

Toward Standardized Performance Evaluation of Flow-guided Nanoscale Localization

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Abstract—Nanoscale devices featuring Terahertz (THz)-based wireless communication capabilities are envisioned to be deployed within human bloodstreams. Such devices are envisaged to enable fine-grained sensing-based applications for detecting events (i.e., biomarkers) for early indications of various health conditions, as well as actuation-based ones such as the targeted drug delivery. Intuitively, associating the locations of such events with the events themselves would provide an additional utility for precision diagnostics and treatment. This vision recently yielded a new class of in-body localization coined under the term “flow-guided nanoscale localization”. Such localization can be piggybacked on THz-based communication for detecting body regions in which events were observed based on the duration of one circulation of a nanodevice in the bloodstream. From a decades-long research on objective benchmarking of “traditional” indoor localization, as well as its eventual standardization (e.g., ISO/IEC 18305:2016), we know that in early stages the reported performance results were often incomplete (e.g., targeting a subset of relevant performance metrics), carrying out benchmarking experiments in different evaluation environments and scenarios, and utilizing inconsistent performance indicators. To avoid such a “lock-in” in flow-guided nanoscale localization, in this paper we discuss a workflow for standardized performance evaluation of such localization. The workflow is implemented in the form of an open-source framework that is able to jointly account for the mobility of the nanodevices in the bloodstream, in-body THz communication between the nanodevices and on-body anchors, and energy-related and other technological constraints (e.g., pulse-based modulation) at the nanodevice level. Accounting for these constraints, the framework is able to generate the raw data that can be streamlined into different flow-guided localization solutions for generating standardized performance benchmarks.

Index Terms—Flow-guided nanoscale localization, Terahertz, performance evaluation methodology, precision medicine;

I. INTRODUCTION

Recent advances in nanotechnology are paving the way toward nanoscale devices with integrated sensing, computing, and data and energy storage capabilities [1]. Among others, such devices will find applications in precision medicine [2], [3]. A subset of such applications envision the nanodevices being deployed in the patients’ bloodstreams. As such, these nanodevices will have to abide to the environmental constraints limiting their physical size to the one of the red blood cells (i.e., smaller than 5 microns). Due to such constrained sizes,

their sole powering option will be to scavenge environmental energy (e.g., from heartbeats or through ultrasound-based power transfer) utilizing nanoscale energy-harvesting entities such as Zinc-Oxide (ZnO) nanowires [1]. Due to constrained powering, such devices are expected to be passively flowing within the patients’ bloodstreams.

Recent advances in the development of novel materials, primarily graphene and its derivatives [4], herald nanoscale wireless communications in the THz region (i.e., 0.1-10 THz) [3]. In the context of the above-discussed nanodevices, wireless communication capabilities will enable two-way communications between them and the outside world [5]. Fully integrated nanodevices with communication capabilities are paving the way toward sensing-based applications such as oxygen sensing within the bloodstream for detecting hypoxia (i.e., a biomarker for cancer diagnosis), as well as actuation-based ones such as non-invasive targeted drug delivery for cancer treatment.

As recognized in recent literature, nanodevices with communication capabilities will also provide a primer for flow-guided localization in the bloodstream [3], [6]. Intuitively, such localization would enable associating the location of the nanodevice with a detected event (e.g., hypoxia, target for drug targeted delivery), providing medical benefits along the lines of non-invasiveness, early and precise diagnostics, and reduced costs [6]–[8].

Flow-guided localization is in an early research phase, with only a few works targeting the problem [6]–[8]. The main challenges include i) a centimeter-level range of THz-based in-body wireless communication at nanoscale, ii) energy-related constraints stemming from energy-harvesting as the sole powering option of the nanodevices, iii) high mobility of the nanodevices within the bloodstream, with their speeds reaching 20 cm/sec. Flow-guided localization proposals have made an encouraging progress in addressing the above challenges, yet we argue that the research and further advances on such localization are needed and still to flourish.

