Activating Location-Based Storytelling in a City: Geofence Identification from Crowdsourced Mobile Sensing

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Abstract

Location-based storytelling is a key strategy in smart tourism, enabling immersive engagement through narrative content triggered by user movement. This study proposes a data-driven framework for designing *enclosure*- and *viewpoint-geofences* that align with storytelling modes, leveraging GPS horizontal-accuracy clustering and motion-sensor noise filtering to detect meaningful spatial engagement zones. We introduce a lightweight decision-tree classifier using cluster duration and motion variability features to distinguish valid indoor stays from transient or noise-induced clusters. In a field experiment with 12 participants in Akita City, our method achieved 94 percent classification accuracy and a 0.96 F_1-score under leave-one-out cross-validation. Furthermore, our qualitative comparisons imply the geofence identifications can outperform baseline techniques such as HDBSCAN and stay point detection. The results demonstrate the practical potential of the proposed approach for context-sensitive geofencing in urban tourism. This framework advances autonomous, adaptive geofencing for enriched tourist experiences.

1. Introduction

Location-based storytelling has emerged as a key strategy in smart tourism, aiming to deepen visitors' engagement with local culture, heritage, and urban environments (Kasemsarn and Nickpour, 2025). Rather than simply navigating from one site to another, tourists are now invited to experience places through narrative layers that unfold in response to their movement. These stories—delivered at the right place and time—can include observation tips, historical facts, architectural commentaries, or even personal anecdotes linked to the space, thus enhancing the cognitive and emotional resonance of a site.

A fundamental technology that enables such dynamic storytelling is geofencing. By defining virtual boundaries around specific geographic areas, geofencing allows digital systems to recognize when a user enters, exits, or moves near a point of interest (POI). This spatial awareness enables applications to trigger relevant narrative content in real time, making the visitor's experience more immersive and responsive to their physical surroundings (Boletsis and Chasanidou, 2018). Although originally developed for purposes of asset tracking and proximity-based marketing, geofencing has found new relevance in tourism services by facilitating the delivery of personalized regional stories based on users' real-world interactions with places.

Designing effective geofences in complex urban environments presents considerable challenges. Specifically, GPS signal accuracy can significantly fluctuate due to factors such as urban canyons, indoor environments, and interference from physical structures (Parent et al., 2013). Additionally, the temporal resolution of location sampling, i.e., how often a position is recorded, may lead to missed detections or false triggers (Garzon et al., 2017). Beyond these technical limitations, developers must also consider the intent and structure of the storytelling itself. Elements such as the spatial scale of a POI, the anticipated user behaviours, and the desired storytelling mode (e.g., immersive versus observational) all influence how and where geofences should be set. A small sculpture viewed from a plaza may require a different approach than a museum visited from within.

Against these backgrounds, this study seeks to advance location-aware services into the realm of story-aware systems that more precisely align with user engagement patterns. Section 2 discusses the diverse factors—ranging from spatial typologies to user transition dynamics—that inform geofence design from a storytelling perspective. This leads to the recognition that understanding interaction patterns is critical for tailoring geofence parameters effectively. To address this, Section 3 introduces a classification framework for detecting geofence zones using mobile sensor data collected from actual tourist behaviour. We focus particularly on landmark features, which exhibit varying engagement patterns depending on whether they are entered, observed from afar, or bypassed altogether. Section 4 presents the findings from in-situ experiments that test the framework's performance in real-world environments. Finally, Section 5 concludes with a reflection on the implications for future development of autonomous, adaptive, and narrative-driven geofencing systems in smart tourism.

2. Key Perspectives of Geofence Designs for Regional Storytelling

In the context of smart tourism, designing effective geofences requires more than just technical precision—it also necessitates a nuanced understanding of how stories are tied to places and how people experience those places. This section explores the storytelling-oriented considerations that influence geofence design. Three keys perspectives, that is, feature types, transition dynamics, and interaction patterns, offer a conceptual foundation for designing geofences that align not just with physical space, but with the narrative logic of how visitors encounter and engage with it.

