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SENSELET: Distributed Sensing Infrastructure for Improving Process Control and Safety in Academic Cleanroom Environments

Semiconductor cleanrooms are used to fabricate devices with feature sizes that can be much smaller than a dust particle. Hence, any environmental deviations in temperature, or humidity around fabrication instruments may become the root cause of hundreds of transistors failing during the manufacturing. Furthermore, researchers work with dangerous chemicals in cleanrooms and violation of safety may lead to disastrous consequences. Therefore, we have developed an affordable, locally-controlled distributed sensing infrastructure, called *SENSELET*, for academic cleanrooms. It provides highly effective services for environment sensing around scientific instruments, sensory data collection and visualization, indoor localization, and instrument proximity detection for safety of researchers.

Semiconductor cleanrooms provide a pristine environment to fabricate devices with feature sizes much smaller than a dust particle. A dust particle landing on a silicon wafer can be the root of hundreds of transistors failing during manufacturing. For next-generation computers and displays, transistors and LEDs are becoming increasingly smaller and more complex in order to provide larger computation powers or pixel densities in a smaller package. With critical dimensions down to nanometers in size (10,000 times smaller than the width of a hair), tight process control is necessary. Furthermore, to yield successful devices, humidity, temperature, and pressure around cleanroom instruments must be strictly controlled. Shown in Figure 1, we can see the optical microscope image of developed photoresist in a controlled environment that forms sharp waveguides versus photoresist showing delamination attributed to excess humidity of the cleanroom [1,2].

To enable this control, *real-time automated sensing of environment data* around a cleanroom's instruments must be collected. Hence, we need a sensing system to ensure correctness of physical experimentation.

The automated sensory data collection not only benefits the researchers when fabricating devices, but also cleanroom administrators responsible for the upkeep and operation of these instruments. These specialized microscopy tools cost hundreds of thousands of dollars and can be a significant expense for smaller academic cleanrooms, such as the cleanrooms in the Holonyak Micro & Nanotechnology Laboratory (HMNTL) at the University of Illinois, Urbana-Champaign. Hence, it is critical to monitor and maintain these instruments for as long as possible. Automated sensing of the external temperature of a vacuum pump may show trends that indicate when parts are *wearing down* so that *preventative*

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maintenance can be done more efficiently and costly failures can be avoided.

Beyond improving device fabrication, a sensing system is critical for improving the *safety of cleanrooms*. Dangerous chemicals and gasses are often involved in the semiconductor device manufacturing process so being able to monitor for leaks and the function of safety equipment is critical. Additionally, systems to monitor personnel can detect the proximity between users and instruments, ensure access control, and help locate people in case of an emergency.

While large, industrial cleanrooms can afford to implement customized high-performance distributed sensing systems (e.g., [3]) that are often very costly, smaller academic cleanrooms often do not have that luxury. Therefore, we develop an affordable and scalable sensing cyber-infrastructure, called SENSELET (Sensory Network Infrastructure for Scientific Lab Environments), to enable academic cleanrooms to improve their process control and safety.

The challenges for SENSELET are: (a) SENSELET is a campus cyberinfrastructure tailored to cleanrooms where the environment monitoring system has to accommodate the layout of cleanrooms, cover every corner of these cleanrooms, and yet follow a tight budget. (b) Cleanrooms are often equipped with expensive scientific instruments (e.g., microscopes), and detecting anomalies in environmental data is of significant value to cleanroom administrators to react promptly in case of emergency. (c) User-friendly interpretation of data must be available for cleanroom administrators and researchers to gain new insights. (d) Proximity detection must distinguish users in white protective suits and achieve high location accuracy in complex indoor spaces.

Considering these challenges, SENSELET is developed as an edge-cloud two-tier architecture, collecting temperature and humidity measurements, which are stored, analyzed, and visualized at the private cloud, and monitored by cleanroom managers. SENSELET deploys watchdog algorithms to automatically restart sensors and provide reliable sensor readings. Wi-Fi sensing and cleanroom cameras are used for indoor localization and proximity detection.

The SENSELET benefits are: (1) It is a powerful tool to monitor cleanrooms, and send alerts in case of hazardous events. (2) Researchers become aware of changing environmental conditions during their experiments. They can correlate their yielded samples with external environmental samples, and they can better reason about their sample defects. (3) Localization and proximity detection assist in safety provisioning.

The first section presents the SENSELET architecture and its environment monitoring service. The next section discusses indoor localization and proximity detection services. We conclude in the last section.