Based on the above argument and the knowledge generated through decades of research on “traditional” indoor localization, we posit that, at this early stage, there is a need for a framework for objective performance evaluation of flow-guided THz-based nanoscale localization. Specifically, the research on indoor localization in early stages was suffering from the inability of comparing the performance of different approaches in an objective way. In other words, the reported performance results were often incomplete (e.g., targeting a single metric such as localization accuracy and ignoring the other important ones such as the latency in reporting location estimates), utilizing different performance indicators (e.g., mean vs. median accuracy), and utilizing different evaluation

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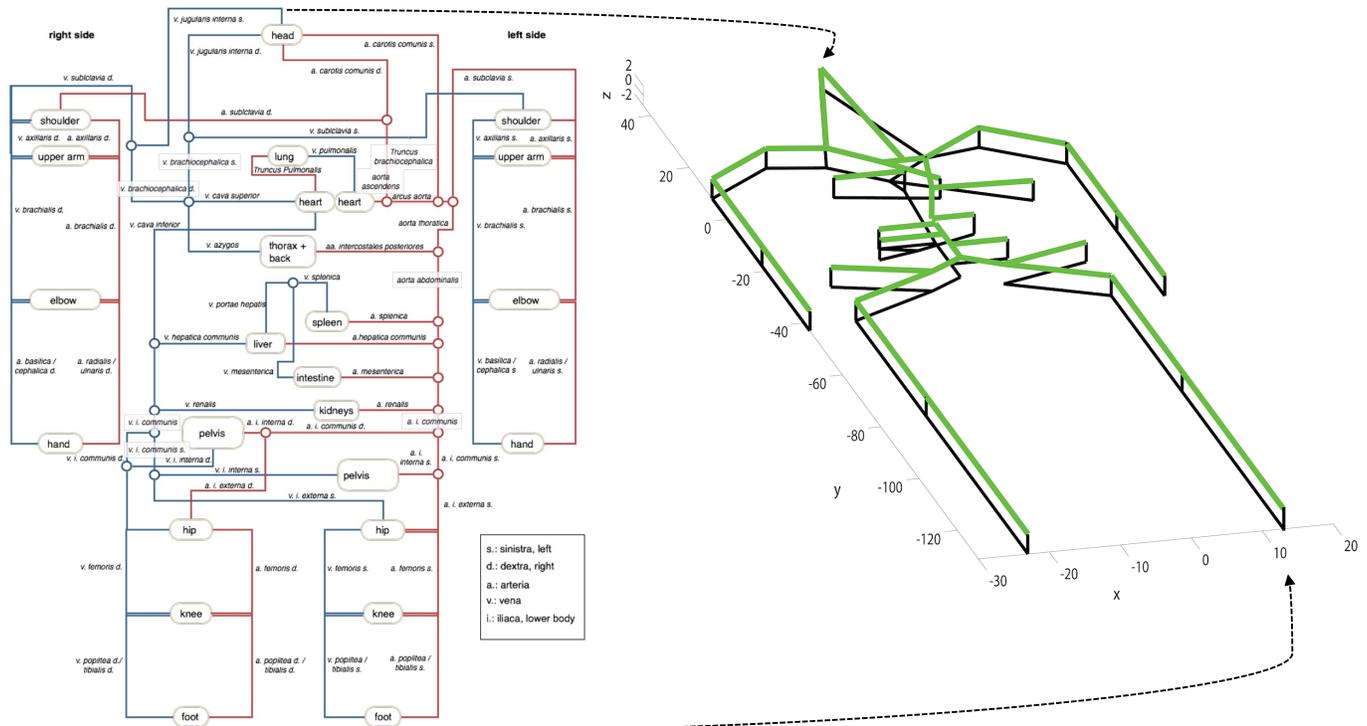


Figure 1. Nanodevice mobility in the BloodVoyagerS [13]

environments and scenarios. These issues were eventually recognized in the community and addressed through projects such as the EU Evaluation of RF-based Indoor Localization Solutions for the Future Internet (EVARILOS) [9] and NIST Performance Evaluation of Smartphone Indoor Localization Apps (PerfLoc) [10], as well as with indoor localization competitions such as the one from Microsoft at the ACM/IEEE IPSN conference [11], eventually resulting in the development of an ISO/IEC standard for objective benchmarking of indoor localization approaches [12].

With this article, we aim at avoiding the initial “lock-in” in the comparability of flow-guided localization by proposing a framework for standardized performance evaluation of such localization approaches. Specifically, we discuss the fundamentals of flow-guided nanoscale localization, provide the categorization of existing approaches, and discuss the limitations of their current performance assessments. This is followed by proposing a workflow for standardized and objective performance assessment of flow-guided localization. In addition, an open-source network simulator is provided that implements the discussed workflow and provides the community with the first tool for realistic and objective assessment of flow-guided localization. Finally, we demonstrate the performance of the current state-of-the-art flow-guided localization solution.

