Vsens Toolkit: AR-based Open-ended System for Virtual Sensors

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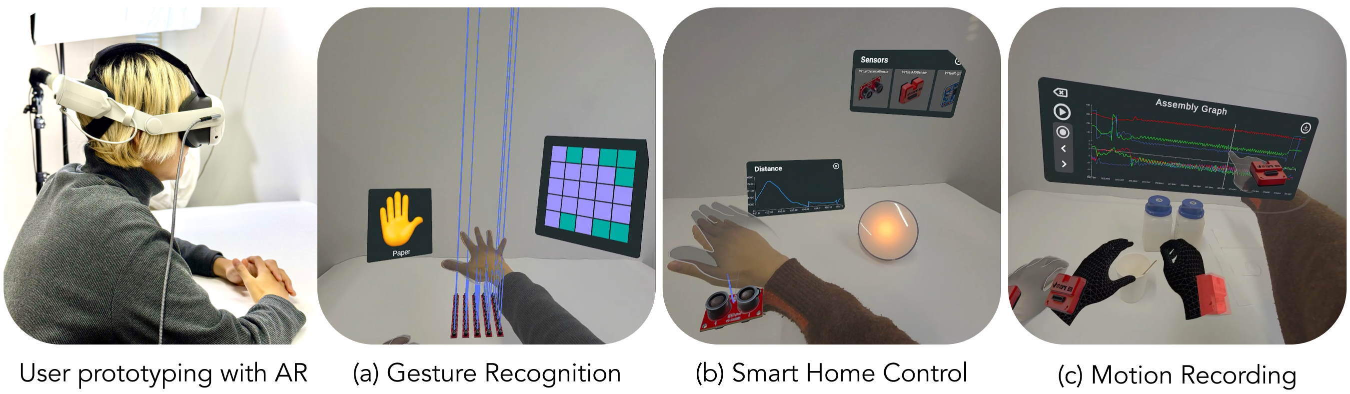

Figure 1: We present *Vsens* Toolkit, an AR-based open-ended system for virtual sensor practices. The system allows users to create customized scenes in augmented reality by utilizing multiple virtual sensors, virtual entities, and animations. It supports the design, prototyping, and preliminary evaluation of HAR systems through synthesized data from simulation.

Abstract

The emergence of virtual sensors in recent years has opened up new possibilities for the development of human activity recognition (HAR) systems. For instance, we can synthesized virtual sensor data for those scarce datasets, such as accelerometer data, from the widely available multimedia resources online through cross-modal approaches. However, existing solutions on virtual sensors primarily focus on batch pipelines, relying heavily on lengthy processing workflows and sophisticated computer vision techniques, which often lack interactivity and flexibility for the usage in customized and small-scale scenarios. In this work, we present the *Vsens* Toolkit, an AR-based open-ended system for virtual sensors, which serves as an preliminary exploration of the user interface for virtual sensors. It integrates functionalities such as scene construction, data collection, data augmentation, and visualization. In this interactivity demonstration, we showcase exemplar scenarios including wearable accelerometers, capacitive sensing, wrist-worn sensor tracking, and sandbox for free exploration (Figure 1).

CCS Concepts

• **Human-centered computing** → **Interactive systems and tools**.

Keywords

Augmented Reality, Virtual Sensors, Open-ended Practice

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1 Introduction

Advances in electronics and machine learning envision a future where people are surrounded by numerous Internet of Things (IoT) sensors and stepping further towards the ubiquitous computing.

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The human activity recognition (HAR) systems embedded in everyday interfaces have been endowed with more powerful capabilities with the development of miniaturized sensors and advanced machine learning techniques. The emergence of virtual sensors have promote the development of HAR systems from multifaceted aspects of reliability, scalability, and accessibility. The core idea of virtual sensors lies in simulation. By creating digital twins of humans or objects, combined with physical simulations, it become possible to acquire data across a wide range of scenarios or sensor configurations, substantially minimizing the costs associated with traditional data collection process. For instance, the cross-modal data acquisition allow them to generate virtual samples for scarce datasets (e.g., accelerometer [13] or Doppler radar [2]) from the abundant ones such as video; further more, their adjustable nature in virtual environment enables various ways of augmentation [8, 36], fostering richer datasets while enhancing both model generalization and application customization.

