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SociTrack: Infrastructure-Free Interaction Tracking through Mobile Sensor Networks

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ABSTRACT

Social scientists, psychologists, and epidemiologists use empirical human interaction data to research human behaviour, social bonding, and disease spread. Historically, systems measuring interactions have been forced to choose between deployability and measurement fidelity—they operate only in instrumented spaces, under line-of-sight conditions, or provide coarse-grained proximity data. We introduce SociTrack, a platform for autonomous social interaction tracking via wireless distance measurements. Deployments require no supporting infrastructure and provide sub-second, decimeter-accurate ranging information over multiple days. The key insight that enables both deployability and fidelity in one system is to decouple node mobility and network management from range measurement, which results in a novel dual-radio architecture. SociTrack leverages an energy-efficient and scalable ranging protocol that is accurate to 14.8 cm (99th percentile) in complex indoor environments and allows our prototype to operate for 12 days on a 2000 mAh battery. Finally, to validate its deployability and efficacy, SociTrack is used by early childhood development researchers to capture caregiver-infant interactions.

CCS CONCEPTS

• **Networks** → **Network mobility**; • **Human-centered computing** → *Ubiquitous and mobile computing systems and tools*; • **Computer systems organization** → Sensor networks.

KEYWORDS

Infrastructure-free, Dual-radio architecture, Social interactions

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1 INTRODUCTION

The need for high-fidelity interaction tracking data is well-known, but it might now be more pressing than ever before. The study of proximal interactions is crucial in many settings. Changes in interaction behaviour are believed to be an important indicator of cognitive decline and the onset of Alzheimer's disease [16]. Patterns of social interactions are an indicator of informal informational networks and underlying power dynamics in a workplace [62]. Caregiver-infant interaction patterns have been shown to be important for early childhood development [85]. And of course, close physical interactions are of medical interest as they are a critical factor in the spread of diseases, like SARS-CoV-2 [18, 56, 74].

Scientists lack *high-fidelity* data—sub-meter accurate distance histories at sub-second sampling—on contact networks in the wild [3]. Current wide-area social interaction studies have to rely almost exclusively on self-reporting and public surveys [37, 51], which are highly subjective [55], subject to bias [10], and lack fine-grained quantitative metrics [62]. As a result, public health policy guidance on social distancing is based on limited studies taken in small populations and highly controlled settings. We lack understanding of spreading distances at scale in real-world environments to obtain improved, empirical models and take effective counter measures.

The desire for high-fidelity interaction data is not exclusive to epidemiology. In our evaluation, we consider the successful deployment of this technology by childhood development specialists, who are seeking a better understanding of the impact of physical proximity between caregivers and infants [20, 85]. Further demands for rich interaction data include applications researching interracial and intercultural relations [9, 52], transit design [25], and workplace dynamics [44, 55]. Hence, technologies and tools that flexibly facilitate proximal interaction tracking are likely to find many applications which differ in key parameters like detection latency, update frequency, spatial resolution, network density, and system lifetime. This breadth of applications motivates the design of an adaptable, general-purpose interaction tracking system.

The biggest challenge in designing a measurement system for high-fidelity interaction tracking is meeting *in situ* deployment requirements. It must operate *wherever* a cohort travels, which precludes relying on supporting infrastructure (this includes so-called ambient infrastructure such as WiFi, cell towers, or GPS). Due to the highly dynamic nature of mobile groups, the system must perform online network formation to constantly guarantee up-to-date information on cohort membership and ensure that all pairwise interaction data is collected. Finally, the measurement system must be unobtrusive to minimise the Hawthorne effect, where participants change behaviour once they are conscious that they are under observation [32, 85]. This means a suitable system must be wearable and lightweight, and also maintain low energy consumption to avoid frequent attention (i.e. recharging).

Summarising, we identify four challenges:

c_{FIDELITY}	Sub-meter accuracy and sub-second sampling
c_{INFRA}	Infrastructure-free (in situ) operation
c_{MOBILE}	Fast detection and frequent network switches
c_{DEPLOY}	Unobtrusive, wearable, and long-lasting

No prior interaction tracking system tackles all four challenges. Many systems build on low-power narrowband radios, such as IEEE 802.15.4 or more recently Bluetooth Low Energy (BLE), as these technologies have minimal deployment constraints and offer established solutions for infrastructure-free and highly mobile operation [2, 14, 53–55, 62, 64, 75]. However, narrowband radios have fundamental fidelity limits [46], and in practice these systems (even when leveraging information such as signal strength) are restricted to coarse "near/far" estimates. In contrast, a plethora of indoor localisation systems provide high-fidelity tracking, but they rely on infrastructure and cannot observe cohorts outside of instrumented spaces [35, 42, 43, 47, 71]. One recent system, Opo [37], achieves fidelity and mobility without infrastructure, but is restricted by the use of ultrasound to capture only short-distance (3 m), line-of-sight interactions, which imposes severe deployability restrictions.

We introduce a new platform, *SociTrack*, designed for high-fidelity interaction tracking studies that emphasises autonomous operation across a range of scenarios. SociTrack is self-contained, with no requirement of infrastructure support or limitations on deployment methodology. The platform is designed to capture interactions among highly mobile individuals. It builds dynamic networks capable of collecting pairwise distance information between all cohort members at up to 16 Hz with 14.8 cm 99th percentile accuracy. SociTrack can be worn by people of all ages during their normal day-to-day routines for up to two weeks. Further, the platform aims to constrain deployment scenarios as little as possible: it presents users with parameters to configure it to their needs, tools to predict its performance accordingly, and interfaces for real-time inspection and adaptation. In the design and implementation of SociTrack, we make the following core contributions:

- Our design exploration in Section 4 shows that the trade-offs required by any single communication technology do not allow the development of high-fidelity, infrastructure-free interaction tracking of mobile nodes with high deployability. To realise such a system, we introduce a heterogeneous architecture that exploits the individual strengths of BLE and ultra-wideband (UWB) radios.
- We improve state-of-the-art UWB ranging protocols on two key dimensions: Section 5 explains how we reduce message complexity from quadratic to linear with regard to network size and show that careful scheduling of broadcast packets can further result in a 50% reduction of messages, which increases lifetime by 102%.
- We demonstrate a configurable protocol that enables flexibility at deployment time with predictable, deterministic performance. Section 6 shows that this allows usage across a breadth of applications and promotes exploration.

In Section 8, we evaluate the SociTrack system's performance on various micro-benchmarks and consider its efficacy for real-world studies of domain scientists by deploying it with psychology researchers for an infant tracking scenario. Finally, we close with a consideration of upcoming hardware advances. While we develop and test SociTrack using custom hardware, Section 9.3 discusses emerging smartphones and wearables and shows how future global deployments could be as simple as a software update.

2 MOTIVATION

In this paper, we focus on the problem of long-term tracking of interaction distances among members of a cohort. These measures are important in the study of stress [25], human-robot interaction [82], epidemiology [68], and child development [85]. While small-scale experiments allow the collection of high-fidelity interaction data in laboratory settings, conscious observation can strongly influence behaviour [17, 77] and consequently cause scientists to miss critical cases such as neglect of an infant by their caregivers [85] or lead to the collection of data that misses the primary effects of caregiver-infant attachment relationships [20]. Thus it is critical to be able to measure behaviour in people's natural environments, where interactions occur organically [3, 70].

System requirements. The list of interested domains is large, and the potential application space for the platform is broad, so we start by distilling a common set of requirements. First, the collected data must be high-fidelity. While exact requirements are unique to specific applications, scientists across domains have called for systems that can collect interaction data with sub-meter accuracy at sub-second sampling (c_{FIDELITY}) [12, 85]. To be able to drop-in to an unknown environment, a system cannot require deploying infrastructure nor can it make assumptions about potentially existing infrastructure (c_{INFRA}), which makes traditional instrumentation-based techniques not only impractical but inadequate. People must be able to move freely, which requires the measurement system to form dynamic networks and continuously discover and update cohort membership throughout the duration of the experiment (c_{MOBILE}). To support natural measurements of behaviour, the collection system cannot rely on orientation (i.e. require line-of-sight between participants) and must be low-impact on the wearer (c_{DEPLOY}).

