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Adaptive Probabilistic Model Using Angle of Arrival Estimation for IoT Indoor Localization

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Abstract—The industrial demands for accurate localization systems have been rapidly increasing after the introduction of the Internet of Things (IoT) concept. Self localization and tracking transmitting sources are considered essential parts of IoT applications.

In this paper we studied the possibility of applying angle of arrival (AoA) estimations to localize an IoT transceiver device in an indoor environment. Furthermore, we propose an adaptive probabilistic model which works on top of the AoA estimation technique to improve the localization accuracy. The experimental results show the potential of using AoA-based localization for indoor environments. The results furthermore show that the proposed adaptive probabilistic model outperforms the traditional static probabilistic model in terms of the localization accuracy and the stability of the position estimate.

Index Terms—Internet of Things IoT, indoor localization, Angle of Arrival AoA estimation, adaptive localization probabilistic models, MVDR algorithm.

I. INTRODUCTION

For decades, indoor localization techniques have drawn a great deal of attention, either for tracing and positioning systems or for improving the performance of communication systems. Ever since the introduction of the Internet of Things (IoT) concept, long-range transmission and localization with minimum power consumption have been considered as essential parts for IoT developments [1]. Low power communication standards such as DASH7 [2] or Low Power Wireless Area Network (LPWAN) standards such as LoRa [3] or Sigfox [4], have recently gained significant interest from the industry, because of their capabilities in long range communication with minimal power consumption. This is possible due to the fact that IoT devices are usually required to transmit only small amounts of information, and in turn they do not need large operating bandwidths. There are many methods that have been used for localization systems such as [5] (but not restricted to), Received Signal Strength (RSS), Time of Arrival (ToA), Time Difference of Arrival (TDoA) and Angle of Arrival (AoA) estimation. Due to the IoT signal's small bandwidth and transmitted power, the AoA-based localization technique seems suitable for such applications.

Over the years, many Angle of Arrival (AoA) estimation techniques have been proposed. In general, there are four main kinds of algorithms; techniques based on optimal beamforming [6], techniques relying on signal and noise subspaces [7], [8], probabilistic approaches using maximum likelihood (ML) [9], and methods applying sparse representations [10], [11].

The optimal beamformer minimizes the output power of the undesired interference, while maintaining a constant gain along the look direction. The implementation of this algorithm is reasonably simple, while the estimation accuracy of it depends on the number of snapshots and the array size. On the other hand, the subspace-based algorithm exploits the signal subspace of the input covariance matrix of the received signals. There are two well-known techniques using the subspace-based algorithm: the MULTiple Signal Classification (MUSIC) [7] and the Estimation of Signal Parameters via Rotational Invariance Technique (ESPRIT) [8]. MUSIC and ESPRIT techniques consider the eigen-structure of the input covariance matrix to decompose the observation space into a signal subspace and a corresponding orthogonal noise subspace. Although both MUSIC and ESPRIT are considered super resolution estimation techniques, their estimation performance degrades rapidly in estimating correlated sources. The performance of the ML method is superior to the optimal beamformers and subspace-based algorithms, in low Signal to Noise Ratio (SNR) conditions or with a small number of snapshots. It performs well in correlated signal conditions. On the other hand, ML algorithms are usually computationally intensive due to the iterative nature of the parameter searches involved. Recently, the sparse representation algorithm drew great attention in the AoA estimation field, which not only improves the AoA resolution performance, but also can be applied to a small number of snapshots and highly correlated or even coherent signals. Though, the sparse representation methods depend heavily on convex minimization techniques, which in some cases require a significant amount of computing power.

In this paper we applied an adaptive beamforming AoA estimation technique to localize an IoT transceiver device in an indoor environment using an adaptive probabilistic model on top of the AoA estimations to improve the localization accuracy. The IoT transceiver is a small USB device implemented

TABLE I: DASH7 Classes

Class	Symbol Rate	Modulation Index	Δf
Lo-Rate	9.6 kbps	1	9.6 kHz
Normal	55.555 kbps	1.8	100 kHz
Hi-Rate	166.667 kbps	0.5	83.334 kHz

with the DASH7 Alliance Protocol using a low-power sub-1 GHz RF frontend.

