are shown in Fig. 1. Feedforward neural networks require inputs, v_i, and outputs (targets) o_i for the purpose of developing a mapping from input to output space. This is frequently a non-linear process, requiring the ability to determine the relevant discriminates necessary to create classification boundaries. Each of the six clients was provided with its own training set, i.e., six networks (A-F) were trained individually on their respective input/output patterns.

Normally, one would consider gathering a large data set to describe the signature of a building, but we decided to utilize a minimal number of points to determine whether our procedure would be efficacious when applied in other environments. Sixteen data points were decided upon mainly because they mapped the engineering complex reasonably well at 6.1 m intervals. This is clearly an insufficient number of training sets to yield a reliable neural network. Studies have shown that sparse sets can produce unpredictable results during the consultation mode. Therefore, we interpolated the data from each measurement statistic of each transmission location, producing a much larger set of training patterns.

All sixteen observations were used to perform the interpolation mentioned above but none of them were used to train the networks, in order to reduce bias. Each measurement statistic (Table 2) was interpolated yielding 134 synthetic training sets corresponding to measurements taken at two-foot (61 cm) intervals. It is certainly understood that interpolation can yield unpredictable consequences and should be used with caution. All inputs were submitted to their respective neural networks along with target values corresponding to the rectangular coordinates of the server and each was trained separately. We experimented with several small networks but the number of hidden layers and nodes (transfer functions) were eventually determined by trial and error. This yielded nine nodes in one hidden layer and two nodes in the output layer corresponding to the rectilinear coordinates of the server. The nodes in the hidden layer were sigmoidal (hyperbolic tangent) to accommodate the non-linear characteristics of the problem, and the output nodes were linear.

The maximum output value of the sigmoidal function is ± 1, so all target values were normalized by the greatest distance traversed by the transmitter (48.8 m) to enable convergence. It is possible that neural network topology is dependent on the layout of the environment being modeled, meaning that the network structure is likely to be problem dependent. During the training session, we presented each network with 134 synthetic sets of input and target vectors, covering most of the engineering complex. Approximately 600 training epochs were required to reach the designated error criterion of 10^{-4}. At this point the original data points were introduced as controls to test the networks.

V. Results and Discussion

In this section we discuss the results of our experiments. The nature of this building is conducive to the production of constructive and destructive interference, i.e., multipath propagation. For this reason we feel that a neural network approach is appropriate to map out the radio signatures of the server. In addition, each client can relay its packet statistics to a central node, enabling identification of the mobile unit. In order to merge the contribution of each network, it is necessary to combine the output (x-y pos.) from each, yet averaging them affords undue influence from receiver networks positioned further from the server, possibly skewing the results. To compensate, a Gaussian weighting function was employed to reduce the effects from distant clients. The expression is shown here

$$w_i = Exp\{-[(x_i - x_i')^2 + (y_i - y_i')^2]/k\} \qquad (4)$$

where (x_i, y_i) are the coordinates of the client and (x_i', y_i') are the output of that specific network. The spreading factor was determined empirically to: $k = 2$. The 16 measured values were applied to the networks and the weighted results are shown in Fig. 2. The circles represent the true locations of the server and "+" shows the estimated locations using the weighted average (4). Most of the locations along the main corridor are mapped well by the network, although the greatest difficulty is at locations 1, 2, 6, 7, 13, and 14. This is not surprising because neural networks typically attempt to develop smooth output transitions and these specific locations approach discontinuities. We expected the 16 measured points to provide an acceptable outcome since the synthetic data was derived from them. This is verified in Fig. 4. Here, a single network near the target location usually provided satisfactory results. It is logical that an entirely new data set would provide a lower level of correlation between the neural network outputs and the true target positions. To test this, we measured packet statistics from four additional locations one week later to determine whether the network would be able to predict transmitter position with any degree of accuracy. We also deliberately chose locations that were not identical to those from the previous set of measurements.