Example scenario. Early childhood development psychologists are interested in studying the interaction patterns of caregivers and infants in their natural environments [85]. In proposed experiments, the reliable capture of short-lived interactions (e.g. check-ins) as well as sub-meter accuracy is important to infer behaviours (c_{FIDELITY}). Measurements must follow clusters of family members wherever they go (c_{INFRA}), covering environments that might be impossible to instrument due to their public nature, unavailability of electricity and connectivity, or sheer extent. Members must be expected to continuously split up and rejoin over the course of the day (c_{MOBILE}), such as when family members go to work and school, pursue individual free-time activities or do the chores together. Finally, devices must be small enough to be comfortably worn by an infant and should remain unobtrusive to caregivers (c_{DEPLOY}). Section 8.1 will evaluate SociTrack's performance in this and other real-world application scenarios.

Platform	Ranging method	Infrastructure	Size [cm^2]	Spatial resolution [cm]	Temporal resolution [s]	Maximal range [m]	Lifetime [d]
WASP [71]	NB ToF	Yes	N/A	50	0.04	30	0.42
SurePoint [42]	UWB ToF	Yes	21.8	50	0.08	50	0.04
iBadge [15]	UL/RF TDoA	Yes	38.5	10	N/A	3	0.21
Opo [37]	UL/RF TDoA	No	14.0	5	2	3	3.9
Sociometric [44, 81]	RSSI + IR	No	~50	100	2	10	1
Social fMRI [2]	RSSI	No	N/A	500	300	N/A	N/A
Smartwatches [55]	RSSI	No	21.2	600	10	6	0.71
SociTrack	**UWB ToF**	**No**	**21.4**	**15**	**0.06**	**64**	**12**
Scenario							
Office – Employee workplace dynamics		Yes		50	2	20	5
Elderly care – Habit monitoring		Yes		500	30	10	14
Family – Caregiver-infant patterns		No		20	0.5	10	7
Sports – Player tracking and analysis		Both		20	0.2	50	0.08

Table 1: Previous systems cannot cover the complete design space, particularly lacking in infrastructure-free solutions with high spatial resolution. SociTrack provides an adaptable solution that can be configured for various scenarios and which offers a wide trade-off space between network size, spatial and temporal resolution, and lifetime, explored in detail in Section 6. Note that the given performance figures show-case the individually obtainable results of target scenarios, as discussed in Section 8.3, and are not all obtainable simultaneously.

3 RELATED WORK

Interaction tracking and related technologies have a long history in mobile computing research. The primary differentiation of SociTrack is realising high-fidelity tracking (sub-meter, multi-Hz) with no constraints on deployed infrastructure (i.e. anchors) or sensor placement (i.e. line-of-sight). Table 1 summarises how SociTrack compares to existing systems and addresses the needs of various target application scenarios.

c_{FIDELITY}: **Interactions are more than proximity.** Many systems either provide only coarse-grained (often 2-5 m) distance resolution between members through signal-strength measurements [2, 41, 62] or simply report nearby presence [14, 54]. Modern versions are often Bluetooth-based and highly deployable as they leverage smartphones and wearables [55]. While appealing in their accessibility, these proximity-based systems provide limited insight into the nature of interactions [75, 76], which requires sub-meter accuracy [13, 82]. They cannot provide key spatial insights, e.g. the significance between 1-2 m distancing efforts for disease spread [12].

c_{DEPLOY}: **Technology limits interaction capture.** Some systems provide finer-grained distance estimation by leveraging the propagation speed of waves. However, the underlying technology can impose strong limitations on the deployability of a system. For example, Opo [37] exploits the time difference of arrival between an ultrasonic chirp and an IEEE 802.15.4 radio packet to achieve 5 cm ranging accuracy. However, ultrasonic signals are challenging in complex, indoor environments, as reflections can persist in the channel for over 50 ms [47] and therefore limit the sampling frequency. Reflections also reduce effective range: because Opo cannot distinguish the direct path from a reflection, it assumes all interactions beyond 3 m are reflections. Similar multipath issues impede other acoustic solutions [66]. Finally, ultrasonic transducers are highly directional; in Opo, errors grow once the sensors are more than 45° off of direct line-of-sight. Because measurements rely on the successful reception of ultrasonic chirps, objects that obstruct line-of-sight, such as other people or wearing the sensor inside a pocket, prevent ranging altogether. In contrast, SociTrack's UWB-based solution is resilient to multipath interference and permits high-frequency, orientation-independent ranging despite non-line-of-sight.

c_{INFRA}: **What about indoor localisation?** While not originally targeted at interaction tracking, many indoor localisation systems can provide the needed accuracy from detailed position estimates. As narrowband radios are limited in fidelity and acoustic solutions are restricted in deployability, we focus on the localisation systems that also use UWB for its accuracy and deployability potential. SnapLoc [35] emphasises scale by supporting unlimited tags, SurePoint [42] highlights long-tail accuracy by introducing diversity ranging, and RFind [49] and Slocalization [65] reduce tag power to nanowatts via backscatter techniques; but all of these systems require fixed infrastructure in every room to operate. A common trend in localisation system design is asymmetry: to improve performance and SWaP (size, weight, and power) of nodes, complexity is pushed into infrastructure. Our applications, however, cannot afford this trade-off.

c_{INFRA}: **"Infrastructure-free" localisation.** Several localisation systems do not require additional deployment of infrastructure as long as they can take advantage of ambient infrastructure, such as WiFi [45, 79, 84]. While leveraging existing infrastructure can mitigate deployment cost in certain home and business settings, it is still an incompatible constraint for wide-ranging interaction tracking applications. For example, infant interaction tracking must operate in places where WiFi may be nonexistent, such as in the car, during a picnic at the park, or on a hike. While there are some early ideas that leverage new wide-area infrastructure such as LoRa [39], evidence from both indoor and outdoor cellular localisation suggest that neither coverage nor fidelity will be sufficient [63, 69, 72]. Ultimately, to ensure reliable operation anywhere a cohort may travel, an interaction tracking system cannot rely on infrastructure, neither explicitly deployed nor opportunistically used.

c_{MOBILE}: **Stochastic or scheduled?** Unsynchronised and unscheduled networks require no coordination but use the available channel inefficiently and are limited in scale [1]. Stochastic operation is what limits Opo [37] to 2 s sampling. Systems like ALPS [47] and UPS+ [48] demonstrate that it is possible to use the ultrasonic

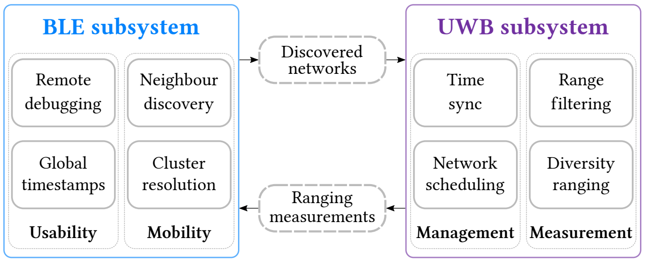

Figure 1: Task separation between BLE (left) and UWB subsystem (right). While the former handles external links for real-time data offload and neighbour discovery, UWB is used for network communication and distance estimation.

channel to realise sub-meter and multi-Hz tracking fidelity, but require infrastructure support to schedule ranging events. SociTrack is the first system to support all fidelity, deployability, and mobility challenges without relying on supporting infrastructure.

4 SYSTEM DESIGN

The goal of SociTrack is to provide high-fidelity interaction measurements while minimising constraints on how and where the system can be deployed. First and foremost, SociTrack needs a reliable mechanism to measure the distance between cohort members. Across the array of acoustic, optical, and wireless ranging technologies, only radio-based measurement techniques allow sensors in pockets, cope with cluttered environments, or register room-wide interactions. Of the radio-based methods, only UWB provides an accurate and robust ranging primitive [46]. The historic drawback with UWB is its energy-inefficiency in the face of mobile sensors.

