Orientation-Awareness and Wireless Systems

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Abstract—This work explores the potential benefits of orientation awareness in wireless systems in the context of source localization. Precise and reliable inertial measurement units have become a standard feature on almost all smartphones available today, and they are becoming increasingly popular for other devices as well. The measurements provided by such sensors can be employed as side information in a number of application scenarios, including inference. Indeed, orientation information combined with the asymmetry of antenna radiation patterns can lead to substantial performance gains in localization algorithms. This article focuses on source localization based on received signal strength. Improvements are assessed from both a theoretical and an experimental perspective. Reported findings offer supporting evidence to the claim that orientation-awareness can improve performance in a significant manner.

I. INTRODUCTION

Wireless devices have become an intrinsic part of everyday life for a large portion of our society. Mobile platforms are commonly employed for work, social exchanges, and entertainment. The wide adoption of these devices and, in particular, smartphones has had a significant impact on technological innovations. For instance, phones have greatly accelerated the development of batteries and digital cameras. Moreover, contemporary mobile devices must serve several purposes, operate on multiple spectral bands, yet they must remain affordable.

This scientific inquiry is motivated by two prime aspects of an evolving wireless landscape. First, mobile phones often double up as gaming controllers. As such, most contemporary mobile devices come equipped with precise and reliable inertial measurement units (IMUs). This implies that many mobile devices are orientation aware. While these sensing units are used extensively for entertainment, they are yet to be fully integrated into other smart tasks such as communication or inference. Second, the prescribed form factor for many mobile devices severely restricts the real estate dedicated to radio frequency (RF) frontends. This, in turn, produces many challenges in the design of antennas. As a result, the radiation patterns of mobile devices are frequently asymmetrical. Together, these two facets of modern wireless devices, orientation-awareness and RF pattern asymmetry, give rise to algorithmic opportunities to enhance the performance of wireless systems at essentially no additional hardware cost.

In this article, we illustrate how these components can work in tandem by revisiting the classical problem of source localization. Specifically, we wish to show, both theoretically and empirically, how substantial performance gains can be achieved by integrating the side information afforded by IMUs into the problem formulation. Before delving into the specifics of the problem we wish to address, it is instructive to briefly review past contributions pertaining to localization.

Target localization is a topic that has attracted considerable attention over the past decades, with many variants of the problem formulation and a plethora of application scenarios [1], [2], [3]. The quintessential setting for such estimation tasks is the processing of measurements acquired through multichannel antenna arrays [4], [5], [6], [7]. In this context, the RF frontend is designed specifically for the inference task and radiation patterns are shaped carefully. Contrastingly, in more recent studies, data acquisition is often performed by mobile devices and sensor networks [8], [9], [10], [11]. The latter formulations introduce new challenges such as limited resources at individual nodes and sampling in an asynchronous fashion.

As mentioned above, this article explores one aspect of this shift from application-specific, costly acquisition devices to distributed systems based on utilitarian hardware. To explore the potential benefits of orientation-awareness, we first review the system model and describe the mathematical task at hand. We then present results for localization based on received signal strength. These results showcase both the practicality and value of the proposed scheme. Moreover, the paradigm discussed in this article, incorporating orientation as side information for inference tasks, can be applied to other contexts. This statement should become clear as we proceed forward.

II. SYSTEM MODEL

The system model we adopt is straightforward. A single source transmits a known signal at a prescribed power using an isotropic antenna. This signal is simultaneously acquired by a collection of sensing devices; these devices can be smartphones or portable computers. Every device is equipped with an IMU and, as such, it is aware of its own orientation. Furthermore, each device possesses a detailed map of its own antenna characteristics, including antenna gain as a function of signal polarity and angle of incidence. Lastly, the locations of the sensing units are known precisely. This latter piece of information can be obtained, for instance, using the global positioning system (GPS).

The common goal for the distributed system is to estimate the location of the source. We assume that the sensing units have the ability to communicate with one another and share their gathered data. For the purpose of inference, each unit gets a single, noisy measurement. The noise components are assumed independent. This setting is somewhat rudimentary,
yet it is rich enough to showcase the potential gains associated with orientation-awareness.