The remainder of the paper is structured as follows: In section II, an introduction of the DASH7 protocol will be presented. The basic data model of the Uniform Linear Array (ULA) system will be introduced in section III. Section IV presents the adaptive AoA estimation method that has been used in this paper. In section V, the proposed adaptive probabilistic localization model for AoA estimation will be introduced. A description of our experiment will be presented in section VI. In section VII, the experimental results are presented. Finally, in section VIII, the conclusions and the future works will be discussed.

II. DASH7 ALLIANCE PROTOCOL

The DASH7 Alliance Protocol (D7AP) is an industry alliance standard for wireless sensor and actuator communication over unlicensed Sub-1 GHz bands specified and promoted by the DASH7 Alliance [12]. Below we will present some of the DASH7 system parameters [13].

A. Air Interface

D7AP RF signals are formed by applying a Gaussian Frequency Shift Keying GFSK modulation scheme which can be expressed as

$$g(t) = Ae^{(i2\pi(f_c t + \Delta f \int_0^t \frac{m(\alpha)}{m_p} d\alpha))} \quad (1)$$

where A is the transmitted signal's amplitude, f_c is the carrier frequency, Δf is the frequency deviation of the FSK signal, m_p is the baseband signal's amplitude, and $m(\alpha)$ is the transmitted digital signal with a Gaussian shape filter response. According to the D7AP specification, the DASH7 signals can be categorized into three Channel Classes with different parameters as shown in Table I.

B. Packet Structure

The D7AP signal is a Data Aided signal, which means that there is a unique data set that will be transmitted at the beginning of the transmission and that it is well known by the receiver. Figure 1 illustrates the packet structure of the D7AP, which contains a Preamble, a Sync Word, and a Payload. The Preamble is a series of binary symbols (max 64 bits) of 10101..., used for the purpose of calibrating data rate circuits on the receiver. The Sync Word is a block of 16 binary symbols used to align the packet payload. The packet payload contains encoded data. Additionally, power ramp-up and ramp-down periods may precede and follow the packet, these periods should be kept as short as possible, used for the purpose of meeting the channel stopband requirements.

Fig. 1: DASH7 Packet Structure [13]

III. DATA MODEL

At the receiver, and after tuning the local oscillator (LO) with the carrier frequency of the received signal, the received digital baseband signal can be expressed as:

$$x(k) = A_r e^{(i(2\pi\Delta f \sum_0^k \frac{m(\alpha)}{m_p} + \phi_e))} \quad (2)$$

where A_r is the received signal's amplitude, k is the digitized time index and ϕ_e is a constant arbitrary phase due to the phase difference between the transmitter and receiver. The demodulation process of the received signal can be illustrated as follows:

- 1) Extracting the phase $\Phi(k)$ of the baseband signal

$$\Phi(k) = 2\pi\Delta f \sum_0^k \frac{m(\alpha)}{m_p} + \phi_e \quad (3)$$

- 2) Taking the derivative of $\Phi(k)$

$$\frac{d\Phi(k)}{dk} = 2\pi k_f m(k) \quad (4)$$

where k_f is the frequency sensitivity and it is equal to

$$k_f = \frac{\Delta f}{m_p} \quad (5)$$

the derivative of the digital form of the phase $\Phi(k)$ is performed as:

$$\frac{d\Phi(k)}{dk} = \Phi(k) - \Phi(k-1) \quad (6)$$

- 3) Time synchronization and bits decimation must be performed.
- 4) Payload detection based on the Sync Word bits.
- 5) To decode the payload data, further data de-whitening and FEC decoding (optional) are required.

In the presence of an Uniform Linear Array (ULA) Antenna system at the receiver side, the received signal vector can be expressed as:

$$\mathbf{x}(k) = [x_1(k) \dots x_n(k) \dots x_N(k)]^T \quad (7)$$

in which

$$x_n(k) = A_r e^{(i(\Phi(k) + \psi_n))} \quad (8)$$

where N is the total number of ULA elements and ψ_n is the phase difference between each element in the array with respect to a reference element and equals to

$$\psi_n = \frac{2\pi}{\lambda_c} d_n \cos(\theta_r) \quad (9)$$

where λ_c and θ_r are the received signal's wavelength and AoA, respectively. d_n is the inter element spacing of the receiver antenna array.