Our key design insight is that while UWB is necessary to achieve high-fidelity ranging, we can mitigate its deficiencies on a modern platform by complementing it with another technology. A decade ago, an additional radio IC might have doubled the cost of a system—today, a Bluetooth chip and supporting passives represent just 8.7% of our prototype board BOM costs. With access to multiple technologies in one system, the central design question then is how to best apportion tasks across the available subsystems. Naively, one might simply use the comparatively energy-expensive UWB radio exclusively for ranging (where there is no alternative), and Bluetooth for everything else. However, as we will show in this design discussion, a blended approach in which responsibilities are shared results in a more capable overall design.

4.1 Why is Mobility a Struggle for UWB?

UWB radios are generally not used in infrastructure-free designs with mobile nodes. The issue lies in UWB's high receive power draw, which results from the need to integrate energy below the noise floor over a wide bandwidth and the necessity to heavily process and despread the received signal [78]. Discovery protocols require efficient listening however [23], and benefit from a balanced energy budget between transmission and reception of packets [67]. The UWB radio [21] used in SociTrack averages up to 554.1 mW while listening, 24× more power than its BLE radio [57] at 22.7 mW. Furthermore, the transmit and receive power draw is less balanced; the Rx/Tx ratio of UWB is 4.0 compared to 1.5 for BLE. This high and unbalanced energy consumption makes UWB particularly poorly suited to discovery. A UWB-only system is forced to sacrifice lifetime or discovery latency. But quick discovery is critical, otherwise short events such as a caregiver briefly checking in on an infant will be missed. By employing BLE instead of UWB, we can reduce discovery costs by 93% and enable long-term mobile deployments.

4.2 SociTrack Protocol Design

Figure 1 gives an overview of the major components of the SociTrack protocol and how SociTrack partitions tasks. Before any devices are discovered, only the BLE subsystem searches for neighbours and the UWB subsystem is powered down. During subsequent steady-state operation, both the BLE and UWB subsystems remain active, as they handle different aspects of network maintenance. Designing a protocol atop two radio technologies can be both beneficial, as they operate independently without concern of mutual interference, and challenging, as the availability of BLE and UWB links between nodes may vary due to differing propagation characteristics in complex, indoor environments.

Initial discovery. We must first design a discovery mechanism. Less mobile systems can treat discovery as a "startup" problem, a rare event before steady-state operation. In highly mobile settings, nodes can frequently switch networks and encounter new neighbours, thus discovery must occur continuously. Additionally, nodes may spend significant periods isolated from others, such as when an instrumented family member is at work, and must be able to rely on an efficient discovery mechanism to maintain lifetime. Finally, we also leverage the ubiquity of BLE on commercial devices to enable in-field inspection and debugging, requiring the discovery protocol to be compatible with standard BLE advertisements.

We select BLEnd, a state-of-the-art BLE discovery protocol, as it delivers highly predictable performance and supports deployment-time adaptation to trade-off discovery latency and energy use [40]. Off-the-shelf BLEnd assumes an isolated network communicating only with other BLEnd nodes, and therefore exclusively sends standard *un*connectable BLE advertisements that it detects with periodic scans. With SociTrack, we are also interested in supporting communication with consumer devices (e.g. using smartphones for monitoring) and therefore opt for connectable advertisements. In addition to real-time remote debugging, we leverage this gained connectivity to directly inform the sender of an advertisement of neighbours and achieve simultaneous bi-directional discovery. This enables us to halve the number of advertisements and reduce energy consumption by up to 50% compared to the original design while maintaining the same discovery latency. We further incorporate empirical characteristics such as radio start-up costs into the design to improve the efficacy of our discovery optimisation algorithm.

Cluster formation. Once nodes discover each other, they seek to form (or join) a cluster. To bootstrap such a local network, two orphans discovering each other will form a cluster and elect the node with higher ID as the leader. Discovery advertisements are then updated to indicate an active cluster and include the current cluster lead's ID. If an orphan encounters an existing cluster, it will join as a regular member even if it has a higher ID to avoid churn.

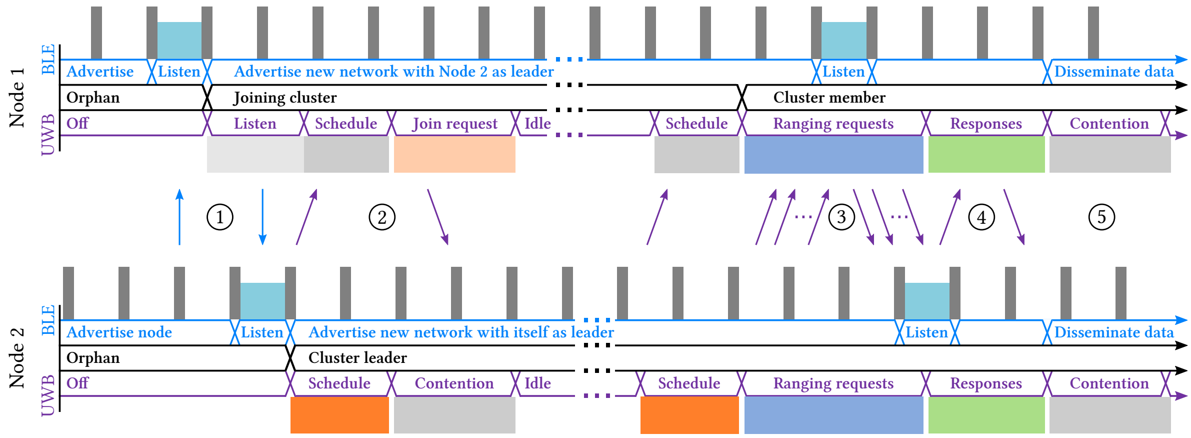

Figure 2: (1) Two nodes initially discover each other by periodically transmitting BLE advertisements and detecting the presence of other nodes and networks when scanning. (2) Once a leader is determined, it initiates a UWB round consisting of schedule distribution and contention access so other nodes can register. Next, requesters and responders are scheduled and start ranging with each other. In contrast to prior diversity ranging protocols, ranging requests (3) and responses (4) are separated in time and occur entirely deterministically using broadcasts. (5) The gathered range information can then be disseminated to other devices such as laptops and smartphones over Bluetooth.

Steady-state operation. Figure 2 shows initial discovery, followed by steady-state operation. During steady-state, the BLE radio continues to perform discovery to handle subsequent joins and departures. In addition, the UWB radio begins to manage cluster operation. The leader disseminates a schedule to all nodes, cluster members perform the scheduled ranging events, and then the cluster handles potential membership changes. Section 5 will examine ranging in detail, so it is sufficient to treat ranging as a black-box for now.

Our network design is inspired by Glossy [26], the current state-of-the-art protocol for reliable multi-hop network communication among mobile nodes. Glossy concurrently transmits packets from multiple nodes to reliably synchronise and flood information through a network. Re-transmit timing is controlled directly by the reception of other packets, which eliminates topology-dependent state and thus makes it well suited to highly mobile sensors. While Glossy was originally implemented on top of IEEE 802.15.4, it has also been shown to work for both BLE [5] and UWB [42] networks.

SociTrack employs UWB flooding using Glossy on the UWB radio during the `Schedule` and `Contention` phase, seen in Figure 2. In principle, only the ranging strictly requires the higher energy radio. However, it is important that the ranging events are precisely scheduled, and establishing an accurate shared clock between the BLE and UWB radios would be non-trivial. More importantly, UWB and BLE can exhibit different propagation in complex, indoor environments. Disseminating the schedule on the same radio used for ranging ensures that all devices within ranging distance will be able to perform measurements, even when lacking BLE connectivity.

Re-discovery. Because the UWB network is based on flooding and the BLE network is point-to-point, they have different connectivity graphs. This means that when a new node discovers a cluster via BLE, it must somehow let the cluster *lead* know of its presence, even though it may not be in direct range of the leader. To address this, the cluster lead schedules a contention-access window in each UWB round during which new nodes may flood requests. Naively, it would be highly energy-expensive for an orphan node to continuously listen on its UWB radio for a potential contention window. However, because it was first initiated through BLE discovery, the consequent UWB registration mechanism succeeds immediately.