II. RELATED WORKS

A. Performance Evaluation of THz Nanoscale Systems

As argued in [13], simulating the performance of a given system allows for completely controllable experimental conditions and environments. In combination with repeatability and

cost-efficiency, these advantages make simulations a valuable tool to evaluate new algorithms, especially at early research stages. Given that the research on flow-guided localization is still in a preliminary stage, simulating the operation of such systems can be considered as a natural first step in the assessment of their performance.

This was only meagerly recognized in the scientific community, with BloodVoyagerS [13] being the first tool that provides a simplified bloodstream model for simulating the mobility of the nanodevices within it. The simulator covers 94 vessels and organs, with the origins of the coordinate system placed in the center of the heart. The spatial depth of all organs is equated, with the reference thickness of 4 cm mimicking the depth of a kidney, resulting in the z -coordinates of the nanodevices being in the range between 2 and -2 cm (cf., Figure 1).

The simulator further assumes that the arteries and veins are set anterior and posterior, respectively. Transitions from the arteries to veins happen in the organs, limbs, and head. In the heart, the blood transitions from the veins to arteries, i.e., the blood model transitions from posterior to anterior. The flow rate is modeled through the relationship between pressure difference and flow resistance. This results in the average blood speeds of 20, 10, and 2–4 cm/sec in aorta, arteries, and veins, respectively. Transitions between the arteries and veins are simplified by utilizing the constant velocity of 1 cm/sec.

TeraSim [14] is the first simulation platform for modeling THz communication networks which captures the capabilities of nanodevices and peculiarities of THz propagation. TeraSim is built as a module for ns-3 (i.e., a discrete-event network simulator), implementing physical and link layer solutions tailored to nanoscale THz communications. Specifically, at the physical layer the simulator features pulse-based communica-

tions with an omnidirectional antenna over distances shorter than 1 m, assuming a single, almost 10 THz wide transmission window. At the link layer, TeraSim implements two well-known protocols, i.e., ALOHA and CSMA, while a common THz channel module implements a frequency selective channel model, assuming in-air wireless communication. We will utilize BloodVoyagerS and TeraSim as the starting point in the development of the envisioned simulator.

B. Evaluation Methodologies for Flow-guided Localization

As argued, research lessons on the performance evaluation of indoor localization systems can to an extent be applied for objective and standardized assessment of flow-guided localization. The EU EVARILOS project was among the early efforts aiming at such performance assessment for RF-based indoor localization [9]. Within the project, a performance assessment methodology was developed, which included a number of evaluation scenarios, envisioned capturing the performance of evaluated solutions along a heterogeneous set of metrics including localization accuracy, latency, and energy consumption, and assessing and mitigating the negative effects of RF interference on the performance of the evaluated solutions. The project also yielded a web platform populated with raw data that can be inputted in an indoor localization solution for its streamlined performance assessment along a number of standardized scenarios. A similar approach was followed in the NIST PerfLoc project, however with a set of possible solutions to be evaluated extending beyond only Radio Frequency (RF) to Inertial Measurement Unit (IMU)-based, Global Positioning System (GPS)-supported, and other hybrid approaches. Finally, the IPSN/Microsoft Indoor Localization Competition [11] was among the first efforts to support back-to-back evaluation of different indoor localization approaches along the same set of conditions.

The above-discussed and consequent efforts yielded the following lessons: i) performance comparison of different indoor localization approaches can be carried out in an objective way by following the same evaluation methodology, i.e., utilizing the same environments, scenarios, and evaluation metrics, ii) such evaluation can be streamlined by providing a set of raw data captured along a standardized evaluation methodology, which is envisioned to be used as an input to an indoor localization solution, and iii) the performance of RF-based indoor localization can be degraded by both self-interference and interference from neighboring RF-based systems operating in the same frequency band.

In the current outlook on the performance assessment of existing flow-guided localization, the approaches from [7] and [8] are evaluated in a rather simplified way accounting solely for the mobility of the nanodevices as modeled by BloodVoyagerS. As such, their performance assessments ignore many potential effects of wireless communication (e.g., RF interference), as well as energy-related constraints stemming from energy-harvesting and, consequently, the intermittent operation of a nanodevice [1]. It is also worth mentioning that [6] carried out a limited performance evaluation assessing the number of nanodevices needed for localizing a nanodevice