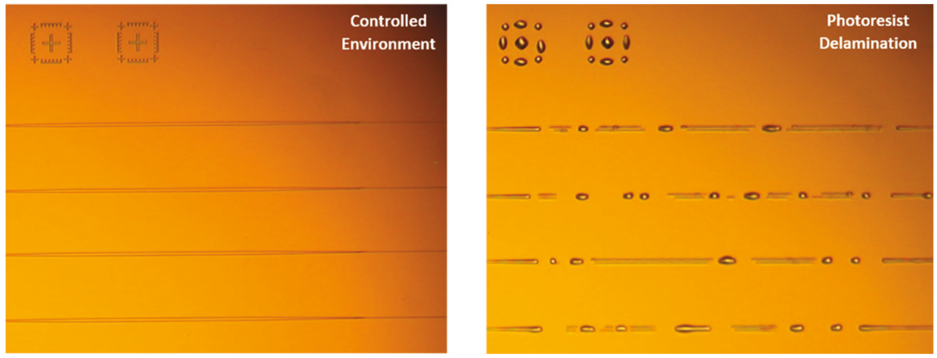

FIGURE 1. Data in controlled environment (left) and data due to excess humidity of cleanroom (right).

SENSELET ARCHITECTURE AND ENVIRONMENT MONITORING SERVICES

SENSELET is a distributed sensing infrastructure for academic cleanrooms. SENSELET's two-tier architecture has four components: Environment Monitoring, Localization and Proximity Detection, Data Storage, and Visualization as shown in Figure 2. We discuss here the Environment Monitoring, Data Storage and Visualization components, and present Localization and Proximity Detection in Section 3.

Environment monitoring employs SENSELET edge devices, called *SenseEdges,* which we place inside cleanrooms. SenseEdges focus on sensory data acquisition, reliability assurance, and communication with the private cloud, called SenseCloud, located on the campus. As shown in Figure 2, SenseEdge consists of a Wi-Fi-equipped single board computer (Raspberry Pi), and a commercial off-the-shelf sensor(s), soldered to the single board computer. Our solution is significantly easier to deploy in almost every corner of cleanrooms than existing Ethernet gateway-based industrial solutions for cleanroom sensing. The Ethernet gateways put constraints on the availability and abundance of Ethernet ports inside these rooms. Also, even though soldered sensors are less convenient than wireless sensors such as Zigbee sensors, the board computers can directly power these sensors, hence they last significantly longer. Other industrial sensing solutions, such as Samsung SmartThings Hub [3], could not be considered for our deployment since these solutions require a remote cloud outside of campus, monthly usage fees to access data, and closed solutions towards scaling with new sensors and services as cleanroom administrators need.

"Sensing Reliability" is of great importance to cleanroom administrators. One crucial aspect of this reliability lies in 24-7 availability. The monitoring service must be highly available, and even a temporary service outage could potentially miss the reporting of hazardous conditions, leading to catastrophic results.

We design a *Watchdog* mechanism on SenseEdge. As the reset signal from SenseCloud to SenseEdge could be corrupted or delayed, we let SenseEdge monitor its health on its own and reset itself when necessary. SenseEdge sends heartbeats to the SenseCloud and waits for SenseCloud ACKs. If SenseEdge receives successfully an ACK from SenseCloud, it knows that it is healthy at this time, otherwise, after a number of failed heartbeats it knows that communication between itself and SenseCloud failed and it should reset itself. In our implementation, we leverage the Linux kernel module `softdog`, which monitors ACKs from SenseCloud and restarts SenseEdges when ACKs are not received for some preconfigured time interval.

The environment monitoring data are collected at SenseCloud via Wi-Fi network. At SenseCloud, we run a time-series open source database, called InfluxDB [4], because time-series databases are optimized for compression, storage and query of time-series sensory data. Queries of time-series data are of interest to cleanroom administrators to audit environment data at specific time points in history, and to researchers to get their data corresponding to times of their experiments instead of irrelevant data. SenseCloud storage employs a strict access control service based on IP whitelisting. SenseCloud deploys the Grafana visualization tool [8], which provides web-hosted charts, graphs, query builders, and alerts. Grafana allows users to attach rules to their dashboard panels that give off alerts. Users can configure these rules and schedule them as to how often and under what conditions an alert should send a notification to cleanroom administrators.