Adaptive contention. Reactivity is essential for mobile networks, which requires SociTrack to gracefully handle the case when many nodes appear in a short interval. For example, during a merge operation, ranging is effectively paused for nodes of the joining cluster until they are scheduled in the new cluster. To mitigate substantial measurement gaps, the cluster lead adjusts the contention duration depending on the count of join requests in the previous round using multiplicative gains (by doubling, maintaining, or halving the number of available contention slots). This manages to quickly satisfy the network demand, as seen in our evaluation in Section 8.3.

Cluster interference. A ubiquitous problem in traditional sensor networks is collision avoidance between two active clusters, as nodes usually listen only when scheduled to reduce energy consumption. SociTrack's heterogeneous radio architecture is uniquely suited to effortlessly detect and resolve such a conflict. During steady-state, inter-network communication occurs exclusively over UWB. The BLE subsystem meanwhile continuously attempts to discover new nodes. When a cluster member discovers another active cluster with a higher leader ID than its current cluster, it will attach to the new cluster and start advertising it. Because this discovery occurs out-of-band, we enable collision detection and cluster resolution without influencing on-going measurements.

Detecting departures. In a multi-hop network, it is often the case that a node is not in one-hop range of the leader. When flooding packets, all nodes re-transmit identical payloads concurrently, so it is impossible for the leader to detect whether a specific node failed to participate during schedule dissemination. During the ranging events (which are detailed in the next section), packets do contain IDs; however, these packets cannot be flooded as they are used for time of flight measurements, so the leader cannot observe ranging packets of a node that is more than one hop away. As a consequence, the leader cannot easily detect whether a node may have left the cluster. For this reason, nodes are automatically dropped from the schedule after a fixed number of rounds and must re-register in a dedicated contention-access window (see Figure 2). Cluster members can track their own network dwell time and proactively notify the leader when they are close to expiration. When the leader leaves the network, we avoid bootstrapping a new network from scratch by promoting the second-highest node to automatically take over if too many rounds have passed without receiving a schedule from the leader. Conversely, if a former leader deschedules all its members, it becomes an orphan again.

External communication. BLE provides the unique advantage to permit connections to many commercial devices such as laptops and smartphones. We leverage this ability to disseminate measurements in real-time for deployment monitoring and in-situ remote debugging. Additionally, we exploit the time-awareness of such devices to enrich our data with global timestamps which a leader distributes inside the network to facilitate data analysis.

5 RANGING PROTOCOL DESIGN

Pairwise ranges compose interactions, which makes their accurate and efficient collection critical. Optimising the performance of the UWB channel for high-fidelity ranging is well-studied in prior work [42]. Instead, our protocol contributions focus on making collecting ranges efficient in the absence of powered infrastructure nodes, reducing redundant messages, and incorporating flexibility depending on available energy.

Overview. The goal of the ranging protocol is to get an accurate estimate of the time of flight (ToF) of radio packets between every pair of nodes in a cluster. In the simplest case, one node starts a ranging event by transmitting a *request* to which another node *responds*; based on the timing of the response and its contents, the *requester* can estimate the ToF to the *responder*.

Diversity improves ToF. To reduce variance in ToF estimates, state-of-the-art UWB ranging protocols [42, 43] employ diversity by *requesting* on multiple physical channels. This diversity is achieved by alternating between different transmit or receive antennas and switching frequencies. In our implementation, each node has three antennas with a polarisation offset of 120° and can select from three non-overlapping frequency channels, offering up to $3 \times 3 \times 3 = 27$ individual measurements. These measurements are converted to a single range estimate by taking a system-dependent percentile out of the samples, generating a result that is both accurate and precise [42]. Note that while the *requester* transmits a series of packets, the corresponding reception energy consumption is much higher at responders; there is asymmetric energy cost during a ranging event. Traditional infrastructure-based designs exploit this asymmetry by offloading responding to powered "anchor" devices. As all SociTrack nodes are identical, any combination of devices must be able to perform ranging. They therefore act as *hybrids*, each rotating through both requester and responder responsibilities.

Broadcasts enable scale. For infrastructure-based systems with fixed "anchors", mobile nodes need only range with known reference points to establish position. Because we assume all nodes are mobile, relative position to a subset of nodes is insufficient to obtain a full pairwise interaction graph. To ensure coverage, all nodes must therefore range with one another. In a straight-forward unicast design, a cluster with n nodes will require $O(n^2)$ packets to capture all pairwise ranges which would not scale efficiently. Instead, in SociTrack, both requests and responses are sent as broadcasts, which requires only $O(n)$ messages. In contrast to previous approaches in which all nodes immediately respond to a request, we achieve linear complexity by sending aggregated batch responses after all requests have been transmitted. Notice that this is only possible because we apply network-wide scheduling of all packets.

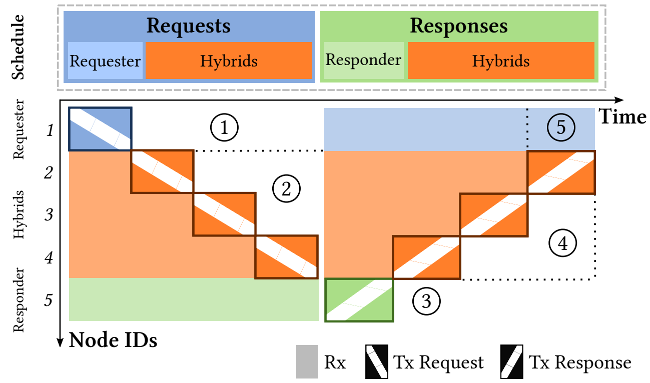

Figure 3: (1) Exclusive requesters transmit and then wait to receive responses. (2) Similarly, hybrids stop listening after their own transmission. Therefore, the number of active hybrids is steadily declining. (3) While exclusive responders continuously listen during the requesting phase, they afterwards respond and return to sleep first. (4) For responses, hybrids are scheduled in reverse order to balance energy consumption. (5) If nodes have gathered sufficient responses, they can independently stop listening to save energy.

Ranging pyramid. A range is a symmetric measure: for every pair, only one node needs to request while the other responds. We leverage this insight to reduce energy consumption by an additional 50%. The very first hybrid acts as the requester for all pairs, so it can sleep during all other request transmissions. Consequently, it must listen at the end when all others send their responses. The last hybrid scheduled for requests will be the responder for all pairs, so it must listen to all requests, but can sleep immediately after sending its response. Through this reversing of the scheduling order of hybrid nodes for the responses, we balance energy consumption across the network. This results in a "pyramid schedule" as shown in Figure 3. Using our system model introduced in Section 6, we find this protocol increases the lifetime of a network of 10 nodes ranging at 1 Hz by up to 102% compared to the state-of-the-art [42].

Beyond hybrids. In some deployments, full pairwise connectivity may not be required. For example, if infrastructure nodes ("anchors") can be deployed, they do not need to range with one another. Instead, such a resource-rich node can act as an *exclusive responder*, enabling other nodes to range with them at minimal cost and offloading listening costs to mains-powered devices. Similarly, if some nodes are severely energy-limited, they may choose to act as *exclusive requesters*, sending requests, but never responding.

