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Synchronization of Multiple Independent Sub-Array Antennas: An application for Angle of Arrival Estimation

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Abstract—In this paper we present a new algorithm to synchronize multiple individual receiving sub-array antennas to form an augmented array antenna system. This augmented array antenna has a large antenna aperture that can be used for angle of arrival (AoA) estimations and it provides a better AoA estimation accuracy than the individual sub-array antennas. The proposed algorithm synchronizes the time and the frequency of the different sub-array antennas, using a joint Maximum Likelihood (ML) optimization for a data aided received signal. The phase coherency between the sub-array antennas is achieved by using a combination of the least mean square (LMS) and ML algorithms. The experimental results and the simulation example show that the proposed algorithm 1) is stable in estimating the augmented array antenna pattern, 2) provides more accurate AoA estimations than the individual sub-array antennas 3) has no limitation to the structure of the augmented array antenna in space and 4) converges very fast. Furthermore, the experimental results prove the feasibility of using AoA estimation techniques for Internet of Things (IoT) localization in outdoor environments.

Index Terms—LMS algorithm, ML algorithm, Angle of Arrival AoA estimation, pattern beamforming, array signal processing, IoT Localization, adaptive array antenna systems.

I. INTRODUCTION

The capability, of the array antenna systems, to extract spatiotemporal information from the environment dimensions, made the array antenna signal processing an active research topic for the past decades [1]. The Angle of Arrival (AoA) parameter estimation of the received signal is considered a very important aspect in array antenna signal processing. Knowing the direction of a specific transmitter is crucial information for any communication system. Given this information, the receiver can optimize the reception to the signal of interest and suppress the undesired signals. Furthermore, this information provides the capability for the communication system to localize the transmitted device.

Similar to the discrete Fourier transform (DFT), which discretizes the signal in the time domain to give information about it in the frequency domain, the array antenna does the same in space. It discretizes the received signal in the spatial domain to give information about its spatial wavenumber.

Accordingly, the larger the array antenna aperture, the more spatial resolution can be achieved (i.e. better AoA estimation accuracy). However, the manufacturing process of a large array antenna aperture with fully synchronized and phase coherent RF-channels is very expensive and complex.

Ever since the introduction of the Internet of Things (IoT) concept, long-range transmissions with minimum power consumption are considered essential to IoT developments [2]. Low power communication standards such as DASH7 [3] or Low Power Wireless Area Network (LPWAN) standards such as LoRa [4] or Sigfox [5], 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. Lately, the localization and tracking of the transmitting sensors are becoming important feature of any IoT network. In a recent research by BniLam et al. [2], extensive experimental results show the potential of using an AoA-based localization system with an IoT transmission standard. The cost and complexity of deploying a large array antenna system at the receiver side are considered major challenges for using AoA-based localization techniques for the IoT applications.

Over the past years researchers started to introduce new methods to increase the array antennas' degrees of freedom. In other words, these methods increase the array antenna angular resolution and can estimate the AoA parameter of more simultaneously received signals than the number of receiving RF-channels. Notably, Pal and Vaidyanathan [6] introduced a new array geometry, which is capable of increasing the degrees of freedom of linear array antennas by distributing the antenna elements non-uniformly in space. They applied the Khatri-Rao multiplier on the received covariance matrix and the spatial smoothing technique to de-correlate the system's covariance matrix. Using the same array antenna geometry, Salama et al. [7] substitute the spatial smoothing by the least square adaptable least absolute shrinkage (LASSO) optimization to maintain the same degrees of freedom.

Compressive sensing with random projection solution is considered another approach to increase the array antennas' degrees of freedom [8] - [11]. This solution majorly consists of using a large array antenna with a fixed analog complex random weight. The outputs of these antenna elements will be summed into the input of a limited number of fully synchronized and phase coherent RF-channels.

Although the aforementioned methods show promising results in estimating the AoA parameter of more simultaneously received signals than the number of receiving RF-channels, these methods have some limitations. They either use array antennas with a specific geometry or require substantial additional analog hardware such as in [11]. This lack of flexibility makes them less suitable for mainstream or large-scale applications.