In Figure 3, we show five sensors S0 – S4 and instruments inside the HMNTL lithography cleanroom. Figure 3 (right) visualizes the data from S0-S4 with upper panel showing temperature, and lower panel showing humidity measurements. The visualization shows that SenseEdge devices are able to capture well variations in temperature and humidity measurements.

LOCALIZATION AND PROXIMITY DETECTION SERVICES

For security and safety reasons, a cleanroom administrator needs a service that can record users' locations and proximity to instruments precisely. Traditional ID card-based access control typically provides room-level record only. Surveillance cameras only [5] do not work well in cleanrooms either, because users wear the same type of protective suits, which makes it hard to distinguish them by appearance. Although localization techniques based on Wi-Fi signals work well in indoor spaces and achieve low cost [6], their accuracy (1- 2m) is not enough as the instruments in cleanrooms are even closer to each other.

In SENSELET, we build localization and proximity detection services, shown in Figure 4, based on the fusion between Wi-Fi fingerprints and computer vision techniques.

The location sensing subsystem is a client-server system, in which the client uses the user's mobile device and the server

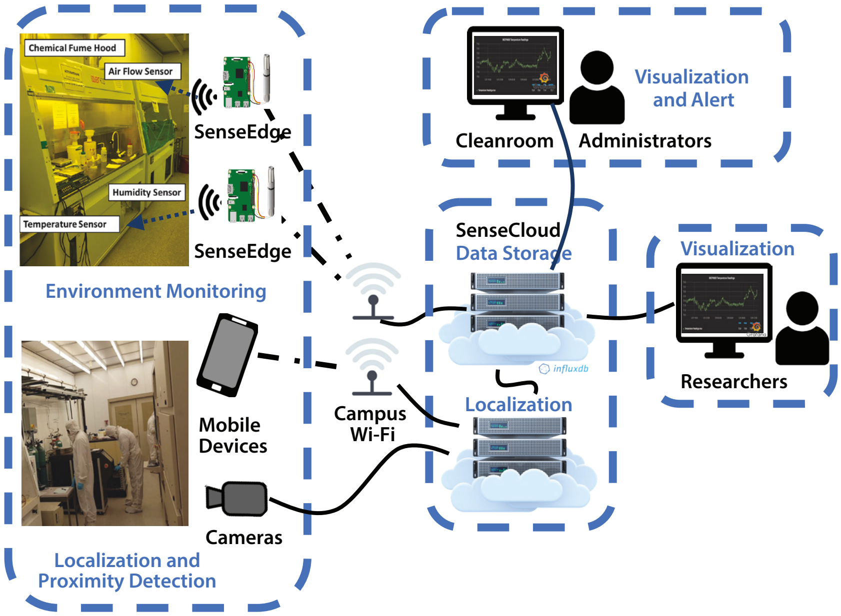

FIGURE 2. SENSELET Architecture.

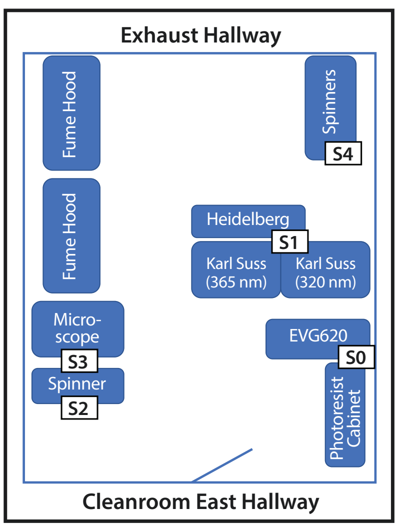

FIGURE 3. Deployment of SENSELET (left) and visualization of collected data (right).

resides in SenseCloud. The used localization method, MMLOC [7], consists of offline and online phases.

Offline Phase: In cleanrooms, because of diverse factors, such as installation positions, barrier positions, and power levels, each access point (AP) generates a unique RSS distribution. During the offline phase, we first divide the indoor space into small grids with a constant size (e.g., 1 m × 1 m), and measure the RSS from each APs at the center of each grid. In each grid, the RSS values from the APs are named as the fingerprint of that grid. Due to many factors such as signal fading, the RSS measurement result for an AP is not constant. To improve the localization accuracy, for each AP, we record multiple RSS values in each grid. We store the measurement results in SenseCloud and build a mapping between grid locations and fingerprints.

Online Phase: The client keeps measuring the RSS from each AP, caches the most recent results and periodically uploads them to SenseCloud. For each AP, the uploaded results contain multiple cached values. The server compares the uploaded RSS values with the stored fingerprints, and finds the best matched fingerprint. Then, the grid mapped to the fingerprint is the estimated user's location.