2.1 Feature Types

Urban spaces are composed of a wide variety of spatial features, ranging from discrete landmarks such as monuments and statues, to expansive environments like boulevards, plazas, or historic districts. These features vary not only in size and form but also in their cultural meaning and the types of engagement they invite. Despite this diversity, many existing location-based guide systems tend to treat all POIs uniformly, failing to account for their distinct spatial and semantic characteristics. Conventional systems often treat a monument and a public park as equivalent units, despite their vastly different user interaction patterns and spatial extents (Sun et al., 2020). To address this limitation, research introduced the concept of hierarchical POI structures, wherein larger, compound POIs (super-POIs), such as a historic district, can encapsulate smaller embedded POIs, like buildings, gardens, or statues (Wang et al, 2018). This layered model helps better reflect the nested nature of spatial experience in urban tourism.

Building on this, our prior research has adopted Kevin Lynch's influential theory on urban elements (Lynch, 1960), which categorizes city spaces into five types: paths, edges, districts, nodes, and landmarks. Each type suggests a different spatial logic and storytelling opportunity. For instance, streets or corridors support narrative sequences, while landmarks serve as focal points for symbolic or interpretive stories (Sasaki et al., 2024). Recognizing these distinctions enables designers to construct more meaningful geofence structures that respect the semantics of space.

2.2 Transition Dynamics

A second dimension in geofence design for storytelling involves the temporal ordering of user experiences—or what we refer to as transition dynamics. In a location-aware system, users rarely encounter POIs in isolation; their experience is shaped by the path they take and the sequence in which stories are delivered. Prior interactions leave cognitive traces that influence how future content is perceived. For example, repetition of the same content at previously visited sites can diminish user engagement, particularly in exploratory settings where novelty is highly valued (Tokita et al., 2019). Therefore, geofencing systems should incorporate a form of memory—tracking which stories have already been delivered to a user—to avoid redundancy and preserve narrative freshness.

Temporal awareness can also be more formally modelled in geofencing operations. Specifically, a temporal-aware geofencing approach ensures that the activation is dynamically adjusted based on the user's recent interaction history (Garzon et al., 2014). For example, a story about a city gate might only trigger if the user visited a related castle within the last hour. Such logic introduces a contextual filter based on time, allowing stories to respond not just to place, but also to narrative sequence and recency.

2.3 Interaction Patterns

Among the three factors, this study places special emphasis on interaction patterns—that is, how users physically and spatially engage with a particular place. This dimension is particularly important for landmarks, which can be experienced in different ways depending on whether users enter the space or view it from a distance. Based on this distinction, we indicate two types of geofences: *enclosure-geofences* and *viewpoint-geofences*.

Enclosure-geofences are triggered when users enter a defined spatial boundary, such as a museum, gallery, or temple complex. These geofences are best suited for immersive storytelling, where content is delivered in response to close-range, interior interaction. Visitors may walk through multiple zones, encounter displays, or engage in site-specific activities, and the narrative should unfold accordingly.

Viewpoint-geofences, on the other hand, are activated at external observation points—such as scenic overlooks, architectural vistas, or strategic angles from which landmarks are viewed. These are more appropriate for interpretive storytelling, which frames the site visually and contextually, often highlighting its historical significance, symbolic meaning, or aesthetic form from a distance.

Figure 1 presents representative examples of both *enclosure*- and *viewpoint-geofences*, along with the corresponding storytelling strategies they support. By differentiating these interaction modes, we can better tailor the structure, trigger conditions, and narrative content of geofences to match the lived experience of site visitors.

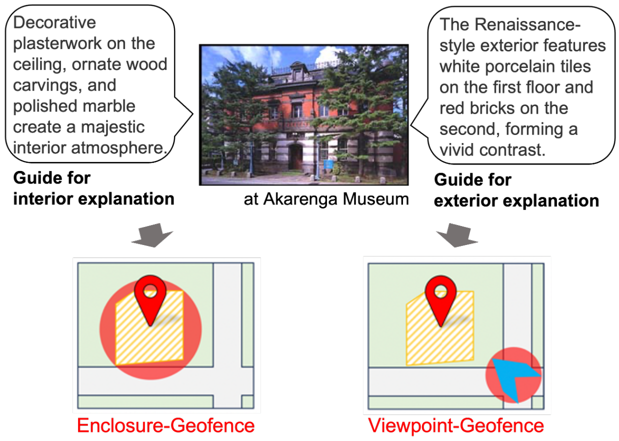

Figure 1. Examples of *enclosure-geofence* and *viewpoint-geofence* with corresponding guide content. Interior guides describe spatial details from within, while exterior guides focus on the appearance from a specific viewpoint.