In a previous paper [12], we presented a technique to synchronize two sub-array antennas to form one augmented array antenna system. The technique was formulated as a 2 dimensional optimization problem. In this paper, we modified the previous technique to be used as an AoA estimation algorithm with multi-dimensional optimization problems. The new algorithm is capable of synchronizing multiple incoherent sub-array antennas to form one augmented array antenna system. The resultant augmented array can provide more accurate AoA estimation in the azimuth and elevation domains than each individual sub-array antennas. The proposed algorithm has been tailored to increase the array antenna angular resolution (i.e. the AoA estimation accuracy) in the presence of a single narrowband received signal, which is a widely used setup for the majority of self-localization systems. Furthermore, the proposed algorithm does not require a specific antenna elements' distribution in space or additional analog hardware implementation as the case for the aforementioned methods.

The synchronization process in the algorithm is divided into two stages. The first stage focuses on synchronizing the time and frequency of the two sub-array antennas. The synchronization is achieved by using a joint Maximum Likelihood (ML) optimization for a data aided received signal (i.e. the transmitted signal has a unique data set at the beginning of the transmission, which is recognized by the receiver). The second stage is enforcing the phase coherency between the two sub-array antennas; this process is achieved by using Least Mean Square (LMS) and ML algorithms.

The remainder of the paper is structured as follows: in section II, a full mathematical derivation for the proposed algorithm is introduced. Section III presents an overview of the optimization solution. An overall summary of the algorithm is presented in section IV. The experimental setup and the experimental results are presented in sections V and VI, respectively. A simulation example is presented in

section VII. Finally, in section VIII, the conclusions of this paper are drawn.

II. THE PROPOSED SYNCHRONIZATION ALGORITHM

Assume there are M individual array antennas, which are distributed in the space at the receiver side, as shown in figure 1. The received sampled signal vector with discrete index k can be expressed as:

$$\mathbf{x}(k) = [\mathbf{x}_1(k) \dots \mathbf{x}_m(k) \dots \mathbf{x}_M(k)]^T \quad (1)$$

where

$$\mathbf{x}_m(k) = [x_{(m,1)}(k) \dots x_{(m,n)}(k) \dots x_{(m,N_m)}(k)] \quad (2)$$

where $()^T$ is the transpose operator and N_m is the number of antenna elements in the m -th sub-array antenna. For narrowband signals, $x_{(m,n)}(k)$ can be expressed as

$$x_{(m,n)}(k) = A_r s(k) e^{i(\psi_{(m,n)} + \Theta_m)} \quad (3)$$

where A_r is the received signal amplitude, $s(k)$ is the sampled transmitted signal, $-\pi \leq \Theta_m \leq \pi$ is the random phase difference between the reference sub-array antenna and the m^{th} sub-array antenna, and $\psi_{(m,n)}$ is the phase difference due to the spatial displacement of antenna (m, n) with respect to a reference point in space. In order to have a fully

Fig. 1: A schematic of multiple individual sub-array antenna systems, where D/C is the down converter and ADC is the analog to digital converter.

synchronized array antenna system constructed of M individual sub-array antennas, it is required that these sub-array antennas are synchronized in time and frequency, and coherent in phase. These two processes are tackled separately, as explained in the following subsections.

A. Symbol and Carrier Frequency Synchronization

All the RF-channels in each sub-array antenna are synchronized in time and frequency and coherent in

phase, thus the time and frequency synchronization process is only required for one received channel of each individual sub-array antenna. In the following derivation, we considered the first received channel $x_{(m,1)}$ of every m -th sub-array antenna to be subjected for the time and frequency synchronization process. Assuming that a signal has been transmitted over an Additive White Gaussian Noise (AWGN) channel, the complex baseband representation of the received signal can be described as [13]

$$x_{(m,1)}(t) = A_r e^{i(2\pi f_d t + \Theta_c)} s(t - \tau) + \zeta(t) \quad (4)$$

where f_d is the frequency offset, Θ_c is the unknown carrier phase, $s(t)$ is the baseband of the transmitted signal, τ is the propagation delay between the transmitter and receiver, and $\zeta(t)$ is the complex AWGN with zero mean.

For Eq.(4), there are some observations to be made, first of all for a digital system, τ is equal to

$$\tau = \xi T_s + \nu T_s \quad (5)$$

where T_s is the symbol interval, $\xi \geq 0$ is an integer delay, which represents the symbol synchronization number and $-0.5 < \nu < 0.5$ is a fractional propagation delay. Secondly, since the transmitter and the receiver are not synchronized Θ_c can be expressed as [14]

$$\Theta_c = -2\pi f_c \nu + \Theta_r \quad (6)$$

where f_c is the carrier frequency and Θ_r is the random phase due to the phase difference between the transmitter and receiver's oscillators.