The received signals covariance matrix ($\mathbf{R}_{xx}$) is one of the most important parameters in array signal processing [14], because it contains all the required information to estimate the AoA of the received signals. $\mathbf{R}_{xx}$ for zero mean and uncorrelated received signal vector is given by:

$$\mathbf{R}_{xx} = \mathbf{E}[\mathbf{x}^H \mathbf{x}] \quad (10)$$

Where $\mathbf{E}[\bullet]$ is the expected value and H is the conjugate transpose operator.

IV. ANGLE OF ARRIVAL ESTIMATION

The AoA estimation for the radio signal mainly depends on the phase difference measurements between the received signals from different antennas in the receiver antenna array system. One of the most famous adaptive processors in array signal processing is the Minimum Variance Distortionless Response (MVDR) [15]. The MVDR algorithm has been adopted by many researchers for AoA estimation [15]-[18]. To explain the MVDR algorithm, let's consider an adaptive array antenna system as shown in Figure 2.

Fig. 2: Adaptive Array Antenna System Schematic

The array output power is given by:

$$|y|^2 = \mathbf{W}^H \mathbf{R}_{xx} \mathbf{W} \quad (11)$$

Where $\mathbf{W}$ is the complex weight vector and given by:

$$\mathbf{W} = [w_1 \dots w_n \dots w_N]^T \quad (12)$$

Minimizing the output power in Eq.(11) while passing the look direction signal undisturbed leads to

$$\mathbf{W} = \frac{\mathbf{R}_{xx}^{-1} \mathbf{c}^*(\theta)}{\mathbf{c}^H(\theta) \mathbf{R}_{xx}^{-1} \mathbf{c}(\theta)} \quad (13)$$

where $*$ is the conjugate operator. Substituting Eq.(13) in Eq.(11) leads to

$$G_{MV}(\theta) = \frac{1}{\mathbf{c}^H(\theta) \mathbf{R}_{xx}^{-1} \mathbf{c}(\theta)} \quad (14)$$

where $\mathbf{c}(\theta)$ is the array steering vector and it is equal to

$$\mathbf{c}(\theta) = [c_1(\theta) \dots c_n(\theta) \dots c_N(\theta)]^T \quad (15)$$

in which

$$c_n(\theta) = e^{(i \frac{2\pi}{\lambda_c} d_n \cos(\theta))} \quad (16)$$

for $\theta = [0 : \pi]$.

V. ADAPTIVE PROBABILISTIC MODEL

Assuming that there is a specific area of interest in which we want to localize a transmitting device, we then divide the area of interest into a grid of points, with each point having a specific location $L_p = [l_p^x, l_p^y]$ with respect to the reference point $L_0 = [0, 0]$. In this position l_p^x and l_p^y are the locations of the point p on the x and y axes, respectively, in a 2D Cartesian coordinate. If there are U AoA estimation units, the u^{th} AoA unit (where $u \in U$) consists of an antenna array system that provides AoA estimations of the received signal. The location of the u^{th} AoA unit is given by L_u .

Combining all the AoA estimates from the U units will provide the estimated location of the transmitter with respect to L_0 . Assuming a Gaussian error distribution on the received signal from each AoA unit, we can define a likelihood function $\mathcal{L}(U|L_p)$ for a measurement U given a position L_p in the grid.

$$\mathcal{L}(U|L_p) = e^{(-\frac{1}{2}(\Theta_U^p - \Theta_U^e)^T \Sigma^{-1}(\Theta_U^p - \Theta_U^e))} \quad (17)$$

where Θ_U^p is the actual AoA vector for each combination of L_p and the AoA units, giving by:

$$\Theta_U^p = [\theta_1(L_p) \dots \theta_u(L_p) \dots \theta_U(L_p)]^T \quad (18)$$

where $\theta_u(L_p)$ can be found by:

$$\theta_u(L_p) = \tan^{-1} \left(\frac{l_p^y - l_u^y}{l_p^x - l_u^x} \right) - \theta_u^0 \quad (19)$$

in which θ_u^0 is the angle between L_u and L_0 . Θ_U^e is the estimated AoA vector and Σ is the distribution's covariance matrix and given by

$$\Sigma = \sigma^2 I_U \quad (20)$$

where σ is the variance of the normal distribution and I_U is identity matrix of size $(U \times U)$.

