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Evaluating Bluetooth Beacon Observations for Classroom Interaction Detection

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Abstract

Traditional classroom observation often rely on human observers in a process that can be labor intensive, time-consuming, and may not fully capture individual student experiences. Sensing technologies, such as Bluetooth Low Energy (BLE) beacons, offer a promising alternative by collecting continuous, real-time data on student proximity and interactions. This paper evaluates the use of BLE beacons as part of a real-time social interaction capture system, called IDEAS. In a laboratory setting, the relationship between beacon signal strength (RSSI), distance, and orientation was examined to validate a proximity detection metric. A preschool classroom study further tested the ecological validity of the real-time location system by comparing interactions detected by the automated system with those recorded by a traditional researcher-led method. In order to align the differing sampling methods of IDEAS and the traditional researcher-led method, we developed an algorithm to down-sample the beacon data. The results suggest a partial alignment between beacon-detected interactions and the ones detected via traditional observations. The limited correspondence could be due to signal loss or inconsistencies in human observations. Incorporating additional sensor modalities, such as audio from wearable recorders, may enhance the system's accuracy. These findings highlight the potential for systems like IDEAS to offer scalable methods for capturing peer interactions and engagement through multi-modal sensor data. Building on approaches used in early childhood education research, incorporating sensing technologies into engineering education could provide richer, continuous insights into student collaboration and classroom dynamics.

Keywords: preschool, observations, data collection

Introduction

Observations in engineering education (EE) play a fundamental role in assessing teaching pedagogies, student engagement and effectiveness of learning environments. Protocols, such as the Classroom Observation Protocol for Undergraduate STEM (COPUS), are widely employed to categorize classroom activities systematically, document interactions between instructors and students, and evaluate the adoption of evidence-based teaching methods [1]. These tools enable educators and researchers to analyze behaviors and instructional strategies, providing valuable insights into classroom dynamics.

In active learning environments, which emphasize student engagement through hands-on and collaborative tasks, observational protocols serve to measure participation in group discussions, problem-solving tasks, and other non-traditional teaching practices. Such observations are particularly relevant in engineering education, where instructional methods must often address the cognitive demands of design thinking and problem-solving. Additionally, these methods help identify challenges such as student resistance to active learning, a common barrier in STEM classrooms [2].

Despite their benefits, many observational protocols have limitations. Some protocols struggle to address the complexity of engineering classrooms, which frequently involve project-based and problem-based activities that demand higher-order cognitive skills. Observer reliability and the structured nature of protocols also present challenges, as variability in data collection and limited adaptability to diverse contexts can reduce the effectiveness of these tools [1, 3]. Observations also tend to be time and labor intensive, which could lead to high expenses [4].

The use of wearable sensing technologies to conduct observations could help address these issues. Sensing technologies could provide the overall dynamics of the classroom as well as a more individualistic student perspective. Sensing technologies could be deployed in classrooms to run throughout the day, without the need for a human observer, reducing the cost of observations.

Previous research has primarily relied on ultrawide-band (UWB) Real-Time Location Systems (RTLS) solutions, to track participant movements with high precision [5, 6]. However, despite their accuracy, these systems are costly (approximately \$14,000 per classroom) and require invasive installation procedures, such as deploying Ethernet cables above classroom ceilings. Additionally, system calibration complexities further limit its scalability, making it impractical for multiple educational settings and widespread adoption.

Bluetooth Low Energy (BLE) systems offer opportunities for scalable RTLS. BLE-based systems approach the real-time location problem from a peer-to-peer perspective. BLE antennae and BLE beacons, worn by participants or affixed to environmental fixtures, establish a wireless data exchange network. From the data exchange patterns between beacons, a proxy for peer-to-peer physical proximity and orientation, called Received Signal Strength Indicator (RSSI), is computed. For example, IDEAS (Interaction Detection in Early Academic Setting) is a multi-modal interaction detection system that used wearable audio recorders and BLE beacons. IDEAS was developed for a project in early childhood education to understand the evolution of preschool social networks and it has been utilized to study the dynamics between a specific student and their classmates. It does so by using voice recorders to gather speech data and it utilizes Bluetooth Low Energy (BLE) beacons to locate a student in proximity to another student [7]. Systems such as IDEAS could be utilized in active learning engineering classrooms in gathering observations. It could evaluate how often students interact with each other or what part of the maker space they utilize the most by using beacons. In addition, IDEAS voice recorders and language processing abilities could help study the language used by engineering students to communicate with each other.