			The scope of this work
Category of in-body localization based on the device type	Gastric capsules and implants	Fiducial markers and other types of nano-implants	Cardiovascular nanodevices
Main assumptions on the device size and mobility level	Macroscale devices Low mobility	Nanoscale devices Low mobility	Nanoscale devices High mobility
Representative localization approaches	Vasishth <i>et al.</i> [15]	Lemic <i>et al.</i> [6]	Gómez <i>et al.</i> [7] Simonjan <i>et al.</i> [8] Lemic <i>et al.</i> [6]
Performance metrics	Localization accuracy Localization delay Energy consumption Reliability	Localization accuracy Localization delay Energy consumption Reliability	Localization accuracy vs. delay Region accuracy vs. delay Energy consumption vs. delay Reliability vs. delay

Figure 2. Categorization of RF-based in-body localization approaches, corresponding applications, their requirements, and relevant performance metrics

at any location in the body in a multi-hop fashion. The derived assessments can, therefore, at this point only serve as a rough indication due to their low levels of realism and subjective evaluation methodologies. In this work, we enhance the realism of such assessments by jointly accounting for the mobility of the nanodevices, in-body nanoscale THz communication between the nanodevices and the outside world, and energy-related and other technological constraints (e.g., pulse-based modulation) of the nanodevices.

III. FLOW-GUIDED LOCALIZATION FUNDAMENTALS

RF-based in-body localization approaches can be categorized based on the type of applications they support, as depicted in Figures 2 and 3. Intuitively, there is a need for localization of in-body devices that are either mobile or nomadic within the body, otherwise their locations could be derived during deployment. The nomadic or mobile devices in the body are envisioned to support three main types of applications [15]. The first is the localization of macroscale devices within the body, specifically for localizing gastric capsules (nb., as there is a clear diagnostic benefit of assigning the measurements of the gastrointestinal system with the locations at which they were taken) and implants (nb., for detecting their movements away from the intended deployment locations). Such devices are not envisaged to feature nanoscale dimensions and their expected levels of mobility are either low (i.e., several cm/hour in the gastrointestinal system) or there is potentially no mobility in case of the implants. This reduces the localization requirements compared to the other two categories in Figure 2, primarily due to the fact that localization can be performed using RF signals in sub-6GHz frequency bands. Thus, there are no stringent requirements in terms of the devices' physical sizes, hence they can feature batteries and do not experience intermittent behavior. A representative of this approach is [15], in which out-of-band aliasing of signals transmitted by an out-of-body anchor at the central frequency of 1 GHz is utilized for localizing a static backscattering diode in the body, reporting cm-level accuracy of the procedure.

The second category targets localizing nanoscale devices that feature low mobility levels, utilized in applications such as tracking fiducial markers (nb., devices that provide accurate target location for tumors or organs which move in respect to surrounding anatomy) and other types of miniaturized implants. Although a subset of such applications can be enabled

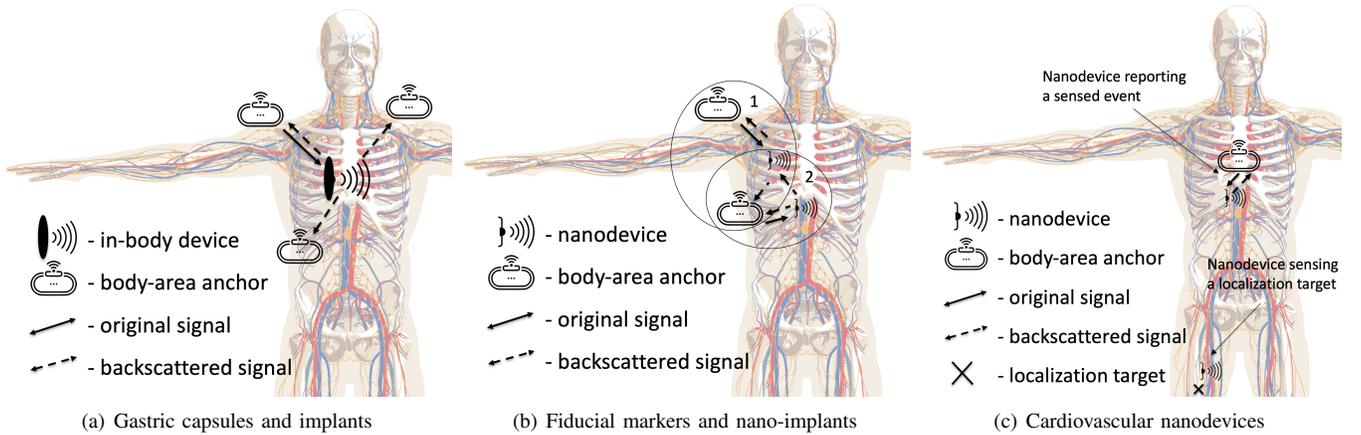


Figure 3. Schematics of different types of RF-based in-body localization approaches