6 SUPPORTING THE DESIGN SPACE

Previously we considered the system design from the bottom-up, identifying and addressing the key technical challenges. Now, we take a top-down view and consider the axes available to researchers who use SociTrack as a platform for their studies. In our discussions with stakeholders and review of literature [37, 76], we identify four key dimensions that drive experimental design:

- **Temporal fidelity:** How quickly is a new interaction discovered, how long must it last to be detected, and what is the corresponding sampling rate of distance measurements? *Ranges from sub-second to several minutes.*
- **Ranging quality:** How accurate and precise do the distance measurements between cohort members have to be? *Ranges from decimeter to room-level.*
- **Deployability:** How bulky are the sensors, where can they be worn, and how long must their battery last? *Ranges from infants to adults, and from hours to a month or more.*
- **Usability:** How do we monitor the system's health and data, and how do we recover the data? *Ranges from paid staff on-site to remote access only.*

The next step is to identify how to parameterise SociTrack to expose the desired experimental dimensions, thereby enabling platform adaptation and design exploration. As hardware capabilities are fixed, we cater to deployability constraints (c_{DEPLOY}) and usability considerations from the start and ensure that restrictive SWaP goals and remote accessibility demands are met. We find that through four configuration mechanisms, we can provide the needed experimental design controls:

- **BLE parameters:** Dictate discovery latency. This drives quick network joins and cluster resolution time, at a trade-off with an increased energy use and corresponding lifetime.
- **UWB update interval:** Controls ranging sampling rate, maximal network size, and energy use.
- **Diversity sampling:** Configures how many antennas and frequency channels are used for each range sample, which affects sampling rate, ranging quality and energy use.
- **Maximum network size:** Bounds the sampling rate and impacts system lifetime, as the duration of an update increases linearly with the network size.

Bridging top-down and bottom-up. Mapping experimental design constraints to a selection of parameters can be challenging and hard to estimate, especially for non-experts. Furthermore, parameter interactions can be subtle. For example, less diversity requires fewer samples per range event which leads to shorter rounds, increases the maximal sampling rate and network size, and reduces energy consumption—but all at the expense of ranging quality.

Therefore, we support pre-deployment exploration of the design space through simulation. For this, we characterise our system using detailed ranging, power, and timing measurements. The resulting open-sourced system model allows scientists to validate system capabilities and tune parameters in advance, as we will demonstrate in Section 8.3. This reduces deployment risks, eases adoption, and promotes time-efficient exploration of novel applications in a diverse set of environments. For experimenters, SociTrack shifts trade-off decisions from *design*-time to *deployment*-time.

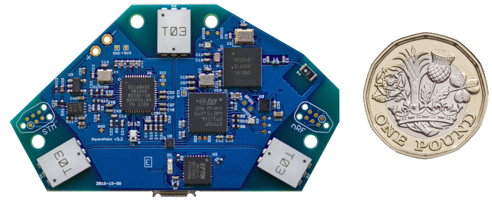

Figure 4: SociTrack's compact size makes it easily wearable for all age groups. It further reduces the awareness of being under observation, as it can be hidden underneath clothing. A plastic case shields the board and battery from external influences.

7 IMPLEMENTATION

We implement the proposed dual-radio architecture, which consists of BLE and UWB subsystems, on a custom PCB shown in Figure 4. The BLE subsystem uses the Nordic Semiconductor nRF52840 as a combination of BLE radio and discovery management MCU and adds an separate real-time clock for timestamping, an SD card for permanent storage, and an accelerometer for activity detection. The UWB subsystem employs a STMicroelectronics STM32F091CC MCU as a ranging controller and DecaWave's DW1000 UWB radio.

Figures of merit. As one of our motivating applications includes instrumenting infants, we pay particular attention to the size, weight, and safety of our implementation. The PCB measures 61×35 mm and weighs 7.7 g. We pair this with a 2000 mAh battery, weighing 34.1 g, and package both in a custom-built, 3D-printed case. This results in a compact, portable system that measures $67 \times 48 \times 19$ mm with a weight of 59.8 g.[1] The realised tracker is small enough to be worn on the wrist, on a lanyard around the neck, on a running belt, or inside a shirt or pant pocket. Infants can easily carry them in the front pocket of a specialised vest, as is common for such experiments. Data collection occurs via an SD card as well as remotely by collecting the data in real-time through BLE advertisements sent by the tracker, which can be visualised or forwarded by a smartphone.

Deployment considerations. As SociTrack is designed to be deployed by non-experts in real-world settings, we provide multiple mechanisms for deployment assistance. Each node can be easily monitored visually via two RGB status LEDs that display the states of the BLE and UWB subsystems separately. For more in-depth monitoring and debugging, a BLE interface exposes characteristics which can be interacted with using a smartphone app for Android and iOS as well as JavaScript applications that we built and provide to researchers. The interface further enables experimenters to configure the device on-the-fly and adjust parameters without requiring direct physical access to hardware in a running experiment, as well as in situ data aggregation and verification.

Research artifacts. All hardware and software artifacts for SociTrack are open source and publicly available on GitHub [11]. In addition, we open source both our modified version of BLEnd (as described in Section 4.2) and a detailed system model (see Section 6). The platform is in active use by our collaborators doing longitudinal research on caregiver-infant interactions.

[1]The size and weight constraints are guided by collaborators who previously deployed $86 \times 56 \times 15$ mm, 59 g LENAs [31] for acoustic infant monitoring.

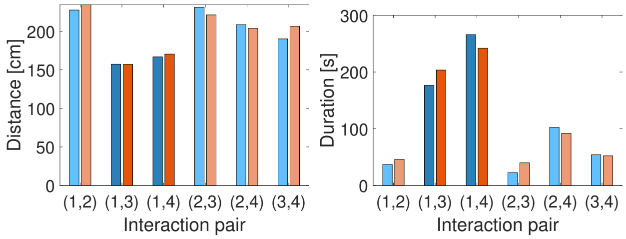

Figure 5: Comparing both the average duration and distance, we observe that Individual 1 encounters distinctly longer interactions over a shorter distance with both Individuals 3 and 4. Ground truth diaries confirm that the pair sat together to meet. All other interactions occur in the hallway with significantly larger distances and briefer duration. Notice that interactions are detected reciprocally (blue and orange bar), suggesting high measurement reliability.

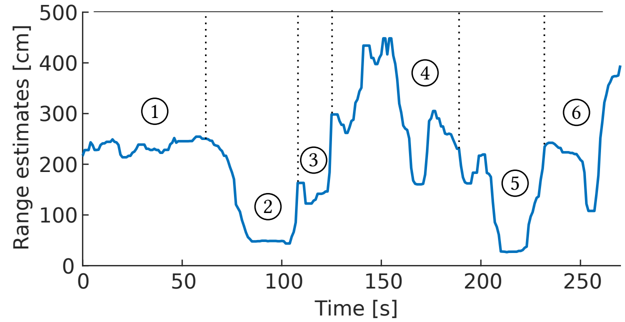

Figure 6: (1) A toddler is initially playing on his own while his caregiver is sitting in the corner of the room. (2) As soon as the infant spots a stranger entering, he quickly seeks comfort in the caregiver's proximity. Once the toddler realises that stranger and caregiver are on friendly terms, (3) he hesitantly greets the unknown person. (4) The infant then explores the room. As soon as the stranger tries to interact with him and join the play, (5) the toddler once again retreats to the caregiver. After having been comforted, (6) the infant accepts the stranger and continues exploring.

8 EVALUATION

To demonstrate the efficacy of our system, we test SociTrack in both controlled experiments and real-world deployments. We first validate the overall functionality of the platform using three of the application scenarios discussed in Section 3. Thereafter, we evaluate the measurement fidelity at varying ranges and show that we achieve decimeter ranging accuracy by leveraging a combination of antenna and frequency diversity. We then demonstrate through simulations using our system model that the system can be easily adapted to diverse scenarios and that our protocol enhancements significantly reduce join latency and message complexity compared to the state-of-the-art. Finally, we investigate SociTrack's deployability and environmental influences on the measurements.

8.1 Validating the Deployment Scenarios

Office interactions. To validate the platform with different groups of people, we first conduct experiments with 4 participants over a period of 10 hours, covering a complete working day. During this period, the platform proves to be reliable for data collection. Despite the significant movement of up to 10 people inside a busy open-plan office space spanning 15 m, nodes on average receive 96.1% of all schedules and accomplish 85.7% of all two-way rangings.