This paper focuses on utilizing the beacons used by IDEAS to detect interactions among classmates in a preschool setting. The purpose of this paper is to assess the accuracy and criterion validity of the BLE sensing system using data gathered in laboratory and classroom settings. In the lab setting, the beacons are tested at objectively measured distances and orientation angles to establish associations with the received signal strength indicator (RSSI), the power of a wireless signal received by a BLE beacon. In this paper, we adopt the RSSI as a proxy for proximity. The criterion validity of the BLE sensing system in a classroom setting is assessed by comparing the interactions detected by the beacons with the interactions detected with a traditional researcher-based observation method. In order to do so, we study the alignment between both observation methods.

Methods

IDEAS' RTLS, available in `https://github.com/hugonvilla/IDEAS_obs`), enables accurate measurements of relative proximity while leveraging an open-source software framework, which enhances flexibility and adaptability across different research contexts. On the hardware side, the RTLS employs wearable *Puck.js* BLE beacons equipped with accelerometers, which are wirelessly connected to antennae affixed to classroom walls using removable Velcro strips. The beacons worn by students are shown in Figure 1 below, where Figure 1a is the beacon sensor and Figure 1b is the beacon placed inside of the vest worn by students. IDEAS employs an open-source software called Pareto Anywhere to retrieve peer-to-peer RSSI data [8]. Pareto Anywhere has been previously utilized in retail settings and for estimating hospital workers' proximity in healthcare studies [9, 10]. We use a support vector machine (SVM) algorithm to process the accelerometry data to detect when students are wearing the beacons, allowing for the automatic marking of valid temporal segments during data collection.

To associate RSSI with distance, two beacons are examined in a lab setting at various distances from each other, with the RSSI between the two beacons collected by the IDEAS system. The beacons are positioned to face each other, ensuring the angle between them is 0 degrees. Each distance is maintained for 1 minute, during which the range of RSSI values is collected. A similar test is conducted to determine whether the beacons need to face each other to be considered an interaction. The test is performed in a lab, where two beacons are positioned at different angles, and the RSSI value corresponding to each angle is measured by the IDEAS system. The distance between the beacons is set to approximately 3 feet.

To study the validity of the beacons in a classroom setting, a peer-mediated intervention strategy is utilized to help integrate a preschool target student, who is socially isolated, into the classroom by pairing them with two designated peers. Socially isolated refers to students who are not engaged in the classroom. This strategy is employed alongside two observation methods: IDEAS and Social Network Observation (SNO).

(a) Bluetooth beacon (b) Beacon in vest

Figure 1: Beacons worn in a vest by the students

SNO is a more traditional approach to observations, where a researcher observes the interactions between the target student and their designated peers and then takes notes on the observed dynamics [11]. The second method, IDEAS, involves students and teachers wearing beacons and voice recorders to detect interactions between the target student and their peers [12]. By comparing the data collected through these two observation approaches, the alignment between the datasets can be evaluated.

SNO monitors the interactions between the target student and their designated peers over a series of cycles. Each cycle is divided into two parts, with each cycle representing a single data point. The first part involves observing the dynamics between the students, while the second part involves taking notes on the observed interactions [12]. Figure 2 illustrates SNO being conducted over 30 cycles. Each cycle lasts 60 seconds, divided into 15 seconds for observation and 45 seconds for note-taking. SNO categorizes each cycle based on the number of designated peers the target student interacted with. For example, if the target student interacts with one designated peer, the interaction is recorded as "one" for that cycle.

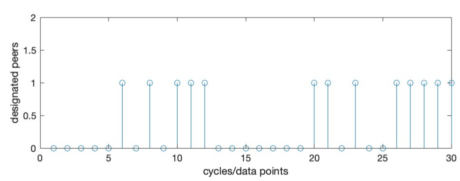


Figure 2: Data gathered by SNO over a 30 minute period

An issue arises when attempting to align the data gathered through SNO with the data collected via IDEAS. As mentioned earlier, IDEAS samples every three seconds, resulting in 600 data points to represent 30 minutes of observing the interactions between the designated peers and the target student, as shown in Figure 3. The blue line represents the interactions with the first designated peer, while the red line represents the interactions with the second designated peer.