We assume that the wireless channel is well abstracted by a log-additive model. That is, received signal strength from the source to a sensing device is expressed as

$$P(d)\,[\text{dBm}] = A + B \log_{10}(d) + L_s + G_a,$$

where $A$ and $B$ are the signal strength decay parameters, $d$ represents the distance between the source and a measurement unit, $L_s$ denotes shadow fading, and $G_a$ is the antenna gain. The mean of $L_s$ can be absorbed in $A$ and, consequently, we can set the mean of the shadow fading component to zero. We assume that $L_s$ possesses a Gaussian distribution, thereby producing log-normal fading. This fading model has been studied extensively in the literature, and a detailed exposition appears in many books on wireless systems [12], [13].

Values for $A$ and $B$ are site-specific and they depend on the profile of the scattering environment.

In general, the orientation of a device can be described using Euler angles or the quaternion framework. However, in this study, we confine orientation to one axis of rotation. We assume that the sensing devices are standing upright in this study, we confine orientation to one axis of rotation. However, for other devices, variations can be very pronounced. The patterns obtained in this controlled environment are considered ground truth for subsequent field experiments.

When the orientation of the sensing device is known, along with the locations of the source and the destination, the impact of the antenna gain on the received power can be accounted for. Let $v = (x, y)$ be the location of the source, and let $v_i = (x_i, y_i)$ be the location of the upright measurement unit. The angle of incidence of the received signal onto the measurement device is given by

$$\theta_i = \text{atan2}(y - y_i, x - x_i)$$

where $\text{atan2}(\cdot, \cdot)$ is the two-argument variant of arctangent. Then, the angle of incidence relative to the orientation of the device is equal to

$$\phi_i = \theta_i - \alpha_i = \text{atan2}(y - y_i, x - x_i) - \alpha_i.$$

A graphical representation of the various angles defined above appears in Fig. 2.

Fig. 2. This figure offers a graphical representation of the various angles involved in computing the contribution of the antenna profile in an orientation-aware sensing device.

When the orientation of device $i$ is equal to $\alpha_i$, the effective gain of the RF frontend is $G_a(\phi_i)$. In this case, the received signal strength becomes

$$P(v, v_i, \alpha_i)[\text{dBm}] = A + B \log_{10}\|v - v_i\| + L_{s,i} + G_a(\phi_i)$$

and the only source of uncertainty is attributable to shadow fading. However, if the orientation of the device is unknown, then $G_a$ contributes to power fluctuations and can be modeled as a second source of noise. For simplicity, we also take $G_a$, when unknown, to possess a Gaussian distribution. This ensures that our problem retains a linear Gaussian structure in the logarithmic domain (power ratio in decibels).

Our objective is to better understand the impact of the information discrepancy between these two scenarios. We wish to characterize the benefits of having access to orientation in terms of performance.

### III. LOCALIZATION TASK

The localization task at hand is to estimate the position of the source using the received signal strength indicator (RSSI) readings collected from several distributed agents. The measurements acquired by the sensing devices are aggregated, and an estimate is produced using the maximum-likelihood
(ML) rule [14]. Since the noise components across sensors are
assumed independent, it is simpler to express the optimization
objective using the additive structure of log-likelihood func-
tions. That is, we seek to maximize the sum of individual
log-likelihood functions.

A. Classical Formulation

In this benchmark setting, devices are unaware of their
own orientation and a decision must be made solely based
on received powers and sensor locations, \{(p_i, v_i)\}. Under
the Gaussian model, individual log-likelihood functions can
be written as

\[
\mathcal{L}(v|p_i, v_i) = - \frac{(p_i - A - B \log_{10} \|v - v_i\|)^2}{2 (\sigma^2 + \sigma_s^2)} - \ln 2\pi (\sigma^2 + \sigma_s^2) \frac{2}{2},
\]

where \(\sigma_s\) is the standard deviation associated with shadow
fading and \(\sigma_s\) denotes the standard deviation corresponding
to uncertainty in antenna gain. Evidently, the constant factors
have no impact on the optimization procedure and can there-
fore be omitted in practice. The maximum-likelihood estimator
for this problem formulation is given by

\[
\hat{v}_c = \arg\max_v \sum_i \mathcal{L}(v|p_i, v_i)
\]

where \(\mathcal{L}(v|p_i, v_i)\) is taken from (2). Bound variable \(v\) in (3)
ranges over the set of all admissible locations for the source.