In order to reliably process the received signals, both time and carrier synchronizations are required. The precision with which one must synchronize in time for the purpose of demodulating the received signal, depends on the symbol interval ξT_s . Usually, the estimation error in the parameter ν for a small fraction of T_s is adequate for practical applications. However this level of precision is generally inadequate for estimating the carrier phase, even if Θ_c depends only on ν . This is due to the fact that f_c is generally large and, hence, a small estimation error in ν causes a large phase error [14].

For symbol and carrier synchronization, we apply a joint ML optimization in which part of the transmitted signal $s(t)$ is known by the receiver (i.e. $s(t)$ is a data aided signal). The joint log-likelihood function (LLF) for the estimation of a set of parameters from a waveform in AWGN is [14]

$$\Lambda [x_{(m,1)}(t); f_d, \xi] = \left| \int_0^{T_0} e^{-i2\pi f_d t} x_{(m,1)}(t) s^*(t - \xi T_s) dt \right| \quad (7)$$

where $()^*$ is the complex conjugate operator and T_0 is the unique data duration. As mentioned above, we disregard Θ_c and ν from the formulation Eq. (7) due to their insignificant effects on the symbol and frequency synchronization problem.

According to the ML criterion, we choose the trial

values that maximize Eq. (7) as the best estimates for the unknown parameters f_d and ξ . In practice, $x_{(m,1)}(t)$ is sampled in time leads to $t = kT_s$, for notational convenience we have abbreviated kT_s by k in the remainder of the paper. This results in a discrete-time version of the LLF as:

$$\Lambda [x_{(m,1)}(k); f_d, \xi] \approx \left| \sum_{k=0}^{T_0} e^{-i2\pi k f_d} x_{(m,1)}(k) s^*(k - \xi T_s) \right| \quad (8)$$

By maximizing Eq. (8), the estimated values $\hat{f}_d$ and $\hat{\xi}$ of f_d and ξ parameters can be found, thus achieving time and frequency synchronization.

B. Phase Coherency for the Sub-Array Antennas

After synchronizing all the sub-array antennas in time and frequency, it is extremely important to impose the phase coherency between all the sub-array antennas. For this task we need to estimate the random phase Θ_m in Eq.(3). We deployed the LMS algorithm (see [15] and [16]) to estimate the optimal weight vector of the augmented array antenna system. This weight vector implicitly will contain the random phase values between the sub-array antennas.

The LMS algorithm is referred to as the constrained LMS algorithm when the weights are subjected to constraints at each iteration, while it is referred to as the unconstrained LMS algorithm when the weights are not constrained at each iteration [16]. In this paper we used the unconstrained LMS in which the weights are updated using a reference signal and no knowledge of the direction of the signal is utilized. The LMS algorithm updates the weights at each iteration by estimating the gradient of the quadratic surface and then moving the weights in the negative direction of the gradient by a small amount. The constant that determines this amount is normally referred to as the step size. A schematic of the iteration process in the LMS algorithm is shown in figure 2.

Fig. 2: A schematic of LMS algorithm.

The weight vector of the LMS algorithm is updated as follows [16]

$$\mathbf{w}(k+1) = \mathbf{w}(k) - 2\mu\epsilon(k)\mathbf{x}^*(k) \quad (9)$$

where $\mathbf{w} \in \mathbb{C}^{N_a \times 1}$ is a weight vector, N_a is the total number of the antenna elements in the augmented array antenna (i.e. $N_a = \sum_m N_m$), μ is a constant that controls the step size of the gradient. If μ is small enough, the process leads the estimated weight vector to the optimal weight. $\epsilon(k)$ is the error between the array output and the reference signal, and can be expressed as:

$$\epsilon(k) = \mathbf{w}^T(k)\mathbf{x}(k+1) - s(k+1) \quad (10)$$

To estimate the implicit random phase vector Θ in the weight vector $\mathbf{w}$, an (M+1)-Dimensional optimization is required. For this task we assumed the parameter estimations have an identical individual distributed (IID) Gaussian error distribution. The likelihood function will then be:

$$\mathcal{L}(\mathbf{w}; \theta, \phi, \Theta) = e^{\left(-\frac{1}{2\sigma}(\mathbf{w} - \mathbf{c}(\theta, \phi, \Theta))^H(\mathbf{w} - \mathbf{c}(\theta, \phi, \Theta))\right)} \quad (11)$$