3. Classification Methods for Geofence Identification

This study proposes a classification framework for assisting geofence designs that align with different storytelling needs in smart tourism, using mobile sensor data collected from tourists' devices. The framework especially focuses on the necessity of identifying *enclosure-geofences*, which correspond to immersive spatial experiences, and *viewpoint-geofences*, which support external observation.

3.1 Necessity of a Data-Driven Approach

While geofence design based on feature types (Section 2.1) and transition dynamics (Section 2.2) can largely be initiated by map-based planning and developer's intention, interaction patterns (Section 2.3) are inherently user-driven and context-sensitive. Users do not always engage with POIs in predictable ways; they may pause unexpectedly at certain viewpoints, or bypass enclosed spaces altogether. This unpredictability makes it difficult to predefine geofences solely through static geographic information. Therefore, a data-driven approach is essential to understand how visitors interact with urban features. By analysing mobile sensor data—such as GPS trajectories, dwell time, and movement speed—developers can detect patterns that indicate either entry into spaces (*enclosure-geofence* candidates) or external engagement points (*viewpoint-geofence* candidates).

3.2 Overview of Classification Framework

To address the variability and unpredictability of user interactions with physical spaces, this study proposes a data-driven framework that identifies candidate geofenced zones from mobile sensor data, particularly GPS trajectories. The goal is to distinguish between indoor zones, corresponding to immersive interactions (i.e., *enclosure-geofences*), and viewing zones, associated with external observation (i.e., *viewpoint-geofences*).

Figure 2 illustrates the overall workflow of the proposed classification framework. The process begins with the collection of raw GPS trajectory data from mobile devices carried by tourists during their exploration of urban environments. Then, the framework applies *GPS Accuracy Clustering* to detect regions where signal accuracy significantly deteriorates. These clusters often indicate indoor environments or densely built-up areas where GPS signals are obstructed. As such, these clusters are treated as candidates for indoor zones. The candidates of indoor zones data often contain noise, such as abrupt location jumps or low-accuracy readings due to environmental factors. Therefore, the second step involves *Noise Detection*, which filters out anomalous or unreliable data points. In parallel, the system analyses remaining location data to identify positions where users repeatedly pause or linger, particularly in outdoor spaces. Such *Stay Point Detection* often correspond to locating where users visually engage with a landmark, such as a viewpoint or scenic spot. As a result, these points are flagged as candidates for viewing zones, which inform *viewpoint-geofence* design.

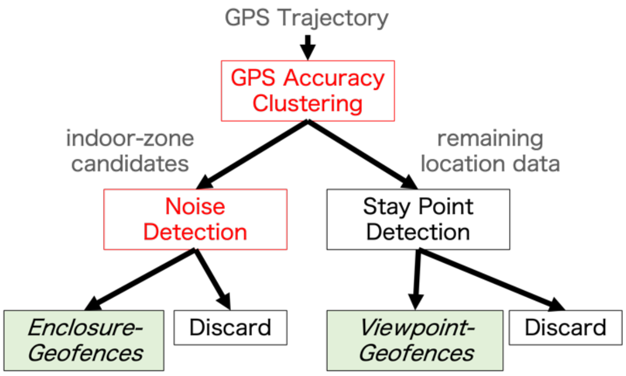

Figure 2. Flow of the classification framework. GPS accuracy clustering is used to extract *enclosure-geofence* candidates, followed by noise detection to filter out irrelevant clusters. Remaining data is passed through stay point detection to identify *viewpoint-geofences*.

3.3 GPS Accuracy Clustering

The process begins with GPS accuracy clustering applied to the entire user trajectory. To detect candidate indoor-zones—areas where GPS signal accuracy degrades due to built-up or enclosed environments—we employ the GPS horizontal accuracy clustering. Let the trajectory be represented as:

$$Tr = \{p_i = (t_i, lat_i, lon_i, h_i) | i = 1, \dots, N\} \tag{1}$$

where t_i = timestamp
lat_i, lon_i = geographic coordinates in 2D
h_i = GPS horizontal accuracy

In practical deployments, the horizontal accuracy value is readily available from the GPS sensor APIs built into modern smartphones. You may also leverage other complementary signals, such as Wi-Fi or barometric pressure changes, instead of GPS horizontal accuracy data (Wang et al., 2016). We first discard any point whose accuracy exceeds an upper bound H_{up} (e.g., 200 meters) and obtain the filtered trajectory data Tr', since extremely poor readings cannot reliably indicate indoor locations. Each remaining point is classified as an indoor candidate if its accuracy exceeds a lower threshold H_{low} (e.g., 10 meters), otherwise as outdoor:

$$s_i = \begin{cases} 1, & h_i \geq H_{low} \\ 0, & h_i < H_{low} \end{cases} \tag{2}$$

The process then scans Tr' in time order and identify contiguous segments where $s_i = 1$. For each such segment running from index e (enter) to l (leave), its geometric centroid is calculated as the core of the indoor segment.