Now, we can define a posterior probability function for the position L_p given measurement U through Bayes' rule:

$$P(L_p|U) = \frac{\mathcal{L}(U|L_p)P(L_p)}{P(U)} \quad (21)$$

If there is no prior knowledge of the transmitter location, we may assume that $P(L_p)$ is uniform (constant) over the range of values of the parameters. In such a case, the value of L_p that maximizes $\mathcal{L}(U|L_p)$ also maximizes $P(L_p|U)$. Therefore, the $\mathcal{L}(U|L_p)$ and $P(L_p|U)$ estimates are identical.

At first we consider σ to be constant for all AoA units under consideration. That is valid for a static environment with a small multipath effect. For a room environment that suffers severely by the multipath effect, using a fixed σ (as we will show in the results) will not provide an accurate localization.

Based on observing the simulations and experimental results, we formed the following opinion, "the sharper the AoA estimation pattern based on the MVDR algorithm, the more trustworthy the AoA estimation". Figures 3a and 3b show experimental AoA estimations (based on the MVDR algorithm) of the received signal from the angles 92° and 144° , respectively. It is obvious that Figure 3a gives a sharper pattern and more accurate estimations than Figure 3b. The non-sharp pattern in Figure 3b is due to the multipath effect and the fact that the impinging signal arrives close to the end-fire region of the antenna array. From the above argument we propose to use adaptive Σ as follows

$$\Sigma = \begin{bmatrix} \sigma_1^2 & 0 & \dots & \dots & 0 \\ 0 & \ddots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \sigma_u^2 & \vdots & \vdots \\ \vdots & \vdots & \dots & \ddots & 0 \\ 0 & 0 & \dots & \dots & \sigma_U^2 \end{bmatrix} \quad (22)$$

Using the adaptive power pattern provided by the MVDR processor in Eq.(14), we estimated σ_u as

$$\sigma_u = \frac{\alpha \bar{G}_{MV}^u(\theta)}{\max(G_{MV}^u(\theta))} \quad (23)$$

where α is a constant and $\bar{G}_{MV}^u$ is the mean value of the MVDR power spectrum for the u^{th} unit.

VI. EXPERIMENT DESCRIPTION

In order to verify whether the proposed adaptive probabilistic model is capable of estimating the location of the transmitter, we conducted an experiment in a room environment. The dimension of the room is $6.45m \times 9.47m$. We used 3 AoA units distributed in the room as shown in the Figure 4. The transmitter and the AoA unit are described in the following subsections.

A. The Transmitter

We designed a D7AP USB transceiver (see Figure 5), based on EZR32LG Wireless Micro Controller Unit (MCU) [19]. The EZR32LG Wireless MCU's are part of Silicon Labs' range of wireless MCU's delivering a high performance and low energy wireless solution. The frequency ranges from 142 to 1050 MHz and the modulation possibilities are (G)FSK, 4(G)FSK, (G)MSK and OOK.

In our experiment, the USB transceiver transmits a Lo-Rate D7AP signal with a payload length of 20 bytes at Ch0 (i.e Ch0 frequency in Lo-Rate equals to 863MHz). The energy consumption budget is illustrated as follows:

- The current consumption of the transmitter is approximately 27 mA.
- The transmitted message contains 64 bits for the Preamble, 16 bits for the Sync Word and 160 bits as a payload. Because the transmission bit-rate is 9.6kbps, the period of transmission is 25 ms.

Fig. 3: Experimental AoA estimation for two element array antenna with $d = 17cm$. Figure a) represents the AoA estimation for an impinging signal from 92° , while Figure b) represents the AoA estimation for an impinging signal from 144° . It is obvious that the sharper pattern gives a more accurate estimate than the wider pattern.

- The current consumption over time is approximately 0.18 μAh . Since the voltage is 3.3 V, the power consumption over time is approximately 0.6 μWh . This leads to an energy consumption per transmission of 2.2 mJ
- Assuming a coin cell cr2032 battery with 2268 J capacity, then it is possible to have around a million transmissions.
- Assuming there is a transmission every 1 minute, the coin cell battery can last approximately 2 years.

B. AoA unit

Each AoA unit contains two off the shelf USRP's. The Universal Software Radio Peripheral USRP [20] is a Software Defined Radio (SDR) frontend device. The USRP down converts the received signal and sends digitized I/Q baseband samples to the host processing system. There are many USRP products, in our experiment we used the USRP B210. The USRP B210 provides a fully integrated single-board SDR solution with two synchronized RF channels. The B210 covers RF bands from 70 MHz up to 6 GHz and provides up to 56MHz of real-time bandwidth.