through devices that do not feature nanoscale dimensions [15], enabling their full set will require nanoscale entities (e.g., early targeted treatment of small-scale tumors), hence this type is categorized separately in Figure 2. Here, a representative is an early effort in [6], where the authors assume the nanodevices are densely deployed and passively flowing in the bloodstream. For such a scenario, the authors propose an iterative localization concept in which the nanodevices closer to the body surface are localized first with the support from on-body anchors, followed by the usage of the localized nanodevices as both anchors and relays for localizing the nanodevices deeper in the body (cf., Figure 3.b). The authors assume energy-harvesting nanodevices operating at THz frequencies due to size constraints in the bloodstream. Such an approach could conceptually be applied for localizing nanoscale implants within the body. However, further research is needed for addressing the associated challenges (e.g., stringent latency-related constraints for multi-hop communication).

Both of the above-discussed categories of RF-based in-body localization target localizing a (nano)device within the body. This can be viewed as analogous to indoor localization where, within an indoor environment, the goal is to localize a device (e.g., smartphone) at an unknown location. Therefore, evaluation methodologies applicable to traditional indoor localization can also be applied for localization of an in-body (nano)device. Taking the EVARILOS Benchmarking Methodology [9] as an example, the metrics of interest are the point accuracy of localization (i.e., the Euclidean distance between true and estimated locations), latency and energy consumption required for localizing the device, and the reliability of such localization (i.e., probability of reporting a location estimate upon request), as depicted in Figure 2.

The final category is the flow-guided nanoscale localization considered in this work. Here, the goal is to use the nanodevices to detect and localize a target event, not necessarily to localize themselves (cf., Figure 3.c). As discussed earlier, the work in [6] can conceptually support this type of scenarios and is, therefore, included in this category. Nonetheless, the representatives of such localization are [7], [8]. In these approaches, the authors utilize machine learning models for distinguishing a region through which each nanodevice passed during one circulation through the bloodstream. The authors

in [8] base this procedure on tracking the distances traversed by a nanodevice in its circulations through the bloodstream by utilizing a conceptual nanoscale IMU. However, this poses challenges in terms of resources available at the nanodevice level for storing and processing IMU-generated data, and challenges related to the vortex flow of blood negatively affecting the accuracy of IMU readings. The authors in [7] mitigate these issues by tracking the time needed for each circulation through the bloodstream. The captured distance or time is then envisioned to be reported to a beaconing anchor deployed in the proximity of the heart utilizing short range THz-based backscattering at the nanodevice level.

Given that only a body region through which the nanodevice traversed is being detected, these localization approaches are (in contrast to [6]) not designed to provide point localization of the target. This is despite the fact that point localization of the target event would be immensely beneficial for the health-care diagnostics. Moreover, the region detection accuracy and reliability of localization can intuitively be enhanced with an increase in the number of circulations the nanodevices make in the bloodstream. As a trade-off, such an increase would negatively affect the energy consumption of the localization procedure. Therefore, in flow-guided localization the relevant performance metrics such as the point and region accuracies, reliability, and energy consumption should be considered as a function of the application-specific delay allowed for localizing target events (cf., Figure 2).

IV. FRAMEWORK FOR STANDARDIZED PERFORMANCE EVALUATION OF FLOW-GUIDED LOCALIZATION

A. Evaluation Workflow

As discussed previously, enabling flow-guided localization of the nanodevices flowing in the bloodstream requires at least a single anchor mounted on the patient's body. Flow-guided localization approaches in [7], [8] can be enabled with a single anchor strategically positioned in the proximity of the heart. This is because the heart is the only location through which each nanodevice is guaranteed to pass in each circulation through the bloodstream. Additional anchors can be introduced into the system by specifying their coordinates in their configuration file of the simulator, as indicated in