However, existing virtual sensor practices predominantly focus on building sophisticated pipelines [5, 13, 18] or refining specific stages within the workflow [14, 21], excelling in batch data processing but falling short in flexibility and accessibility for agile development or small-scale data collection. Nevertheless, offering support for HAR system development in areas like promoting prototyping and reducing evaluation costs is an inherent capability of virtual sensors and a part of their envisioned future. Yet, how to design intuitive and effective interfaces for virtual sensors that satisfy end-users' demands for developing highly flexible and personalized HAR systems remains largely unexplored.

Augmented Reality (AR) has been explored widely as a tool bridging the virtual space and the reality [6, 7, 40], offering an pathway of bringing the context of surroundings to the computing system. In this work, we present the prototype of *Vsens*, an open-ended and open-sourced AR toolkit aims at facilitating the interactive usage of virtual sensors. Beyond the foundational functions during the collection of virtual sensor data for HAR systems (e.g. loading models and animations), the introduction of AR as the carrier enhance the system with flexibility and user empowerment, including enables user to construct specific simulation environments, define collision volumes for the surrounding space for sensor interaction, or import customized virtual objects, combinations and types of sensors. By incorporating these features, virtual sensors become increasingly agile and accessible, streamlining the prototyping process of HAR systems by lowering the need for extensive hardware knowledge and reducing cost. On the other hand, we have integrated the representative data augmentation functionality of virtual sensors into the system, proposing *Vsens* Toolkit as an exploration of a more accessible interface for virtual sensors and an initial step toward their practical application.

In this Interactivity session, we present the live demo of *Vsens* with three exemplar scenarios including wearable accelerometers, capacitive sensing, wrist-worn sensor tracking, and sandbox for free exploration (Figure 1). With the components provided by our system, users are able to build their own scenes, record motions, dynamically modify sensor deployment, apply data augmentation, and inspect the virtual sensor data in real-time through a variety of visualizations.

2 Related Work

2.1 Virtual Sensors

There have been successful practices of HAR systems based on virtual inertial measurement unit (IMU), as a type of sensor being extensively studied and implemented in wearable devices. Virtual IMU data can be obtained from 3D motion sequences within a virtual environment by calculating the displacement and rotation of key joints along the timeline [41], shifting IMU data acquisition to much richer sources, including motion capture (MoCap) databases [26, 38], manually designed animation [8], human-object extraction from videos [13], or generative modals [17]. Virtual IMU data generated through these methods has been demonstrated to be effective in supporting various applications such as daily activity recognition [14], exercise analysis [33], and sign language recognition [19, 27]. Beyond IMUs, other types of sensors, such as Doppler radar [2, 5], distance sensor [35], or optical sensor [23], have also been proven to be feasible for generation through simulation. In addition to synthesizing sensor data across modalities, another major advantage of virtual sensors lies in their ability to enhance data diversity through physical simulation, extending beyond the traditional data-level augmentations [3, 20]. For instance, with virtual IMUs, we can generate training datasets that improve the generalizability of HAR systems by leveraging joint motion ranges [9], or incorporating fictitious structures such as springs [36].

Existing research on virtual sensors largely focuses on expanding modality transformations and achieving more realistic simulations. As their performance gradually reaches practical application levels in the foreseeable future, it is time to explore ways to better leverage virtual sensors for supporting HAR system development. Mainstream virtual sensor systems lack attention to user interfaces and are primarily used within 3D editors on screen (e.g. widely adopted Unity3D), which often fall short in providing convenient capabilities for handy sensor redeployment and awareness of developers' surroundings. In this work, we use AR as a medium between reality and virtuality, serving as a preliminary investigation towards the practical application of virtual sensors supporting exploratory learning, rapid prototyping, pilot evaluation, and so on.