where $()^H$ is the conjugate transpose indicator, σ is the variance of estimation, $\mathbf{c}(\theta, \phi, \Theta) \in \mathbb{C}^{N_a \times 1}$ is the augmented array steering vector, $\theta \in 0 \rightarrow 2\pi$ and $\phi \in 0 \rightarrow \pi$ are the steering vector azimuth and elevation angles, respectively, and Θ is the random phase vector. $\mathbf{c}(\theta, \phi, \Theta)$ can be expressed as

$$\mathbf{c}(\theta, \phi, \Theta) = \begin{bmatrix} \mathbf{c}(\theta, \phi, \Theta_1) \\ \vdots \\ \mathbf{c}(\theta, \phi, \Theta_m) \\ \vdots \\ \mathbf{c}(\theta, \phi, \Theta_M) \end{bmatrix} \quad (12)$$

If the first sub-array antenna is assumed to be the reference and all the other sub-array antennas have a specific phase difference relative to the first sub-array antenna then $\Theta_1 = 0$. The steering vector $\mathbf{c}(\theta, \phi, \Theta_m)$ can be expressed as

$$\mathbf{c}(\theta, \phi, \Theta_m) = \mathbf{c}(\theta, \phi)\mathbf{c}(\Theta_m) \quad (13)$$

where

$$\mathbf{c}(\theta, \phi) = e^{i\Psi_m} \quad (14)$$

and

$$\mathbf{c}(\Theta_m) = e^{i\Theta_m} \quad (15)$$

in which $\Psi_m \in \mathbb{R}^{N_m \times 1}$ is the m -th sub-array antenna phase vector with N_m number of elements. Ψ_m can be expressed as

$$\Psi_m = [\psi_{(m,1)} \cdots \psi_{(m,n)} \cdots \psi_{(m,N_m)}]^T \quad (16)$$

The log likelihood of Eq.(11) can be expressed as

$$\begin{aligned} \mathcal{LL}(\mathbf{w}; \theta, \phi, \Theta) = & -\frac{1}{2\sigma}(\mathbf{w}^H\mathbf{w} + \mathbf{c}^H(\theta, \phi, \Theta)\mathbf{c}(\theta, \phi, \Theta) \\ & - \mathbf{w}^H\mathbf{c}(\theta, \phi, \Theta) - \mathbf{c}^H(\theta, \phi, \Theta)\mathbf{w}) \end{aligned} \quad (17)$$

By observing Eq.(17) you can find that the term $\frac{1}{2\sigma}$ is a constant, and the first term does not involve the signal's parameters θ , ϕ and Θ , while the second term is a constant for all the estimated parameters due to the structure of $\mathbf{c}(\theta, \phi, \Theta)$. Only the third and fourth terms involve the cross correlation of the adaptive weight vector and the augmented array steering vector. Therefore, by choosing one of the last two terms, the likelihood function may be expressed as

$$\mathcal{G}(\mathbf{w}; \theta, \phi, \Theta) = \mathbf{w}^H\mathbf{c}(\theta, \phi, \Theta) \quad (18)$$

By maximizing Eq.(18), the estimated values $\hat{\theta}$, $\hat{\phi}$ and $\hat{\Theta}$ for θ , ϕ and Θ parameters can be found, thus achieving phase coherency between all the individual sub-array antenna systems.

III. OPTIMIZATION METHOD

As stated in the previous section, it is required to maximize the symbol and frequency synchronization LLF function Eq.(8) as well as the phase coherency LLF function Eq.(18). Eq.(8) is a 2D problem, thus it is computationally possible to examine all the possible sets of parameters within the function and search for the specific set of parameters which peaks Eq.(8). The same is applicable for Eq.(18) when it's used with 2D problems; then only two sub-array antennas are used with a single AoA estimation in the azimuth domain. However for 3D and more dimensional problems (i.e. the augmented array antenna is constructed of more than two sub-array antennas), it's impossible to estimate the specific set of parameters that peaks the LLF function by examining all the possible sets of parameters. For such a case we consider the minimization of the problem as follows:

$$\begin{aligned} & \text{minimize } f(\mathbf{z}) \\ & \text{subjected to } \mathbf{z} \in \Omega \end{aligned} \quad (19)$$

The function $f: \mathbb{R}^u \rightarrow \mathbb{R}$ that we wish to optimize is a real-valued function, and is called the objective function, or cost function. The vector $\mathbf{z}$ is a u vector of independent variables, that is, $\mathbf{z} = [z_1, z_2, \dots, z_u]^T \in \mathbb{R}^u$. The variables $z_1, z_2, \dots, z_u$ are often referred to as decision variables. The set Ω a subset of $\mathbb{R}^u$, called the constraint set or feasible set [17].