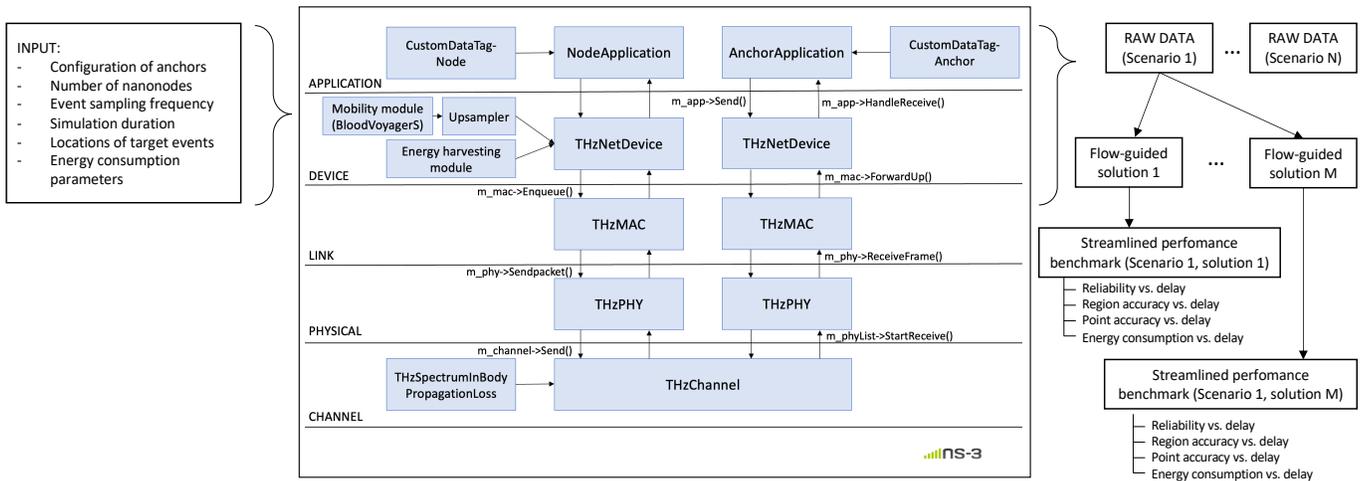


Figure 4. Overview of the framework for standardized performance evaluation of flow-guided localization

Figure 4. The on-body anchors are expected to feature batteries or similar powering sources, hence they are assumed to be continuously operational. Their main roles are to transmit beacon packets and receive the backscattered responses from the nanodevices.

The nanodevices are assumed to feature capacitors for energy storage and ZnO nanowires as the energy-harvesting entities. The capacitor charging is modeled as an exponential process accounting for the energy-harvesting rate and interval (e.g., 6 pJ per sec and per 20 ms for harvesting from heartbeats and ultrasound-based power transfer, respectively) [1]) and capacitor’s storage capacity. The nanodevices are assumed to feature intermittent behavior due to harvesting and storage constraints. This behavior is modeled through the *Turn ON* threshold, i.e., if the current energy level of a nanodevice is above the threshold, the nanodevice is turned on. Once its energy is fully depleted, the nanodevice turns off, followed by a turn on when its energy increases above the *Turn ON* threshold.

Moreover, if the nanodevices are turned on, they are assumed to periodically carry out a sensing or actuation task with a given frequency. Each execution of a task is expected to consume a certain constant amount of energy, hence the more frequent the task, the more energy will be consumed by each nanodevice. The location(s) of the event(s) to be detected is (are) envisioned to be hard-coded by the experimenter, abiding to the constraints of the scenario. Specifically, this location has to be in or near the bloodstream in order to eventually be detected by the nanodevices. The event is assumed to be detected by a nanodevice if i) the Euclidean distance between its location and the location of the nanodevice at the time of the execution of a task is smaller than the predefined threshold (nb., configured to 1 cm in the reported experiments), and ii) the nanodevice is turned on.

Communication between an anchor and a nanodevice is based on passive reception of a beacon, followed by active (i.e., energy-consuming) transmission of a response packet from the nanodevice, as assumed in the representative work from the literature [7]. The anchor is beaconing with the constant beaconing frequency and transmit power. In each

beacon packet, the anchor advertises its Medium Access Control (MAC) address. In the backscattered packets, the nanodevices report their MAC addresses, the time elapsed since their last passage through the heart, and an event bit. The time elapsed since the last passage through the heart and the event bit represent the raw data that can be fed into a flow-guided localization approach for localizing a target. Each time a nanodevice passes through the heart the time elapsed since the last passage is re-initialized to zero in order not to compound multiple circulations. The event bit is assumed to be a logical “1” in case of a successful detection of a target event and “0” otherwise. Similarly, the event bit is reinitialized to “0” in each passage through the heart.

B. Framework Design and Implementation

The framework for standardized performance evaluation of flow-guided localization is depicted in Figure 4. The input to the framework is a set of parameters defining an evaluation scenario. The inputs are envisioned to be passed to the ns-3-based simulator for the generation of raw data to be used for streamlined evaluation a given flow-guided localization solution for the assumed scenario, resulting in a performance benchmark, as indicated in Figure 4. Each streamlined performance benchmark consists of a set of relevant performance metrics, in turn allowing for an objective back-to-back comparison of different approaches in a consistent environment along the same set of scenarios and performance metrics.