Fig. 4: The experiment environment, the red dots represent the AoA units and the black squares represent the transmission points

Fig. 5: The transceiver unit that was used in the experiment

Two B210's were placed on each AoA unit, thus making up two array antennas in each AoA unit. We placed the two array antennas with inter-element spacing d equals to $\frac{\lambda_c}{2}$ for 868MHz band (i.e. $d = 0.17m$), as shown in Figure 6.

Fig. 6: The AoA unit with two array antennas, each array has two elements. The inter-element spacing equals to 0.17 m

TABLE II: The mean estimation error of 30 measurements for the estimated locations in Figure (7). The static probabilistic model operates with $\sigma = 20$ and the adaptive probabilistic model operates with $\alpha = 20$

position	Static model	Adaptive model
1	237 cm	67 cm
2	82 cm	66 cm
3	154 cm	50 cm
4	66 cm	52 cm
5	102 cm	78 cm

VII. EXPERIMENTAL RESULTS

In our experiment, we placed the USB transceivers at fixed locations in the middle of the room (see Figure 4). This choice is based on our experimental study, which shows that, for a localization system of a small antenna array aperture (like the two element array in our experiment), the localization accuracy degrades rapidly in the vicinity of walls and corners.

Figures 7: A-B and 1-5 represent the location estimation based on the static probabilistic model with variance $\sigma = 20^\circ$ and the proposed adaptive probabilistic model with $\alpha = 20$, respectively. The black square in each image represents the actual transmitter location. We conducted 30 measurements per location and the mean estimated error for both the models is presented in Table II. The estimation error is taken as the distance from the exact transmitter location and the maximum intensity point on the probability map, which is basically a maximum posterior estimate of the exact transmitter location. It is obvious that the proposed adaptive probabilistic model outperforms the static probabilistic model by giving a smaller estimation error for all the positions.

To verify robustness of both models with respect to the choice of α and σ , we present the estimation error with different values of α and σ for the adaptive and static probabilistic models respectively in Figures 8a and 8b. From Figure 8a we observe that the effect of α variation for the adaptive model is insignificant, while the variation in σ for the static probabilistic model is significant and there is no optimum value for σ that can perform well for all the locations. Furthermore Figure 8 shows that the adaptive probabilistic model outperforms the static probabilistic model in all the cases.

VIII. CONCLUSION AND FUTURE WORKS

In this paper we studied the possibility of applying the AoA estimation technique to localize an IoT transceiver device in an indoor environment. Furthermore, we proposed an adaptive probabilistic model which works on top of the AoA estimation technique to improve the localization accuracy. Our experiment was conducted in a room of $6.45m \times 9.47m$. The AoA units that have been used in this experiment are constructed of a two element array antenna system with inter element spacing of $d = \frac{\lambda_c}{2}$, while the IoT transceiver is operated at the 868MHz band.

Fig. 7: The location estimations for a room environment based on AoA estimation technique. The black square in each image represents the actual transmitter location. The figures from A to B represent the location estimation using the static probabilistic model when $\sigma = 20^\circ$ and the figures from 1-5 represent the location estimation using the adaptive probabilistic model when $\alpha = 20$. The mean estimation error of each position is presented in Table (II). It is obvious that the location estimation of the proposed adaptive probabilistic model outperforms the static probabilistic model.

The experimental results show the potential of using AoA-based localization for indoor environments. Although the results in the middle of the room give a very accurate estimation, the estimate in the vicinity of the walls and the corners degrade tremendously. This is mostly due to the multipath effect for a small antenna array aperture (like the two element array antenna system in our experiment). For the middle positions the proposed adaptive probabilistic model achieves a sub meter accuracy of all the studied positions, and it is outperforming the traditional static probabilistic model in all the studied positions. In the future we wish to apply a larger antenna array aperture to our adaptive localization system to achieve better AoA estimation, especially in the critical positions in the vicinity of the walls and the corners of the room.

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Fig. 8: Figure a) represents the estimation error versus different α values for the adaptive probabilistic model, while figure b) represents the estimation error versus different σ values for the static probabilistic model. It is obvious that the effect of α variation for the adaptive model is insignificant, while the variation in σ for the static probabilistic model is significant and there is no optimum value for σ that can perform well for all the locations. Furthermore the adaptive probabilistic model outperforms the static probabilistic model in all the cases.

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