The optimization problem above can be viewed as a decision problem that involves finding the optimum vector $\mathbf{z}$ of the decision variables over all possible vectors in Ω . The optimum vector is the one vector that results in the smallest value of the objective function. The only difference between the maximization and minimization problems is that maximizing f is equivalent to minimizing $-f$. Therefore our maximization problem Eq.(18) can be viewed as follows:

$$\begin{aligned} & \text{minimization } -|\mathcal{G}(\mathbf{w}; \theta, \phi, \Theta)| \\ & \text{subjected to } \theta \in 0 \rightarrow 2\pi \\ & \quad \phi \in 0 \rightarrow \pi \\ & \quad \Theta \in -\pi \rightarrow \pi \end{aligned} \quad (20)$$

The minimization problem Eq.(20) optimizes the object function to estimate the random phase between the sub-array antennas as well as the AoA of the received signal. Thus Eq.(20) works perfectly as an AoA estimation algorithm.

In this paper, we optimized the objective function Eq.(20) by using a non linear programming matlab function "*fmincon*" [18], which is a constrained non-linear multivariable minimization function.

IV. ALGORITHM IMPLEMENTATION

A schematical view of the proposed algorithm's implementation can be found in figure 3. Hereby one should also take into account the following:

- The time and frequency synchronization process is only applied to one element of every sub-array antenna system.
- The computational complexity increases with the increase of the total number of the sub-array antennas M .
- The factor μ in figure (2) should be quantified empirically.

Fig. 3: A schematic of the proposed algorithm implementation steps

V. EXPERIMENTAL SETUP

To validate our proposed algorithm, we developed a USB transceiver to transmit DASH7 Alliance Protocol (D7AP) signals as shown in figure 4 and AoA unit as shown figure 6.

A. DASH7 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 (see [19] and [3]). In the following subsections, we will present some of the DASH7 system's parameters [20].

Fig. 4: The USB transceiver unit that was used in the experiment

TABLE I: DASH7 Classes

Class	Symbol Rate	Δf
Lo-Rate	9.6 kbps	9.6 kHz
Normal	55.555 kbps	100 kHz
Hi-Rate	166.667 kbps	83.334 kHz

1) *Air Interface*: D7AP RF signals are formed by applying a continuous phase Gaussian Frequency Shift Keying GFSK modulation scheme which can be expressed as

$$s(t) = Ae^{j\Phi(t)} \quad (21)$$

where A is the transmitted signal's amplitude and $\Phi(t)$ is

$$\Phi(t) = 2\pi h \int_0^t \alpha(\tau) d\tau \quad (22)$$

$\alpha(t)$ for an FSK signal is

$$\alpha(t) = \sum_{i=0}^L a(i)q(t - iT_s) \quad (23)$$

where h is the modulation index, $a = \pm 1$ is the transmitted bit value, L is the number of transmitted bits and $q(t - iT_s)$ is the shape filter response of the transmitted signal (i.e. for GFSK the $q(t)$ is a Gaussian 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. In our experiments, the USB transceiver transmits a Lo-Rate D7AP signal at Ch0 (Ch0 frequency equals to 863.0125 MHz).

2) *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, which is recognised by the receiver. Figure 5 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 (min 32 bits) of 1010..., 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.

Fig. 5: DASH7 Packet Structure

B. AoA unit

The AoA unit contains two off the shelf USRP's. The Universal Software Radio Peripheral USRP [21] is a Software Defined Radio (SDR) front end 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 experiments 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. The two B210s' provide us with 2 sub-array antenna systems, each one of them constructed of 2 fully synchronized and phase coherent RF-channels. They were placed on an AoA unit to form a Uniform Linear Array (ULA), as shown in figure 6.

Fig. 6: The AoA unit with two sub-array antennas, each array has two antenna elements.