2.2 XR Toolkits

In the past decade, researchers have been developing toolkits to support the process of innovation in all ways [15], including providing tutorials and guidance [7, 29], empowering audiences for new technologies[25, 34], integrating with current practices and infrastructures [11, 32], and enabling replication and creative exploration [10, 16]. Within these toolkits, XR stands out as a widely favored platform for tools featuring tutorial [7, 29, 39] and prototyping [6, 12] capabilities. For instance, VRception [6] provides a solution for effectively conducting user studies; SensorViz [12] facilitates multi-level visualization for prototyping, ranging from datasheet specification before purchasing sensors, and live/ recorded sensor data during the development.

In this work, we prioritize simulation as the key contribution in such XR toolkit. While focusing on the visualization of virtual sensor data, we underscore the role of virtual sensors in interacting with objects across virtual and physical environments using AR, and their flexible application in deploying digital humans and motion animations.

3 System Demonstration

3.1 Implementations

The *Vsens* Toolkit relies entirely on a virtual software environment and an head-mounted display (HMD) for straightforward use. The system was developed and tested on *Meta Quest 3*. The software part was developed in the *Unity3D* together with *Meta XR All-in-One SDK*[1]. It consists of three modules that collaboratively produce virtual data: virtual sensors that can be freely placed and combined within AR environments, virtual objects that passively interact with users, and digital humans capable of incorporating various animations. The Vsens Toolkit will be published as an open-source project on GitHub[2], for researchers and developers to conduct tests and create personalized plugins.

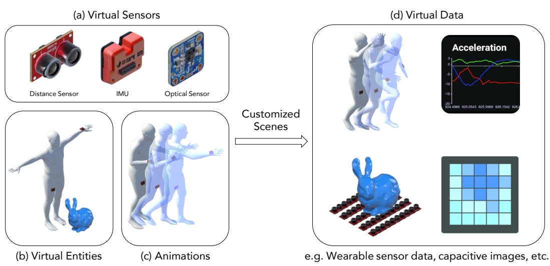

Figure 2: The system allows users to create customized scenes by (a) virtual sensors, (b) virtual entities, and (c) animations, to collect (d) virtual data of various scenarios, such as wearable sensors and capacitive images.

3.1.1 Virtual Sensors Module. In the demonstration, we feature three virtual sensors that have been suggested in prior studies, shown in Figure 2(a): virtual IMUs [41] and virtual distance sensors [35], and virtual optical sensors [23]. The virtual IMU calculates acceleration by performing double integration on displacement over time and also provides gyroscopic information; The virtual distance sensor employs raycast collision detection to calculate the distance between itself and entities with defined collision volumes; The virtual optical sensor can simulate the light intensity at a specific location by calculating the distance and occlusion relationship between the sensor and the light source. These sensors support adjustable sampling rates up to the 120 Hz limit of the simulation engine. Furthermore, they can be seamlessly attached to designated walls, surfaces, furniture, or virtual entities within the AR environment.

3.1.2 Virtual Entities Module. In the *Vsens* framework, a range of virtual entities plays a critical role in the generation of virtual data (Figure 2(b)). These entities include digital humans capable of loading motion animations and movable objects, such as a door, that passively interact with users. Users can import these entities to customize their simulated scenarios, offering a high degree of flexibility. For example, digital humans modified through techniques such as SMPL [22] can produce virtual IMU data that reflect variations in body shape, characteristics, and other conditions. During the demonstration, users will have access to multiple rigid body objects and digital humans to explore these functionalities.

3.1.3 Animations Module. In addition to passive movable objects, the animations in the proposed system are primarily designed to control the motion of digital humans (Figure 2(c)). These animations are composed of forward kinematics (FK) time series for each joint and allow users to import customized animations. The system enables users to interact with the animations by pausing them, adjusting their playback speed, or modifying their amplitude, thereby creating virtual sensor data that reflects various motion styles.

3.2 Supportive Features

3.2.1 Sensor Data Visualization. In our system, users are provided with multi-layered visualization options. For instance, as depicted in Figure 2(a), real-time data visualization is available for individual sensors, such as axes extending from the IMU or bar charts above the distance sensor. Furthermore, as shown in Figure 2(d), time-series graphs display data from multiple sensors, allowing users to examine specific moments of sensor data via touch and export the data to a computer for further analysis. The diverse visualization methods offered by AR enhance users' understanding of sensor feedback in specific contexts and support the effective design of HAR systems.