Throughout the day, the system automatically identifies 81 interactions between the four individuals. Figure 5 shows that pairwise relations vary significantly in both average duration and average distance. In particular, two of the combinations involving Individual 1 show distinctly closer physical relations over a considerably longer period of time. Leveraging our ability to globally timestamp data via synchronization over BLE using smartphones, we correlate the data with a manual log. This enables us to deduce that these pairs correspond to two meetings, during which the individuals were seated. Note that all interactions are automatically detected during post-processing of the data and result in detailed spatial and temporal data which can be further investigated by social scientists. While we only display interactions closer than 250 cm here, the analysis can be extended to include multiple, fine-grained proximity zones [82]. By comparison, a proximity-based system cannot support such post-hoc distance-dependent analysis.

Family dynamics. To evaluate the efficacy of SociTrack for social scientists, we give nodes to partners in developmental psychology. They deploy them for an execution of the classical "Strange situation" procedure [4], which observes the attachment relationships of an infant and their caregiver. Based on how the infant reacts to an unexpected disturbance, activity is categorised into one of four behavioural patterns. For this experiment, a toddler (wearing the node in a small vest) and their father (with the node in his pants' pocket) are placed in a room where scientists can observe the infant's reaction to an unknown person entering it. Figure 6 shows the data from SociTrack measurements, which match the results from visual observation through domain experts. Here, the infant fits the *secure* pattern, happily exploring the room on his own and retreating to the caregiver as a "secure base" in times of distress. While previously only possible in instrumented rooms, SociTrack permits the investigation of such patterns in the wild.

Sports tracking. We are also motivated to support applications such as sports analysis where high-speed tracking and up-to-date network management is essential. We will later in this section show that the combination of multiple frequency channels and antennas allows us to achieve sub-decimeter range measurements in stationary environments. As SociTrack performs 30 different range measurements, the estimates are gathered over a duration of 60 ms and are essentially smeared across a node's vector of motion, potentially impeding the tracking performance of fast objects.

To *investigate the effect of motion* on system accuracy, we design a controlled motion rig that allows the evaluation of measurement accuracy at different speeds and compare it against ground-truth of an optical tracking system. We explore two scenarios in Figure 7: a device attached to a moving model train and one attached to a slot car, both travelling around elliptical tracks. We find that the presence of movement, regardless of speed, introduces about 50 cm of error on average. Despite speeds matching a jogging human at 10 km/h (2.8 m/s), SociTrack provides stable results.

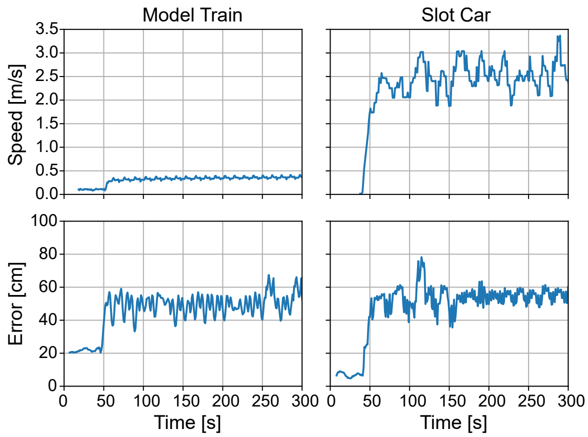

Figure 7: We examine the error of moving nodes through low- and high-speed experiments, with a SociTrack device attached to a model train and to a slot car respectively. Error and speed are presented as a moving average over 10 seconds.

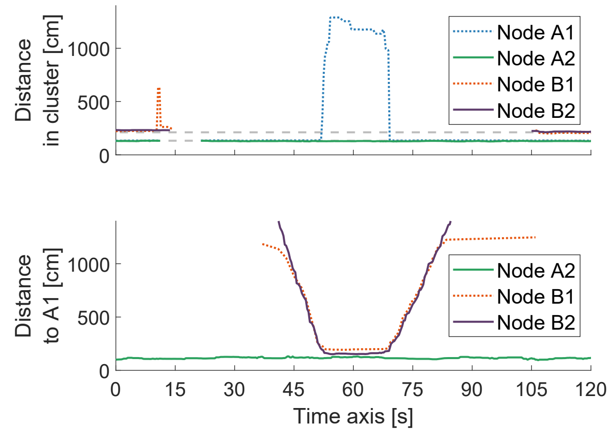

Figure 8: The bottom plot displays the view of node *A1* which correctly discovers the approach of a new cluster of nodes and merges both clusters. When lacking discovery, clusters heavily interfere: In the upper plot, two clusters without this feature repeat the exact same experiment. While they are outside each other's range, they successfully collect pairwise data. Once the two clusters come closer, they start to interfere with each other and observe severely impeded (cluster *A*) or completely blocked (cluster *B*) measurements.

To *investigate the impact of our network management scheme*, we compare a version of SociTrack that mimics traditional single-radio designs (network management feature disabled) with our dual-radio architecture in Figure 8. For this, two clusters (*A* and *B*) of two subjects each approach one another, chat for a bit and then separate again. We observe that SociTrack successfully detects and quickly merges two clusters well before the four subjects are within interaction distance. Furthermore, we also find that without our interference-avoiding discovery feature, ranging would be severely impeded. Indeed, collected measurement data would not only miss interactions between different clusters; due to the interfering schedules of the two clusters which result in jammed communication, intra-cluster interactions would be lost as well.

8.2 Characterising Measurement Fidelity

Next, we analyse whether our system delivers the required measurement fidelity. To begin, we analyse the gain of our ranging protocol, which combines 30 range measurements using antenna and frequency diversity, compared to a single estimate. We gather 34,680 estimates over a distance of 3 m in a static indoor line-of-sight setting. In Figure 9, we observe that each physical channel is precise, with an average empirical 90% confidence interval of 14.7 cm. However, medians exhibit an average error of 30.2 cm. Aggregating the 30 range measurements by taking the 30th percentile of the distance estimates reduces the overall interval to 11.9 cm and the median error to 9.3 cm. Analysing combinations of antenna and frequencies over various ranges, we find that average precision is boosted by more than 19% from antenna diversity, while average accuracy increases by up to 66% using multiple frequency channels.

A second experiment investigates whether distance impacts accuracy. For this, we conduct stationary measurements over four distances (3, 6, 9, and 12 m) as shown in Figure 9. We gather more than 30,000 ranges per distance. While the number of raw outliers slightly increases with distance, we see that the aggregation of measurements improves the empirical 90% confidence interval by at least 82.1% when compared to raw ranges and reduces the 95th percentile error by at least 79.7%. Aggregating channel measurements cuts off the long tail of the distribution of range estimates.

Throughout our experiments, UWB offers excellent connectivity indoors, operating in a cluttered, multipath-rich environment as well as through walls and objects. SociTrack achieves a maximal line-of-sight range of 64 m outdoors and at least 50 m in our longest indoor hallway. The BLE radio communicates up to 28 m, which ensures room-level discovery. With its shorter range, BLE discovery inherently averts accidental triggering while UWB is out of range. Note that after initial discovery, the system's effective measurement distance is only limited by the UWB range.

8.3 Exploring the Parameter Space

Finally, we leverage our detailed system model to investigate the deployment parameters of the protocol, discussed in Section 6, to predict system lifetime. Figure 10 shows that small networks of a few nodes can exceed a week of operation and that larger networks, such as school classes, can attain over two days of constant ranging.

We find that energy usage depends on the modes of *exclusive requester*, *exclusive responder*, and *hybrid* as introduced in Section 5, while the overhead of cluster management is negligible. As exclusive requesters primarily send packets, they can largely avoid listening for packets; notice however the drop in lifetime for networks exceeding 10 nodes due to packet length limitations of UWB, which requires a split of response broadcasts and prolongs listening. On the other hand, exclusive responders listen for all requests, drawing 435 mW while doing so. As a fusion of requester and responder, hybrids would naively require their combined energy costs; exploiting our scheduling scheme shown in Figure 3, we can significantly reduce these costs and achieve infrastructure-free operation.