The phase response for (m, n) antenna element in the ULA antenna can be expressed as

$$\psi_{(m,n)} = \frac{2\pi}{\lambda} d_{(m,n)} \cos(\theta_r) \quad (24)$$

where λ and θ_r are the received signal's wavelength and AoA, respectively. $d_{(m,n)}$ is the distance of the antenna (m, n) relative to a reference point in space.

VI. EXPERIMENTAL VALIDATION

We conducted two experiments to validate our algorithm, and in both experiments we used the setup as described in section V. The first experiment was conducted in an anechoic chamber while the second was conducted in an outdoor environment. For both experiments, the USB transceiver was transmitting a Lo-Rate D7AP signal. The AoA unit's sample rate was fixed to 1M sample per second, and the

LMS algorithm operated with $\mu = 10^{-5}$. It is worth mentioning that, since the transmitter is operating at 9.6 kbps, each transmitted bit was received as 104.166 samples at the AoA receiving unit.

A. Anechoic chamber experiment

This experiment was conducted in an anechoic chamber, where the two sub-array antennas were placed over a pan-tilt system with inter element spacing $d = 0.5\lambda$. We placed the transmitter within 3 meters of the AoA unit. During the experiment we transmitted 300 signals divided equally among the transceiver's azimuth angles 60° , 90° and 120° with respect to the AoA unit's axes.

Figure 7 shows the behavior of the symbol and frequency LLF function Eq.(8). The function provides a very distinctive peak at the specific time and frequency of the received signal, which provides an accurate parameter estimation. Figures 8A and 8B show respectively the time and frequency domains of the received signals from the 4 received RF-channels along with the reference signal $s(k)$. They show that the time and frequency synchronization optimization works efficiently even with neglecting Θ_c and ν from the LLF function Eq.(8). The reference signal $s(k)$ has been obtained by recording the transmitted signal after connecting the transmitter with one channel of the USRP B210 via coaxial cable.

Fig. 7: The symbol and frequency LLF function Eq(8). The function provides a very distinctive peak at the specific time and frequency of the received signals, which provides an accurate parameter estimation.

Figure 9 shows the response of error function Eq.(10) for the 300 received signals. The LMS algorithm reaches the optimum weight vector after less than 50 samples for all the received signals (i.e. within less than 1 transmitted bit's duration). This fast convergence allows the algorithm to be deployed in live applications.

To visualize the algorithm phase stability, we presented the augmented array field pattern in the azimuth domain of all the 300 transmitted signals in figure 10. To produce this figure, we applied a basic

beamforming technique, by using the weight vector $\mathbf{w}$ as the input vector for the basic beamformer, after compensating for the random phase. The phase compensation was achieved by multiply the weight vector with the augmented array antenna steering vector that associated with the estimated random phase vector as follows:

$$G(\theta, \phi) = \mathbf{w}^H \mathbf{c}(\theta, \phi, \hat{\Theta}) \quad (25)$$

where $G(\theta, \phi)$ is the augmented array field pattern as function of θ and ϕ . This field pattern provides maximum value towards the direction of the received signals. It is worth mentioning that due to the antenna elements distribution in one dimension for the ULA, the estimation will be in either θ or ϕ domains, depending on the ULA alignment in space.

Fig. 8: Figure A) represents the time domain for a part of the preamble of the received signal from the 4 RF-channels along with the reference signal, while figure B) represents the frequency domain of figure A. The figures show that the received signals are synchronized in the time and the frequency domains.

Figures 10(A - C) show the augmented array field patterns when the transmitter placed at azimuth angles 60° , 90° and 120° with respect to the AoA unit. The left column images represent the field patterns without the phase compensation (i.e. $\hat{\Theta} = 0$), while the right column images represent the field patterns after compensating for the random the phase between the two sub-array antennas. The left column images show random behavior of the augmented array field patterns, due to the random phase effect. On the other hand, the right column images show very stable field patterns, in which the main lobe focusing towards the transmitting source's direction.

Fig. 9: The error function Eq.(10) response for the 300 received signals. The LMS algorithm reaches the optimum weight vector after less than 50 samples for all the received signals (i.e. within less than 1 transmitted bit's duration)

It is also noticeable that the corrected filed patterns (the right column images) are more stable in the broadside region than the endfire regions. This behavior is due to the ULA structure. The ULA pattern near the endfire region provides a wide field pattern relative to the broadside region, which effects the algorithm accuracy in estimating and compensating the random phase. Nevertheless, the proposed algorithm is capable of estimating and compensating the random phase between the sub-array antennas for all the received signals effectively.