We evaluate our service in a 40 m^2 cleanroom. There are many obstacles and thus the environment is complex. We deploy four Tenda AC1200 APs uniformly around the room. In the offline phase, we divide the experiment field into 40 grids and collect the RSS fingerprints using four Android smartphones (Samsung Nexus S). In each grid, we collect 30 RSS values from each AP. During the online phase, we use another Samsung Nexus S to measure RSS in the 40 grids, and in each grid it caches and uploads two RSS values for each AP.

The average errors are 3.08 m, 2.09 m and 1.67 m when the number of APs used for localization ranges from one to three. When all four APs are used for localization, the average accuracy achieves 1.15 m. The results show that, as long as each grid is covered by enough APs, our system can achieve good performance in cleanrooms.

The video segments from a monocular camera, mounted on the cleanroom ceiling, are sent to SenseCloud to run the *proximity detection* (see Figure 4). The algorithm is as follows: (1) Background-foreground subtraction highlights different blobs. (2) The contour detection selects the blobs that correspond to users. (3) We convert 2D coordinates of the user and instrument into 3D through parameters, obtained from a calibration process because it is not possible to get real-time depth information of users from a 2D camera; the only plane that stays the same between background and user is the *floor*; and the distance of user and two instruments can be almost the same in 2D while being different in 3D. (4) The 3D floor coordinates of the user and blobs are used for tracking and checking the nearness to the instrument. (5) Proximity detection results are merged with localization results to localize and identify user using the instrument. The results are stored in SenseCloud.

In Figure 4, we show proximity detection output with two users being tracked, highlighted in green and red boxes, working on instruments marked with circles on the floor. The yellow circle indicates an "available" instrument and green indicates an "occupied." We evaluate proximity detection with a seven-minute video segment captured from one HMNTL cleanroom. We manually label the video segment in frame intervals for ground truth. Our algorithm yields an accuracy of 71%, which is the number of correct instruments that users are working on as compared to the ground truth.

CONCLUSION

To take sensor-edge-cloud solutions, developed for highly controlled and/or artificial environments, and deploy them in academic cleanrooms was non-trivial. We gained several insights: (1) Due to diverse cleanroom users, it was important to understand users' requirements. In SENSELET, the biggest concerns were reliability and availability of data. (2) Enhancing reliability of commodity sensors in SenseEdge required non-computing considerations, e.g., external protection of sensors. (3) Camera's blind spots exist in cleanrooms, which makes it hard to determine always proximity of users to an instrument. Hence, even though Wi-Fi sensing helped in our proximity detection, other sensing technologies are needed to increase accuracy. ■

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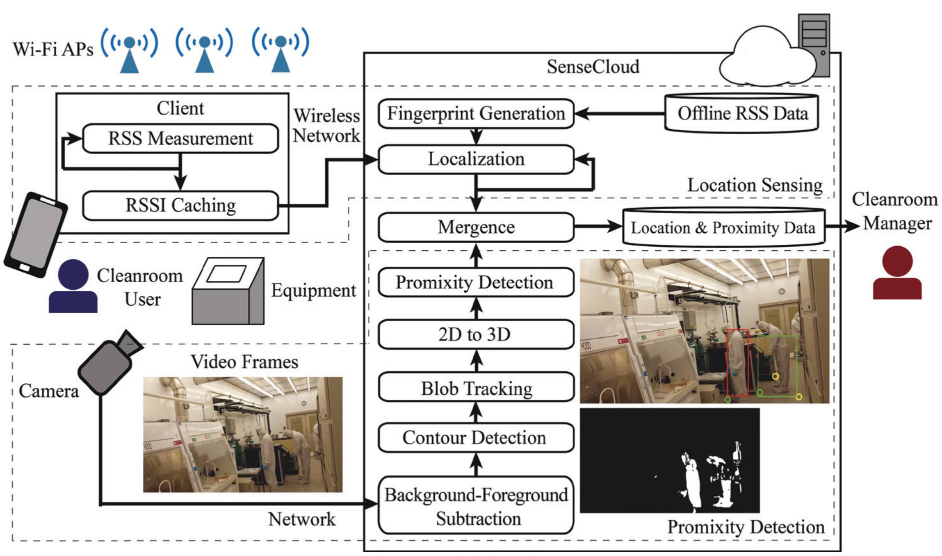

FIGURE 4. Localization and Proximity Detection System in SENSELET.

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