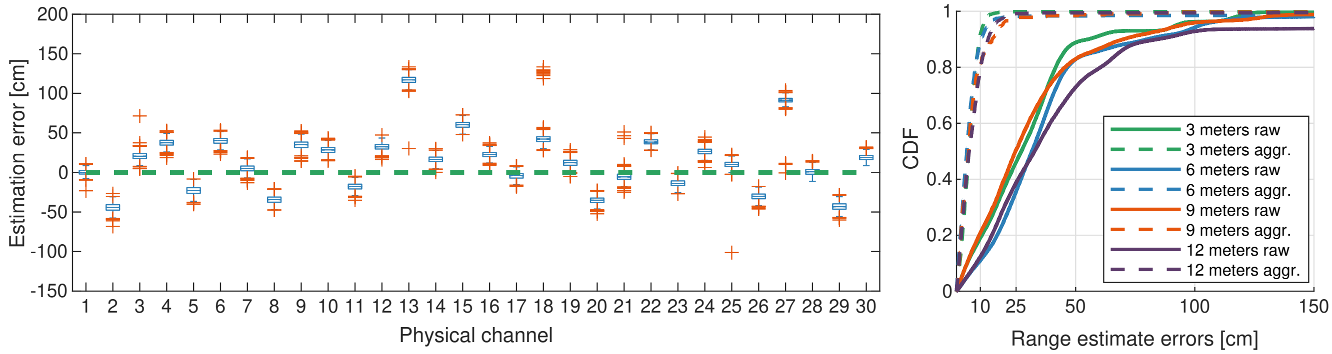

Figure 9: Combinations of frequency bands and antennas result in 30 different observations of the same distance. While each offers precise measurements thanks to UWB's stability, cross-polarisation and small-scale fading can result in systemic accuracy error (left). By *aggregating* over all settings, we obtain results which are both precise and accurate as shown by the dashed curves on the right. We observe that aggregation boosts average accuracy and significantly reduces the long-tail error: the 90th percentile error is decreased by 82.6% at a distance of 3 m, while the 99th percentile error is limited to only 14.8 cm.

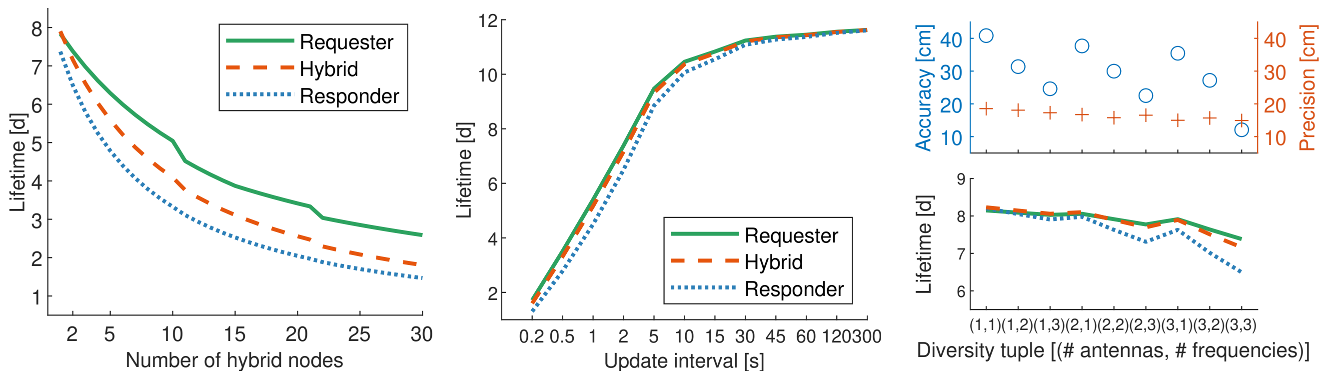

Figure 10: While small networks support more than one week of operation with an update interval of 2 s, even large networks of more than 30 nodes endure for multiple days. The update interval offers scientists the ability to adjust the expected lifetime and run experiments for up to nearly two weeks for a network of two nodes. Decreasing diversity can further boost deployment duration by almost two days for two nodes with an update interval of 2 s, but trades off accuracy and precision, which decrease by up to 237% and 24% respectively.

Scalability. Figure 11 demonstrates the effectiveness of the protocol's dynamic contention adjustment. Compared to SurePoint [42], SociTrack can quickly handle the simultaneous appearance of large groups, such as when students arrive for a class. Furthermore, we observe that the join latency difference between nodes is reduced by 88%. When comparing message complexity, we find that SociTrack outperforms SurePoint as well as a naive, pairwise ranging implementation without any broadcasts [43] by a factor of 3.6 x and 73.6 x respectively for a network of 30 nodes.

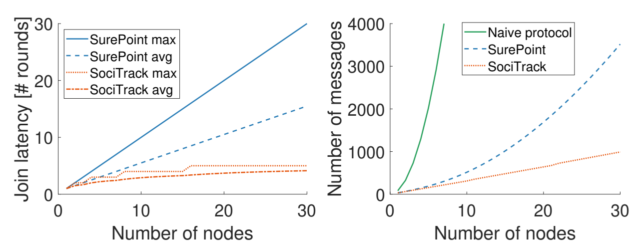

Figure 11: SociTrack automatically adjusts contention slots when a group of nodes joins the network and handles 30 instantaneously appearing nodes within maximally 5 rounds. In contrast, SurePoint requires 6× longer. We further see that SociTrack realises a 3.6× reduction in message complexity compared to the state-of-the-art ranging protocol for such a network of 30 nodes.

8.4 Investigating System Deployability

Directionality. Systems like Opo [37] or iBadge [15], which rely on ultrasound for TDoA measurements, are limited by the field of view of their ranging sensor. They require near face-to-face orientation to detect interactions and acquire ranges. While the UWB antennas used by SociTrack have a significantly more omnidirectional radiation pattern than ultrasonic frontends (e.g. Opo reports a detection angle of 60°), they still exhibit poles of decreased performance. Figure 12 shows that orientation contributes negligible error and hence is not a deployment concern for SociTrack.

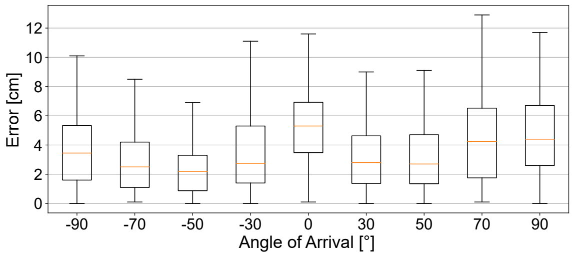

Figure 12: To explore the effect of angle on performance, we position one device at the centre of a 1 m semicircle, and place another at the edge at predefined angles. We perform 120 ranges at each orientation and find that the mean, 25th, and 75th percentiles fall below one decimeter of error for all orientations. Experimental deployments can therefore likely ignore device orientation.

Some applications may desire orientation data, which can be challenging to obtain with radio frontends. The Sociometric badge [81], nominally just an RSSI-based proximity tracker, adds IR transceivers to detect when proximate cohort members are facing one another. A similar orientation detector could easily extend SociTrack, but is out of scope for this work.

NLoS from human bodies. The human body is a well-known attenuator, which might reduce the effective range or fidelity in crowded environments. While we did not observe any sustained connectivity losses in our deployments, we also explore the possible impact of through-body transmission by placing two nodes 5 m apart and then having additional volunteers stand directly in the line-of-sight path. When the first individual steps in, variance in range estimates increases insignificantly. When the second individual steps in, the range estimation error occasionally spikes to around 4 m, which likely indicates that ranges are being recovered from a non-line-of-sight (NLoS) reflection. These measurement spikes can however be effectively eliminated in post-processing through median filtering with filter widths of 3-5 samples.

Next, we investigate whether the distance estimation is still being correctly represented if people are sitting with their backs to each other, a common situation encountered in office spaces and public transport. For this, we position two subjects 2 m apart with devices attached to their chests and compare the data gathered with them either facing each other, them setting behind each other, or with their backs to each other. We find that in all three cases, the measurements are stable over time. We observe that distance estimates slightly increase, possibly due to the decreased propagation speed of radio signals in tissue, which can be as much as 8 times slower for muscles [80]. The presence of a single person between nodes results in an average overestimation of 19 cm, which increases to 46 cm for two people as shown in Figure 13.