If a new indoor segment is detected before the user moves beyond a predefined buffer radius D, the new segment is considered part of the previous cluster and is merged accordingly (Figure 3). This strategy accounts for brief periods of high GPS accuracy that may occur indoors, such as passing near windows, where signal quality temporarily resembles outdoor conditions. By allowing short, localized transitions without splitting the indoor zone, we improve robustness against false exits.

Now, the process confirms the segment $[e, l]$ as a valid indoor cluster and assign it a unique ID. However, this signal-based heuristic is not infallible. Low GPS accuracy may also occur in outdoor settings—such as under dense foliage, in urban canyons, or during the warm-up phase of the GPS sensor—leading to potential false positives. Furthermore, some technically indoor locations, such as underground passages, may serve purely as transit spaces and thus are unsuitable targets for storytelling content.

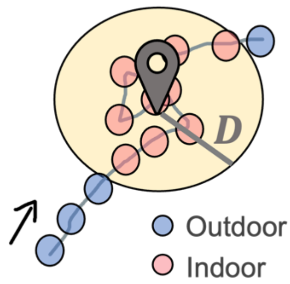

Figure 3. Cluster merging based on distance buffer radius D. Outdoor points (blue) are merged with the preceding indoor cluster (pink) if they remain within the buffer radius D from the cluster centroid. This accounts for brief indoor GPS accuracy improvements, e.g., near windows, and prevents false exits.

3.4 Noise Detection for Indoor Zone

Although GPS accuracy clustering is effective for identifying potential indoor zones, it may also capture irrelevant or transient clusters, such as GPS fluctuations in corridors, brief pauses near entrances, or signal loss during transitions. To address this, we introduce a noise detection step that filters out such spurious detections using a supervised binary classification approach.

This study constructs a feature vector for each candidate indoor cluster based on smartphone sensor data, aiming to characterize both user motion and GPS signal stability during the cluster's duration. The selected features include:

- $accel\_avg$: mean acceleration
- $accel\_var$: variance of acceleration
- $hacc\_avg$: mean horizontal GPS accuracy
- $hacc\_var$: variance of horizontal GPS accuracy
- num_point: number of GPS data points in the cluster

To compute acceleration-related features, we first derive the magnitude of 3-axis acceleration at each time step by computing the root sum square of the x-, y-, and z-axis values:

$$a(t) = \sqrt{a_x(t)^2 + a_y(t)^2 + a_z(t)^2} \qquad (3)$$

To suppress high-frequency noise, a low-pass filter is then applied to the resulting time series. The filtered acceleration signal is used to compute the average ($accel\_avg$) and variance ($accel\_var$) over each cluster.

Each feature is designed to capture a different behavioural or technical indicator. $accel\_avg$ reflects the overall movement level of the user. Lower values typically indicate pausing or standing still, which are common during indoor stays. $accel\_var$ helps distinguish between consistent stillness and fluctuating movement. $hacc\_avg$ serves as a direct indicator of signal quality. Higher values imply degraded GPS precision, which often occurs indoors. $hacc\_var$ captures fluctuations in GPS signal stability. True indoor clusters may exhibit not only high inaccuracy but also unstable readings over time. num_point reflects the duration and density of the data. Short-lived clusters with few points are more likely to be noise, whereas valid indoor probably stays typically span longer periods with consistent sampling. Together, these features are expected to form a complementary set that balances motion analysis and signal reliability, allowing the classifier to effectively separate meaningful indoor stays, such as visits to enclosed spaces, from noisy clusters caused by incidental movement or unstable GPS reception.

Based on exploratory scatter plot analysis and cross-validation experiments, this study implements a decision tree classifier to predict whether each cluster corresponds to a valid geofence zone. The classifier demonstrates high interpretability and is able to separate indoor-stay patterns from noise-prone clusters effectively.