The architecture of the simulator follows a well-established ns-3 layered model, as depicted in Figure 4. The *AnchorApplication* module implements continuous beaconing with a predefined period (nb., with 100 ms being a default value). Each beacon packet is forwarded to the *THzNetDevice* module toward the communication stack implemented within the TeraSim simulator. The link and physical layers implement the ALOHA protocol and TS-OOK modulation, respectively.

The THz channel is modeled by calculating the receive power for each communicating pair of devices and scheduling the invocation of the *ReceivePacket()* method accounting for the corresponding propagation time. The channel model entails

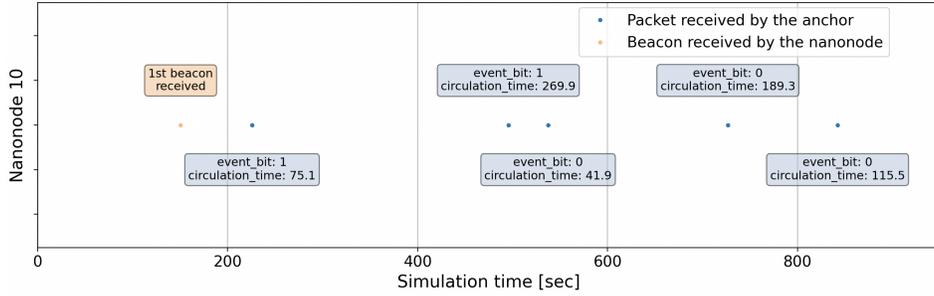


Figure 5. An example raw data output

in-body path-loss and Doppler terms [8]. The path-loss is calculated using the attenuation and thickness parameters of the vessel, tissue, and skin. The Doppler term is accounted for by evaluating the change in relative positions between the nanodevices and anchors with time. The *ReceivePacket()* method checks for potential collisions by calculating the SINR and discarding the packet if the SINR is below the predefined threshold for reception. Alternatively, the packet is passed through all the way to the application layer of the nanodevice. At the nanodevice level, the receive power of the beacon is used for setting up the transmission power of the packet to be backscattered. This is followed by backscattering the response packet from the nanodevice toward the anchor by utilizing the same procedure as for the transmission of the beacon.

The anchors are assumed to be static entities and feature sufficient energy for continuous operation. The nanodevices are assumed to be energy-harvesting entities that are mobile within the bloodstream. To model their mobility, we have integrated BloodVoyagerS in our simulator, as visible in Figure 4. Invoking a BloodVoyagerS execution results in generating a Comma Separated Value (CSV) file that specifies the locations of the nanodevices in the bloodstream within a simulation time frame, sampled at 1 Hz. Since ns-3 is an event-driven simulator, at each BloodVoyagerS-originating location of a nanodevice, the nanodevice is assumed to carry out a sensing/actuation task. Given that for certain applications carrying out such tasks could be required more frequently, we provide an upsampler for BloodVoyagerS-originating locations sampled at 1 Hz. As the vessels in BloodVoyagerS are modeled using straight lines, the upsampling is based on linear interpolation with a small random component drawn from a zero-mean Gaussian distribution, representing vortex flow of blood and minor changes in the diameters of veins, arteries, etc. At each new location, the nanodevice is expected to carry out a task for detecting an event of interest.

C. A Snapshot of Framework-generated Outputs

A snapshot of outputs generated using the framework is depicted in Figures 5 and 6. In the generation of the outputs, we have utilized a single anchor positioned in the center of the heart, 64 nanonodes sampling for target events at 3 samples per second, ultrasound-based energy-harvesting at the nanodevice level [1], the overall simulation duration of 1000 sec, and the Euclidean distance for detecting a target event of 1 cm.