Future work could utilise recent advances in UWB connectivity graphs [22] and ML-based UWB channel analysis [8, 36, 50, 73, 86] to automatically detect non-line-of-sight conditions and correct errors with ranges from other links. In addition to UWB ranging, one could augment the distance estimations with traditional, coarse-grained BLE RSSI data that is gathered through the periodic BLE advertisements in case the primary ranging system should fail.

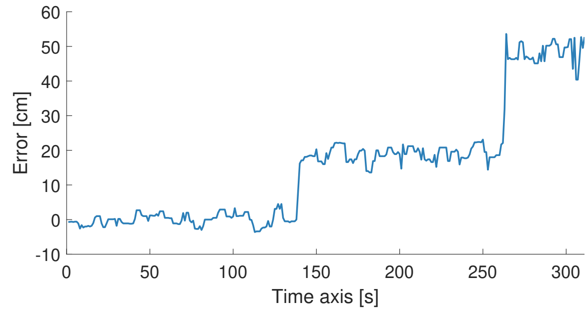

Figure 13: Compared to the ground truth at the start, we find that the blocked line-of-sight through one (after 140 s) or two (after 260 s) people leads to an overestimate of the physical distance.

9 DISCUSSION

SociTrack is a first-of-its-kind platform. Here, we consider some potential extensions for the platform and place our contributions in a broader context. We close with a look at how future systems might leverage insights from SociTrack and the impact potential of the availability of high-fidelity interaction tracking.

9.1 External Adoption Experiences

We find during our collaboration with partners in psychology that seemingly minor features, unrelated to the core sensor design, can significantly improve SociTrack's efficacy for non-technical users in the field. For example, at small scale, unscrewing cases to remove boards for charging is feasible, but when deployed in the homes of volunteers unaffiliated with the research team, it is undesirable. While splash-resistant charging ports exist, we suggest that future designs strongly consider wireless charging. New chips make the implementation of such technology near-turnkey, and a port-free case design significantly reduces potential vulnerabilities of devices in the wild, particularly for small-scale research prototypes. Similarly, initial designs included a switch to disable the sensors while not in use. In practice, this introduced risk that end-users would accidentally disable measurements during a study. The less error-prone solution for real-world deployments is to use an RTC that allows study administrators to filter for times of interest.

Finally, to support deployments, we designed and tested rich wireless debugging and system monitoring through BLE connections. While this was useful for testing with the research team, when deployed on volunteers, our "backup debugging" of colour-coded LEDs has proven to be much more practically relevant—it is easier for non-technical users to verify that the sensor is "all green" or to report an "orange flashing" than to manage a companion smartphone application. Encapsulating meaningful state into easily identifiable colours and patterns is hence critical to facilitate user feedback. We intend to implement and extend these features in an upcoming hardware iteration.

9.2 Benefits of the Dual-radio Architecture

Enabling infrastructure-free precision ranging. While reliable (ToF) ranging used to be a long-standing unanswered problem for mobile systems, UWB radios offer a practical solution to many real-world problems. However, due to their high energy consumption when used as a stand-alone system, the technology was not applicable to wearable systems without relying on externally powered infrastructure. Our addition of a separate discovery radio enables long deployments for low-power systems in a wearable form factor.

Integrating network de-fragmentation. While network bootstrapping is a part of almost any low-power network protocol, the fragmentation of networks due to mobile nodes most often remains an open issue. As nodes avoid idle listening for energy efficiency and only enable their radios at precisely synchronised points in time, progressive network decomposition into clusters and the resulting undetected self-interference is unavoidable in the face of node mobility. In practice, many protocols do not address de-fragmentation and will continue to create additional, smaller networks throughout a deployment; members of these sub-networks are restricted to interact with the few nodes they know. This paper demonstrates that a dual-radio architecture provides a solution that enables the detection and resolution of such clusters without interfering with regular operation or compromising core measurement fidelity.

Handling mobility. Supporting range-based interaction tracking with high node mobility while supporting complete autonomy (i.e. infrastructure-free deployments) requires solving four distinct problems. First, the severe energy restrictions demand a design that limits the use of UWB, a task we solve through a complementary discovery mechanism over BLE. Second, nodes cannot rely on the presence of fixed anchors, thus they must act as hybrids which send both requests and responses to guarantee successful ranging in each encounter. Third, a highly dynamic network structure requires topology-independent multi-hop communication, which we provide using a flooding-based protocol over UWB. Fourth, wide-area mobility leads to network partitioning over time and requires continuous neighbour discovery as well as an efficient de-fragmentation mechanism, which is enabled by the non-interfering, independent dual-radio architecture. Only with each one of these four solutions are we able to build a mobile system that supports infrastructure-free high-fidelity ranging in real-world settings.

9.3 Looking Forward

Evolving hardware. Today, SociTrack relies on custom-designed hardware as UWB radios are not ubiquitously available. This is quickly changing, as new smartphones and wearables include UWB to support location attestation features such as user authentication to devices and spaces. Indeed, Apple's iPhone 11 contains a UWB radio with three antennas [38] and could support our diversity ranging scheme out-of-the-box. As systems with heterogeneous radios become more common, low-cost, large-scale deployments of SociTrack could be started through a simple iOS software update.

Evolving interrogatives. Lacking sub-meter resolution, it would be impossible for behavioural analysis to identify the immediate reactions of the infant in Figure 6 and automatically distinguish between an infant seeking close contact for comfort or playing happily near their caregiver. SociTrack enables us to detect even detailed movement such as when the infant briefly turns away from the caregiver to scan the environment (visible as brief peaks). The ability to collect *in situ* high-fidelity interaction data fundamentally changes the research capacity of social scientists and paves the way for them to investigate questions with unprecedented detail.

Evolving societal needs. In the face of a worldwide health crisis, effective and actionable interaction information is critical. One of the key techniques for mitigating disease spread is limiting contact through social distancing. As SARS-CoV-2 containment failed in early 2020, governments directed people to stay 1 m,[2] 1.5 m,[3] or 2 m[4] apart in an effort to reduce the infection rate. The rationale behind this discrepancy is unclear; it turns out that many administrative healthcare policies are backed by surprisingly little evidence [28, 74], and as a result, inconsistent policies are common [18, 19].

Scientists need tools that enable them to collect representative data in real-world settings to better understand behaviour. Such data provides the foundation for fact-based public policies. While both government agencies and private companies are developing smartphone applications for contact tracing [6, 33], these technical means to detect and limit the spread *after* infections have already occurred must be accompanied by controlled scientific experiments to study precautionary measures that can prevent them. Our hope is that SociTrack can act as research-enabling research and serve as a platform to address urgent questions in social science and beyond.

10 CONCLUSIONS

This paper demonstrates that it is possible to capture pairwise interaction data in situ with sub-meter accuracy and sub-second sampling. It identifies four pillars that make up a measurement system that meets the needs of real-world longitudinal studies for social scientists: it must collect high-fidelity samples—sub-meter, sub-second ranging data—, it cannot rely on supporting infrastructure, it must be robust to participant mobility, and it cannot restrict how and where participants wear measurement devices. We show that constraining a platform to any single communication technology requires sacrificing at least one of these pillars. We then demonstrate that a *heterogeneous* BLE and UWB radio architecture can succeed in satisfying all system requirements. Our experiments illustrate that the ubiquitous use of broadcast packets reduces message complexity for pairwise ranging from quadratic to linear in the number of nodes, and that in concert with careful scheduling, this enables scalable, long-term deployments. Finally, we highlight the tension between the design parameters considered by users and an implementation's configuration options, showing how a system model empowers them to bridge this conceptual gap.

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[2]WHO [83], European Centre for Disease Prevention and Control [29], France [34]
[3]Australia [7], Netherlands [30], Switzerland [60], Germany [61]
[4]United States [27], United Kingdom [24], Canada [58], India [59]

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