B. Orientation-Aware System

When sensing devices are equipped with IMUs, they can
append their orientations to the sensed data. The inference
task then becomes estimating the location of the source
based on received powers, sensor locations and orientations,
\{(p_i, v_i, \alpha_i)\}. We emphasize that to take full advantage of this
scheme, antenna characteristics must be known a priori to the
decision maker. Individual log-likelihood functions turn into

\[
\mathcal{L}(v|p_i, v_i, \alpha_i) = - \frac{(p_i - A - B \log_{10} \|v - v_i\| - G_a(\phi_i))^2}{2\sigma^2} - \ln 2\pi \sigma^2 \frac{2}{2}. \tag{4}
\]

The maximum-likelihood estimator for the enhanced estima-
tion system can be written as

\[
\hat{v}_{oa} = \arg\max_v \sum_i \mathcal{L}(v|p_i, v_i, \alpha_i)
\]

where \(\mathcal{L}(v|p_i, v_i, \alpha_i)\) is the orientation-aware version of the
log-likelihood function.

C. Performance Criterion

Many performance criteria are pertinent for comparing
estimation schemes, and selecting a particular metric often
depends on the intended application for the estimate. In
this study, our goal is to showcase the value of orientation-
awareness. To accomplish this goal, we adopt the ubiquitous
Euclidean distance as a basis for our performance criterion.

Mathematically, we are interested in the mean square error
between the estimate and the true location,

\[
\text{MSE}(\hat{v}) = E[\|\hat{v} - v\|]. \tag{6}
\]

In theory, the expectation is over all possible system realizations. However, in practice, we compute an empirical average
based on a large number of repetitions.

IV. MODEL PARAMETERIZATION

The channel model introduced in Section II is a popular
abstraction for signal attenuation as a function of distance. In
free space, the signal decay in (1) is inversely proportional
to the square of the distance. However, in practical settings,
the decay factor can vary depending on the profile of the
environment. Our results correspond to a suburban area; site-
specific values for \(A\), \(B\) and \(\sigma_s\) are derived empirically.
Parameters \(A\) and \(B\) are obtained by applying the method
of least squares,

\[
(A, B) = \arg\min_{a, b} \left\| \begin{array}{c}
\log_{10}(d_1) \\
\vdots \\
\log_{10}(d_n)
\end{array} \right\|_2^2.
\]

Measurements are taken at distances ranging roughly from
tree to 70 meters, as these lengths are typical of our envi-
roned localization task. Furthermore, these observations are
collected in a controlled manner to avoid signal fluctuations
induced by device orientation. Values for \(A\) and \(B\) are given
in closed form by [15], [16]

\[
\begin{bmatrix}
A \\
B
\end{bmatrix} = (M^H M)^{-1} M^H p.
\]

Our analysis using this estimator yields parameters \(A = -47.9\)
and \(B = -19.5\). Sample points and the corresponding solution
are presented in Fig. 3.

The residual error between observations and the least square
solution is then used to estimate the variance of the log-normal
additive noise component \(L_s\). Specifically, shadow fading
being modeled by a log-normal distribution, its probability
density function is given by

\[
{f}_{L_s}(\ell) = \frac{1}{\sqrt{2\pi}\sigma_s} \exp \left(-\frac{\ell^2}{2\sigma_s^2}\right)
\]
in the logarithmic domain. The expected value of \(L_s\) is
assumed to be zero because, without loss of generality, a non-
zero mean can be absorbed into constant \(A\). Parameter \(\sigma_s\) can
be estimated using the unbiased sample variance

\[
\sigma_s^2 = \frac{1}{n - 1} \sum_{i=1}^n (p_i - A - B \log_{10}(d_i))^2
\]

where \(n\) denotes the sample size. Under the observed data set
and our estimated values for \(A\) and \(B\), the resulting standard
deviation is found to be \(\sigma_s = 4.92\).

To offer additional evidence for our log-normal model, we
perform a Shapiro-Wilk test. The null-hypothesis of this test is
that the samples are normally distributed. If the corresponding $p$-value is less than a prescribed level of significance, then the null hypothesis is rejected. In the present case, the $p$-value is equal to 0.724, which exceeds our level of significance of 0.05. As such, the null hypothesis that the data come from a normally distributed population cannot be rejected. This is the desired outcome in that we can safely proceed with our modeling assumption.

The last attribute that warrants attention is the variance of antenna noise component $G_{a,i}$ when device orientation is unknown. In this case, one can assume that the orientation of the measurement device is uniformly distributed over the unit circle. For simplicity, we assume that $G_{a,i}$ is a Gaussian random variable. When all the sensing devices are identical, then the antenna contributions are independent and identically distributed. Furthermore, their common mean can once again be absorbed into constant $A$ and the associated variance can be determined empirically using the unbiased sample variance estimator. For the type of smartphones employed in our experiment, we get $\sigma_a = 5.00$. Altogether, the process outlined herein for parameter tuning is somewhat standard [12], [13]. These results provide a foundation for our study of orientation-aware, localization systems.