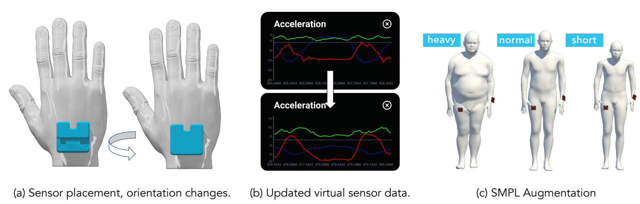

Figure 3: (a), (b) For a recorded animation, users can obtain updated sensor data by adjusting the position and orientation of the sensors. In this example, the IMU was flipped 180 degrees. (c) Digital human model with different body shapes.

3.2.2 Motion Recording & Dynamic Adjustment. Mainstream HMD offer relatively precise hand-tracking capabilities, making it easier to simulate wrist-worn virtual sensors, which are commonly employed in smartwatch-based HAR systems [4, 27]. This functionality differs from digital humans animated through pre-set motions, as it enables users to capture their own hand movements and generate corresponding virtual sensor data. To support such use cases, our system provides features for recording hand animations and subsequently adjusting the position and orientation of sensors (Figure 3). Unlike in real-world settings, where testing different wearable sensor placements and orientations requires repeated motion recordings, our system allows for flexible adjustments and

[1] https://assetstore.unity.com/packages/tools/integration/meta-xr-all-in-one-sdk-269657
[2] https://github.com/KEIO-LCLAB/SensoReality

provides real-time feedback on data changes to evaluate the optimal configuration.

3.2.3 Augmentation. For HAR systems based on wearable sensors, one of the grand challenges lies in the intra-individual and inter-individual variations when performing the same motion [1, 28, 31]. In *Vsens* Toolkit, we employed the skinned multi-person linear model (SMPL) [22], which is a skinned vertex-based model that accurately represents a wide variety of body shapes in natural human poses. SMPL incorporates simulations of natural pose-dependent deformations and soft-tissue dynamics, which enables us to more precisely emulate the variations in IMU signals across users of diverse body types during different movements, which propel simulations towards greater realism.

4 Discussion

The main contribution of the *VSens* Toolkit is to offer a preliminary answer to the question of how to best utilize virtual sensor technology as a practical tool for development and testing. By incorporating key features of virtual sensor technology, including data augmentation, the system aims to leverage AR as a medium to strengthen the link between the simulated environment and the user's real-world surrounds. In this section, we provide a brief discussion to elaborate the challenges encountered by our prototype and envision its future development.

One of the obstacles is the scope of HAR systems that can be easily simulated is limited. Previous works on virtual sensors [2, 13, 35] been limited to the most straightforward use cases of the sensors. However, in the field of Human-Computer Interaction (HCI), the sensing methods employed in interface or HAR system design are often more complex and indirect. For instance, interfaces based on the characteristics of materials or specific physical phenomena are commonly used [24, 30]. Currently, there is no definitive and effective solution to address the simulation problems in these complex scenarios, but with the advancements in generative models and computer graphics [37], virtual sensors are expected to be applicable to more extensive scenarios in the near future.

Another challenge arises in how we assess the reliability of the reference data provided by virtual sensors. It is not possible to a priori evaluation the disparity between virtual sensor data and real-world data in a given scenario, as this depends on factors such as the type of sensor, the quality of motion animations, and the quality of simulation which depends on the hardware. Although the *Vsens* Toolkit reduces the need for specialized hardware and software knowledge during prototyping, enabling designers and hobbyists with less technical expertise to quickly test their systems, a thorough evaluation of the reliability of virtual data, such as how much of it is dependable for reference, requires empirical knowledge regarding the virtual sensors. The challenge of balancing this trade-off is an ongoing topic for exploration and discussion in future research.

5 Conclusion

In this work, we present the prototype of the *Vsens* Toolkit, marking a initial step toward enhancing the practical application and broader accessibility of virtual sensors. By streamlining the prototyping process, reducing the technical expertise required for HAR system development, and minimizing evaluation costs, the toolkit aims to democratize innovation in HAR systems, making them more accessible to a wider range of researchers and practitioners.

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