An algorithm is developed to down sample the IDEAS data points to be represented in 30 data points in total to be compared to the SNO. In this paper, down-sampling refers to the reduction of the amount of data in a set. This aligns with the meaning of down-sampling commonly used in data processing and signal processing. The algorithm has two major variables, x_1 that represents the number of samples extracted from the 20 IDEAS data points and x_2 that represents the maximum percentage of missing data (Nan) values allowed in x_1 samples. This algorithm iterates between

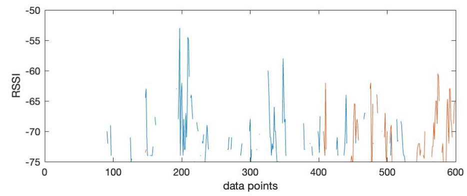


Figure 3: Data gathered by IDEAS over a 30 minute period

20 IDEAS data points at a time for data gathered from both designated peers assigned to the target student. These 20 IDEAS data points represent 60 seconds of observation time. At each iteration, the steps shown in algorithm one is performed.

Algorithm 1 Process IDEAS Data Points

Require: x_1: Number of samples extracted, x_2: Percentage threshold for NaN values
Ensure: Single data point representation for each x_1 samples

1: **for** each set of x_1 samples extracted from 20 IDEAS data points for both peers **do**
2: Count the number of NaN values in the x_1 samples
3: **if** NaN values exceed x_2 percentage **then**
4: Represent the entire x_1 samples with a single data point set to 0
5: **else**
6: Represent the x_1 samples with a single data point set to 1
7: **end if**
8: **end for**

After down-sampling the beacon data for both designated peers, the data from both peers are added together to create a dataset comparable to the SNO dataset. Figure 4 shows the down-sampled IDEAS dataset for both designated peers combined. In this case, x_1 was set to 5 samples, and x_2 was set to 70%. This mimics a similar observation style to SNO, where the first 5 data points correspond to the first 15 seconds of observation conducted by the researcher.

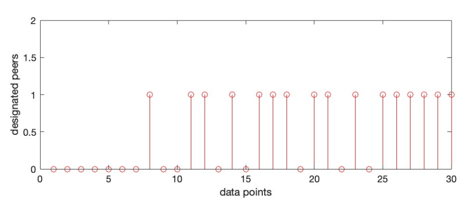


Figure 4: Data gathered by IDEAS translated into SNO format

Equation 1 is used to measure the alignment between the SNO data and the down-sampled IDEAS data. The equation calculates the mean squared error, MSE_j, between the two datasets for each observation. The variable y_i represents the number of designated peers observed by SNO, $\hat{y}_i$ represents the number of designated peers observed by the down-sampled IDEAS data, and n is the number of data samples, which is 30.

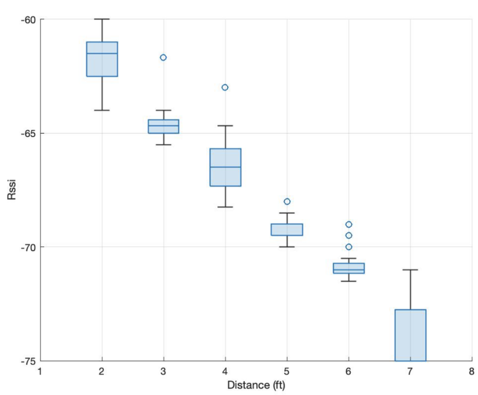
$$MSE_j = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (1)$$

To interpret the MSE_j values calculated for each observation, Equation 2 is used to compute the average mean squared error, $\overline{MSE}$, across the 12 observations for the IDEAS and SNO data. The variable m represents the total number of observations collected.