V. NUMERICAL SIMULATIONS

To assess the potential benefits of orientation awareness in localization, we conduct a preliminary numerical study. The uncertainty area for the location of the source is a square grid of 100 m $\times$ 100 m. The system parameters for the simulations are based on the values obtained in Sections II and IV. More specifically, the source location, sensor locations and the device orientations are generated through software using a pseudorandom number generator. Once these elements are determined, the observations are produced according to

$$p_i[\text{dBm}] = A + B\log_{10}\|v - v_i\| + L_{s,i} + G_a(\phi_i)$$

where $L_{s,i}$ is synthetic, zero-mean Gaussian noise with standard deviation $\sigma_s = 4.92$, and constants $A$ and $B$ are the estimates obtained in Section IV.

The location of the source is then estimated using the classical maximum-likelihood estimator, $\hat{v}_c$ in (3), and its orientation-aware analog, $\hat{v}_{oa}$ in (5). Estimation accuracy as functions of the number of sensing devices appears in Fig. 4. The performance criterion for comparison is the standard mean square error, with the outcomes being averaged over 10,000 random trials.

This plot reveals significant performance improvements when orientation information is integrated into statistical signal processing. We stress that, for this simulation study, the radiation patterns employed for the sensing units come from commercial smartphones. Specifically, the antenna patterns employed throughout correspond to the solid line shown in Fig. 1. Overall, these findings offer strong supporting evidence to the claim that orientation information should be incorporated in inference tasks whenever the observations are acquired through generic wireless devices.

VI. EXPERIMENTAL RESULTS

Next, we turn to field experimentation and we explore how the findings described above translate into pragmatic settings. One important aspect associated with practical testing is the possibility of model mismatch. For this particular experiment, there are several sources of model uncertainty. This includes the effective radiation patterns of the sensing devices, the limited accuracy of their IMUs, the true nature of the wireless environment in which measurements are taken, and the high level of interference in the industrial, scientific and medical (ISM) radio band (2.4–2.5 GHz).
The signal source for this measurement campaign is a customized access point with an isotropic antenna fabricated solely for this study. Commercial Android™ smartphones act as sensing devices. Sample points are acquired using a custom application that leverages the WifiManager, LocationManager, and SensorManager classes found in the API set provided by Google™. Observed values consist of calibrated received signal strength readings.

The samples are logged into a database, and they are post-processed offline. The relative locations of the devices are also recorded from land measurements; this serves as a ground truth for performance analysis. Field trials are subsequently created by randomly selecting small subsets from the gathered data points. A total of 10,000 random subsamples are generated for each scenario. For every such trial, the location of the source is estimated using the classical maximum-likelihood rule given in (3) and its orientation-aware variant in (5). The mean square errors for the two estimators are obtained by respectively averaging \( ||v_c - \hat{v}||^2 \) and \( ||v_{oa} - \hat{v}||^2 \) over the field trials, in accordance with (6). In the expressions above, \( v \) denotes the true location of the source for the corresponding trial. Results for this experiment appear in Fig. 5.

![Experiment Results](image)

Fig. 5. Experimental results corroborating the overall gains associated with orientation awareness.

While the gap between the classic maximum-likelihood algorithm and its orientation-aware counterpart is not as pronounced for the field experiment, the benefits are nonetheless very noticeable. That is, the side information afforded by the IMUs of the sensing devices is quite pertinent in conducting this inference task.

VII. CONCLUSION

Altogether, orientation awareness offers a new means to enhance existing wireless inference and mobile communications. This novel viewpoint of better integrating the physical characteristics of sensing devices into statistical information processing algorithms can provide new insights into the design and operation of efficient wireless systems. The problem formulation adopted in this article, although somewhat elementary, makes a convincing case for orientation-aware algorithms, both from a theoretical viewpoint and a more practical perspective. At this stage, it is straightforward to imagine that one can conduct similar comparative studies with other localization algorithms or inference tasks. Furthermore, some of these ideas can perhaps be transposed to communication systems. This research topic also raises fundamental questions. For instance, given a system with orientation-aware devices, what antenna patterns are conducive to improving performance? Also, can the directional signature of a device be obtained in situ, rather than through careful measurements in control environments? While these and other similar questions are beyond the scope of this article, they hint at a rich research landscape for future orientation-aware systems.

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REFERENCES