Figures 11 shows the AoA estimations per transmitted signal as estimated from the optimization problem Eq.(20). The black dots represent the azimuth angles of the pan-tilt system, while the red stars represent the AoA estimations from the proposed algorithm. The mean absolute error from 300 transmitted signal is 1.1 degrees. The mean absolute error and the variance of estimation for the received signals from 60° , 90° and 120° angles are 1.6, 0.8, and 0.9 degrees and 0.8, 0.06 and 0.1 degrees, respectively. This error is a combination of the human and mechanical error factor on the orientation of the pan-tilt system and the ULA structure effect on the algorithm accuracy. Figure 12 shows the phase response between the sub-array antennas per transmitted signal as estimated from the optimization problem Eq.(20). It is obvious that the phase between the sub-array antennas has a random value for each received signal. One might think that the two sub-array antennas start with an oscillator random phase at the beginning of the operation, but this random phase should be stable and fixed for the whole operation. This is not the case due to the first term in Eq.(6). As mentioned previously, even for the small amount of ν in the time domain will influence the phase severely due to the multiplication with the carrier frequency

($f_c = 863.0125\text{MHz}$). Despite the randomness of the phase between the sub-array antennas, the proposed algorithm could estimate the random phase between the sub-array antennas for all the received signals effectively.

Fig. 10: The augmented array antenna field patterns for the 300 received signals. Figures (A - C) represent the field patterns when the transmitter placed at azimuth angles 60° , 90° and 120° with respect to the AoA unit. The left column images represent the field patterns without the phase compensation (i.e. $\Theta = 0$), while the right column images represent the field patterns after compensating for the random the phase between the two sub-array antennas. The left column images show random behavior of the augmented array field patterns, due to the random phase effect. On the other hand, the right column images show very stable field patterns, in which the main lobe focusing towards the transmitting source's direction.

B. Outdoor Experiment

We conducted this experiment to validate the algorithm accuracy in an outdoor environment. We installed the AoA unit (see figure 6) on the roof of our university building. The inter element spacing for the augmented array antenna is set to $d = 0.4\lambda$. The USB transceiver was placed at 8 different locations varies in distance between 130 meters to 530 meters. During the experiment we transmitted 10 signals per location. The transceiver locations had been estimated using Global Positioning System (GPS) location estimation. The location estimation error of the GPS readings was within 10 meters per location.

Fig. 11: The AoA estimations per transmitted signal as estimated from the optimization problem Eq.(20). The black dots represent the azimuth angles of the pan-tilt system, while the red stars represent the AoA estimations of proposed algorithm. The mean absolute error from 300 transmitted signal is 1.1 degrees. The mean absolute error and the variance of estimation for the received signals from 60° , 90° and 120° angles are 1.6, 0.8, and 0.9 degrees and 0.8, 0.06 and 0.1 degrees, respectively.

Fig. 12: The random phase response between the sub-array antennas per transmitted signal, as estimated from the optimization problem Eq.(20). Despite the randomness of the phase between the sub-array antennas, the proposed algorithm could estimate all the random phases effectively.

Figure 13 shows Google map images for the outdoor environment, the images represent illustrations of the augmented array field patterns (see Eq.(25)) for 5 different locations. As it can be seen that the array pattern generally directed towards the transmission locations. Furthermore, the locations near the endfire have a wider field pattern than the locations near the broadside locations.

Figure 14 shows the AoA estimations from the optimization problem Eq.(20), where the black dots represent the transceiver angular direction based on

GPS readings. The red squares represent the AoA estimations of the proposed algorithm and the stars represent the AoA estimation from the two individual sub-array antennas. One can deduce that the AoA estimation for the augmented array is stable and the algorithm can estimate the random phase between the two sub-array antennas efficiently in a realistic environment. Furthermore, the AoA estimation from the proposed algorithm is more accurate than the two individual sub-array antennas. The mean absolute error of the angular estimation for the augmented array is 4.1° , while it is equal to 8.3° and 7.2° for the first and second sub-array antennas, respectively. This error is a combination of the GPS location estimation error and the algorithm accuracy in a realistic environment with the presence of multipath effect.

Fig. 13: Google map images for the outdoor experiment environment, the images represent illustrations for the augmented array patterns for different transmission locations. As it can be seen that the array pattern generally directed towards the transmission locations.