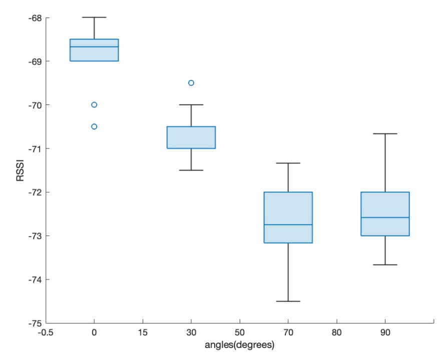
$$\overline{MSE} = \frac{1}{m}\sum_{j=1}^{m}(MSE_j) \quad (2)$$

Results

In a lab setting the correspondence between distance and RSSI has been established. Figure 5a is a box plot that showcases that a specific distance corresponds to a range of RSSI values. The central mark corresponds to the median, and the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively. The whiskers extend to the most extreme data points not considered outliers, and the outliers are plotted individually using the 'o' marker symbol. This demonstrates the capability of beacons to interact at different distances. The maximum RSSI value considered by IDEAS for an interaction between two beacons is -75 dB, corresponding to a distance of approximately 7 feet. Figure 5b illustrates the four angles and their corresponding RSSI ranges. This demonstrates that an interaction is detected at different orientations even when a beacon is perpendicular to the other.



(a) Association between distance and beacon RSSI



(b) Association between angles with beacon RSSI

Figure 5: Association between objectively measured distance (in feet) and orientation angles (in degrees) with beacon RSSI.

To compare the data gathered by SNO to data gathered by IDEAS x_1 is set to 5 data points and x_2 to 70% in algorithm 1, as seen in Figure 6. This configuration results in an $\overline{MSE}$ of 0.9167. Figure 6 illustrates the down-sampling process across all twelve observations, where the blue graph represents the SNO observation, and the red graph represents the down-sampled IDEAS beacon observation. The x-axis represents the data points, while the y-axis indicates the number of designated peers the target student interacted with.

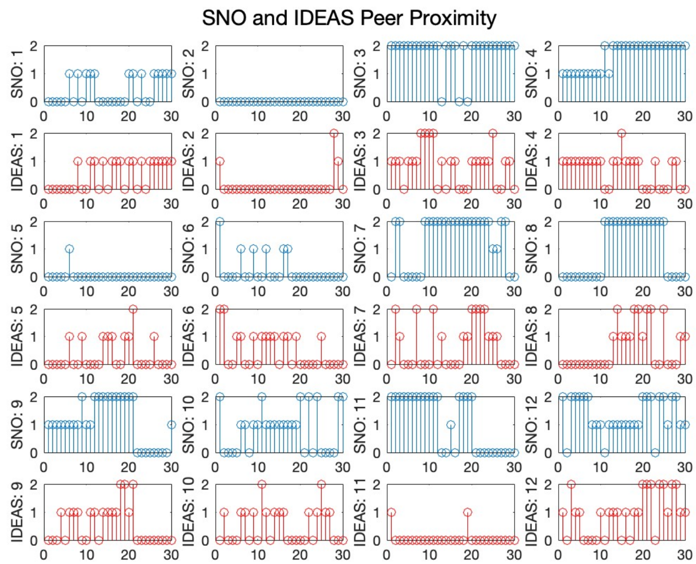
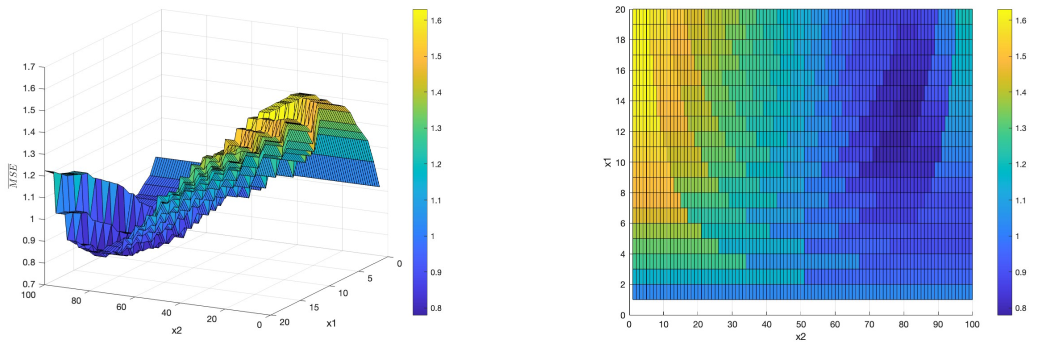


Figure 6: SNO (blue) and down-sampled IDEAS (red) data for the 12 observations.