Figure 5 depicts the raw data generated by an example nanonode during one simulation runtime. The raw data consists of the *circulation_time* parameter indicating the time

passed since the last reception of a beacon from the anchor and the *event_bit* suggesting if the target event was detected since the last beacon reception. The main takeaway from Figure 5 is that, for some raw data instances, the *circulation_time* is larger than 90 sec, which is the maximum circulation time that might occur in a single loop through the bloodstream. This implies that in some circulations the raw data is not reported to the anchor and, when the data is eventually reported, it contains the compound of multiple such circulations. Such behavior is a result of one of the following: i) intermittent operation of a nanonode due to energy-harvesting, resulting in the nanonode sometimes not featuring sufficient energy for sensing or transmission, and ii) self-interference from the other nanonodes and anchors, resulting in reception and transmission errors. In addition, random paths of the nanonodes in the vicinity of the target event (i.e., in an organ, limb, or head) can result in the nanonodes missing the event due to its Euclidean distance from the event never being smaller than the threshold of 1 cm, despite the fact that they went through the loop that contained the event. This implies that the *event_bit* parameter might in some cases be erroneous.

Figure 6 depicts a set of performance metrics generated in a streamlined fashion using the framework. In the generation of the results, we have utilized a modified approach from [7] and 20 randomly sampled evaluation points (i.e., target events) in the bloodstream. The modification in the approach pertains to random selection of the left or right regions given that the approach assuming a single anchor is by-design unable to distinguish between such regions for certain parts of the body (e.g., limbs). As visible from the figure, the reliability of localization increases as a function of localization delay. As an example, the reliability is increased from less than 50% to more than 90% if the delay is increased from 2 to 15 min. Our results again reveal that certain assumptions made in earlier works on flow-guided nanoscale localization ignore several phenomena that are expected to occur in practice, pertaining to unreliable THz-based communication between in-body nanonodes and on-body anchors and intermittent operation of the nanonodes due to energy-harvesting. When these are accounted for as done when utilizing the proposed framework, our results further reveal relatively poor performance of the evaluated flow-guided localization solution in the considered scenario. Specifically, the region detection accuracy is at most 40% and features only a small increase with the delay.

Given that the approach from [7] cannot report point estimates but solely the estimated regions, in the calculation of the point accuracy we have utilized the centroid of a

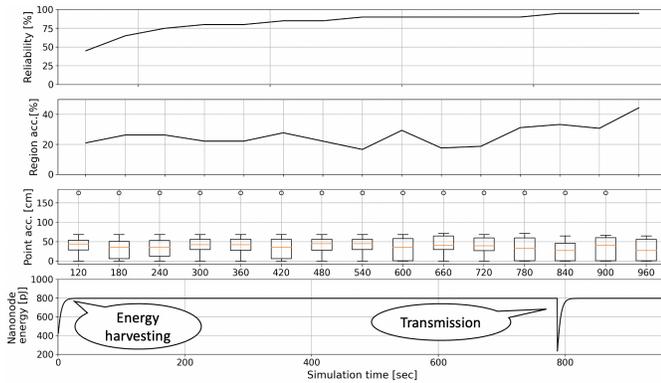


Figure 6. An example streamlined performance benchmark

region as its point estimate. This procedure is well-established in the domain of benchmarking of proximity-based indoor localization solutions [9]. In Figure 6, the depicted point accuracy can be considered as irrelevant, given the low region detection accuracy. In other words, the point accuracy should be derived only for the correctly detected regions in order to express the fine-grained ability of localizing target events. We nonetheless depict the point accuracy even for the case of incorrectly detected regions to draw readers' attention to this issue. The point accuracy is depicted in a regular box-plot fashion, where each box-plot depicts the distribution of localization errors for the 20 considered target events and a given delay. Finally, time-dependent energy level of an example nanode depicted in Figure 6 indicates the energy consumption of different tasks at the nanode level. Such indications are necessary for energy-aware optimizations of the task scheduling to maximize the operational time of the intermittently-operating nanonodes in a similar way as in [1].

V. CONCLUSION

We argue that there is a need for objective evaluation of the performance of flow-guided nanoscale localization. We further argue that such objectiveness can be achieved by utilizing the same evaluation environment, scenarios, and performance metrics. This is achieved by proposing a workflow for performance assessment of flow-guided localization and its implementation in the form of a simulator, providing the community with the first tool for objective evaluation of flow-guided localization. Our results reveal relatively poor accuracy of the evaluated solution in the considered scenario. This is due to unreliable THz communication between in-body nanonodes and on-body anchors and intermittent operation of the nanonodes due to energy-harvesting. Accuracy enhancements are envisioned as a part of our future work along the lines of introducing additional anchors at strategic locations on the body (e.g., wrists) and developing a more suitable machine learning model that accounts for the fact that the raw data might be erroneous (e.g., compounding circulation times). Regardless of the poor accuracy, our results indicate that the proposed workflow and the simulator can be utilized for capturing the performance of flow-guided localization approaches in a way that allows objective comparison with other approaches.

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