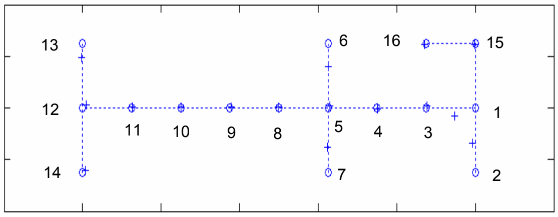

Fig. 2. Position predictions for the 16 original transmitter locations. Circles indicate true locations and "+" represents weighted centroids from the contributions of all networks. The locations match those in Fig. 1. Dotted lines indicate original acquisition path. Each transmission point is separated by 6.1 m.

As expected, the results from the four additional sets were not as good as with the former set so we included a median filter at the output to reduce the effects of outliers. The predicted positions are illustrated in Fig. 3 where the error ranges from 1.02 m at location 20 to 3.5 m at 17. Location 17 is contained within a narrow hallway with many reflective and absorbing materials so this is not unexpected. We feel that these results are significant in that they demonstrate an ability to identify the source within a reasonable margin, yet requiring a minimal training set.

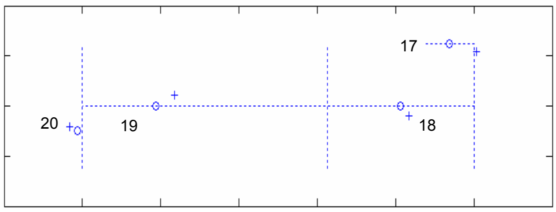

Fig. 3. Position predictions of four additional test points. Circles indicate true locations and "+" indicates system output.

Using the interpolated data was beneficial to demonstrate the effectiveness of our method but in practice it would be preferable to start with a larger data set. Here we assume that the data is smooth and well behaved (as we observed), yet it is certainly possible and likely that significant features could be overlooked. Another issue from Section II deals with the number of elements within input vector v. More study is necessary to determine which parameters have smallest influence on the training patterns so that the dimensionality of the input space can be reduced. Finally, some of the packet statistics seem to have substantial influence on network behavior which needs to be explored, e.g., MAC CRC errors and Packets No Ack received, because variations in these can significantly influence the output.

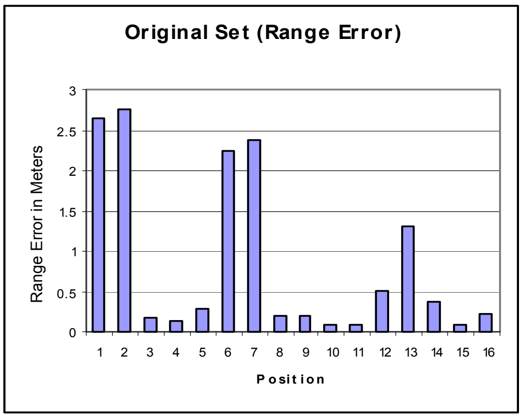

Fig. 4. Range error of system from the original 16 locations using median filter.

VI. Conclusions and Further Work

For the initial phase of this research we concentrated on pattern analysis of a large 2-D model of a building. Although we have dealt with a specific structure it is logical to assume that our methodology can be extrapolated to other complexes. Accurate measurements are very important in this work and a key element is the passive nature of our system. The technique we have described uses state-of-the-art technology while maintaining low cost. The neural networks are trained off-line and require very little computational or transmission overhead during the consultation phase. Clearly there is substantial correlation between the packet statistics and the RF signal strength, but our method focuses on the former in an effort to gather additional attributes. We have noted that RF energy from other sources could influence the results illustrated here although it is very likely that it would affect all clients, meaning that it should have minimal influence on the reception patterns. The most likely explanation for the promise of this approach is that it provides multiple measures, either directly or indirectly, of the SNR at the receiver, which is dependent on server position, and the multipath nature of the building. The result is an improved value of signal strength not directly available in these inexpensive transceivers. To our knowledge this is a new technique that may have the potential to be used in a variety of settings. A nice feature of this scheme is that it does not require any modification or additions to existing technology. An extension of this work will be to determine precisely which of the packet statistics are necessary to provide reliable parameters for position indication.

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