VII. SIMULATION EXAMPLE

In this section, we present a simulation example to show the algorithm's capability of combining several array antennas, with no limitation to the structure of the augmented array antenna in space. We assumed there are 4 sub-array antennas, in which the first sub-array consists of 2 antenna elements while the second and the third consist of 3 antenna elements each and the fourth sub-array antenna consists of 4 antenna elements. The 12 antenna elements are distributed over a circular plane to form a Uniform Circular Array (UCA) antenna as shown in figure 15.

Fig. 14: The outdoor AoA estimation for 80 transmitted signals in which each 10 had been transmitted for the same location. The black dots represent the transceiver angular direction based on the GPS readings, the red squares represent the AoA estimations from the proposed algorithm and the stars represent AoA estimations from the sub-array antennas. It obvious that the proposed algorithm provides more accurate estimations than the individual estimation of the sub-array antennas. The mean absolute angular estimation error for the augmented array is 4.1° , while it is equal to 8.3° and 7.2° for the first and second sub-array antennas, respectively.

Fig. 15: A Schematic of the UCA with 12 antenna elements and inter element spacing equals to 0.5λ .

The phase response for (m, n) antenna element in the UCA antenna can be expressed as

$$\psi_{(m,n)} = \frac{2\pi}{\lambda} R \sin(\phi_r) \cos(\theta_r - \beta_{(m,n)}) \quad (26)$$

where ϕ_r and θ_r are the received signal's AoA in the elevation and azimuth domains, respectively. R is the radius of the UCA and can be expressed as

$$R = \frac{N_a d_{(m,n)}}{2\pi} \quad (27)$$

and $\beta_{(m,n)}$ is the distribution of the element (m, n) in

the space and can be expressed as

$$\beta_{(m,n)} = \frac{2\pi(n_a - 1)}{N_a} \quad (28)$$

where $n_a = 0, 1, 2, \dots, N_a - 1$.

Figure 16 shows pseudocolor images of the augmented UCA field pattern with different received signals. The images are produced using a Lambert azimuthal equal area projection. In each image, the signal arrives at the augmented array with different AoA parameter in the azimuth and elevation domains. The grid lines in each image were spaced 30° apart. As it can be seen that, the proposed algorithm is independent of the augmented array antenna's structure in space. Furthermore, it is capable of combining several sub-array antennas with various amount of antenna elements to estimate the AoA of the received signal not only in the azimuth domain but also in the elevation domain, simultaneously. The symmetry in the augmented array field pattern along the elevation domain is due to the phase structure of the UCA (see Eq.(26)).

It is worth mentioning that, for this simulation example, the computational time to produce the array weight vector using the LMS algorithm and estimating the azimuth $\hat{\theta}$ and the elevation $\hat{\phi}$ angles and the random phase vector $\hat{\Theta}$ was 0.6 seconds using a normal intel core i7 processor.

VIII. CONCLUSION

In this paper we present a new algorithm to synchronize multiple individual receiving sub-array antennas to form an augmented array antenna system. This augmented array antenna has a large antenna aperture that can be used for angle of arrival (AoA) estimations and it provides a better AoA estimation accuracy than the individual sub-array antennas. The proposed algorithm has been tailored to increase the array antenna angular resolution in the presence of a single narrowband received signal. Furthermore, the proposed algorithm does not require a specific antenna elements' distribution in space or additional analog hardware implementation.

The experimental results and the simulation example show that the proposed algorithm 1) is stable in estimating the augmented array antenna pattern, 2) provides more accurate AoA estimations than the individual sub-array antennas 3) has no limitation to the structure of the augmented array antenna in space and 4) converges very fast.

The computational efficiency, the flexibility and the affordability of the proposed algorithm made it suitable for practical application in general and for IoT localization in specific.

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Fig. 16: The augmented array antenna field pattern pseudocolor images for different received signals. The images are produced using a Lambert azimuthal equal area projection. In each image, the signal arrives at the augmented array with different AoA parameter in the azimuth and elevation domains. The grid lines in each image in this figure were spaced 30° apart. It is obvious that the algorithm can combine several sub-array antennas with various amount of antenna elements to estimate the AoA of the received signal not only in the azimuth domain but also in the elevation domain, simultaneously. The symmetry in the field pattern along the elevation domain is due to the phase structure of the UCA (see Eq.(26)).

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