To further investigate, a three-dimensional plot of the $\overline{MSE}$ is created, as shown in Figure 7a. The range of x_1 values is from 5 to 20 data points, which represents 15 to 60 seconds. The range of x_2 values is from 0% to 100%. By adjusting Figure 7a, Figure 7b is generated which is used in determining which values of x_1 and x_2 result in the lowest $\overline{MSE}$. The Lowest $\overline{MSE}$ is represented by the dark blue while the highest $\overline{MSE}$ is represented by the yellow in the gradient color bar of Figure 7a and Figure 7b. Upon close examination of both Figures 7a and 7b, the x_1 and x_2 values that resulted in the lowest $\overline{MSE}$ were $x_1 = 10$ and $x_2 = 70\%$, which produced an $\overline{MSE}$ of 0.8778. This corresponds to increasing the observation period to 30 seconds, doubling the observation period used in the SNO dataset.

Discussion

There are multiple explanations for the lack of perfect alignment between the IDEAS beacon interaction detection and the interactions detected by the SNO. In certain cases, when the SNO identifies interactions involving one or both designated peers but the beacons do not register these interactions, it may suggest that Bluetooth packets between the beacons are being lost due to technical issues. On the other hand, the reduction in $\overline{MSE}$ when x_1 was increased to 10 data points could suggest that the SNO observers were not strictly adhering to the 15 second observation period. This may be attributed to the human ability to multitask, allowing observers to simultaneously observe and take notes. Another aspect to consider is that some observations have a high MSE value, such as observation 11, that could be leading the $\overline{MSE}$ to be higher as seen in Figure 6. Further research is needed to determine methods to reduce $\overline{MSE}$ across the 12 observations. One potential approach is to examine the incoming and outgoing speech gathered by the voice recorders in the



(a) Three dimensional plot of the $\overline{MSE}$

(b) Two dimensional representation of $\overline{MSE}$ plot

Figure 7: Three dimensional plot of the $\overline{MSE}$ with respect to x_1, number of samples extracted from IDEAS' 20 samples, and x_2, percentage threshold for NaN values.

IDEAS system for the target student and their designated peers. The additional data from the voice recorders could compensate the lost data from the beacons. There is a possibility by combining multiple sensors to gather observation data, sensing technologies such as IDEAS could provide us with more robust data.

To ensure that IDEAS did not disrupt classroom activities, a survey was administered to 40 preschool teachers to assess how students interacted with wearing the sensors throughout the day and whether the teachers encountered any issues due to IDEAS. The survey utilized a Likert scale to measure responses, where 1 corresponded to "strongly disagree" and 5 to "strongly agree." The majority of responses from the teachers were positive. Most teachers reported that students were able to continue their normal classroom activities while wearing the vests shown in Figure 1. Majority of teachers also reported that the days when IDEAS was used to gather observations felt like typical school days, and they did not have to alter their classroom routines or modify what they wanted to say during those times.

While IDEAS has been used to study preschool social networks, its potential to support research on early engineering thinking or engineering education remains an area for further exploration. The review by Lippard et al. (2017) highlights several challenges in assessing engineering thinking in early childhood, including the lack of standardized assessment tools, limited understanding of how engineering thinking naturally develops, and the need for longitudinal data to connect early experiences with later outcomes [13]. By using beacons and voice recorders to track proximity, movement, and language use, systems like IDEAS may offer a promising method for collecting continuous data related to engagement in problem-solving or collaborative tasks. However, given the observed discrepancies between beacon-based data and human-coded observations, such systems should be used to supplement rather than replace traditional observation methods. With further optimization and integration of multimodal data sources, tools like IDEAS may approximate observational data more reliably in classroom settings. As an open-source platform, IDEAS can be extended or customized, which may allow researchers to adapt it for higher education or to capture more nuanced aspects of student interaction.

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