Clusters classified as valid are retained and passed forward as confirmed *enclosure-geofences*. Clusters classified as invalid are discarded to improve the robustness of the geofence detection framework. The performance of this classification approach, along with the contribution of each feature, is quantitatively evaluated in Section 4.

4. Experimental Evaluation

To validate the effectiveness of the proposed framework for geofence classification in smart tourism, we conducted a real-world data collection study and performed a twofold evaluation. First, we assessed the accuracy of the noise detection module using a supervised decision tree classifier applied to clustered trajectory data. Second, we compared our GPS accuracy-based clustering approach with two established spatial clustering methods to demonstrate the practical advantages of our method in urban tourist environments.

4.1 Experimental Settings and Data Collection

To support empirical evaluation, we conducted an in-situ data collection study in Akita City, Japan. The aim was to gather realistic GPS and motion data reflecting typical sightseeing patterns such as entering buildings, pausing at landmarks, and transitioning through open spaces.

A total of 12 participants took part in the study. Each participant was instructed to explore a designated walking route that included both indoor and outdoor points of interest—such as museums, shrines, plazas, and scenic viewpoints. Participants carried an iPhone 11 device equipped with a custom data logging application, which recorded: GPS location (latitude, longitude), GPS horizontal accuracy data, three-axis accelerometer data, and timestamps. On average, each session lasted about 90 minutes, resulting in a total of 35 candidate clusters identified via GPS accuracy clustering.

After the walks, clusters were manually labelled by comparing trajectory maps with known locations of indoor facilities and stop points. Among the 35 extracted clusters, 25 were confirmed as valid indoor stays, while the remaining 10 were identified as noise—caused by GPS drift, underground passage transitions, or brief outdoor stops. This dataset serves as the foundation for the quantitative and qualitative evaluations described in Sections 4.2 and 4.3.

4.2 Evaluation of Noise Detection for Indoor Zone

To assess the effectiveness of our noise detection module, we begin by examining the distributions of each individual feature across the three cluster types:

- Positive clusters (valid indoor stays)
- Negative clusters caused by GPS drift
- Negative clusters caused by underground pass ways

Figure 4 illustrates the kernel density estimation plots for each feature, color-coded by cluster class. From the figure, no single feature alone can sufficiently separate the true indoor clusters (red) from the false detections (blue and green). A single-feature threshold is insufficient for reliable classification. Any attempt to classify clusters using only one variable would either result in high false positives or high false negatives.

To address this, we evaluate combinations of features using a decision tree classifier. Given the high correlation observed between $hacc\_avg$ and $hacc\_var$ (Pearson's r = 0.87), we exclude feature pairs that contain both simultaneously to avoid multicollinearity. In total, nine feature pairs are tested, each subjected to leave-one-out cross-validation (LOOCV). We compute accuracy and F_1 -score for each configuration to quantify classification performance. Furthermore, we compare these pairwise models against a full-feature model using all five features except $hacc\_var$.

Table 1 reports the LOOCV Accuracy and F_1-measure for each of the nine feature pairs and for the full-feature model (all features except $hacc\_var$). First, the two-feature model consisting of $accel\_var$ and num_point achieves the highest discriminative power, with an overall accuracy of 0.94 and an F_1-score of 0.96. In our LOOCV experiments, this pair consistently produced a clear decision boundary: clusters corresponding to prolonged periods of low - variance motion (high num_point, low $accel\_var$) were reliably identified as valid indoor stays, whereas both brief, high-jitter noise and stable but instantaneous drift clusters fell outside this region. By contrast, the decision tree built on the full four-feature set (all metrics except $hacc\_var$) attains only 0.77 for accuracy and 0.85 for F_1-score. Although incorporating additional features such as mean acceleration and mean GPS error might seem to enrich the model, in practice these variables introduce overlap in higher dimensions and weaken class separability. Indeed, no other two-feature combination that omits num_point surpasses 0.83 accuracy—models relying solely on motion or GPS-accuracy metrics deliver at best moderate performance—and the weakest pairings, particularly those involving $hacc\_var$, drop to around 0.60, barely above random chance.

These findings underscore two key insights: (1) cluster duration, as quantified by the number of GPS samples, is the most informative feature for distinguishing genuine indoor engagement from transient or accidental readings, and (2) coupling this temporal indicator with motion variability captures the essence of sustained, low-movement behaviour characteristic of indoor stays. By focusing on these two dimensions, our classifier remains both simple and robust, avoiding the curse of dimensionality while delivering superior performance.

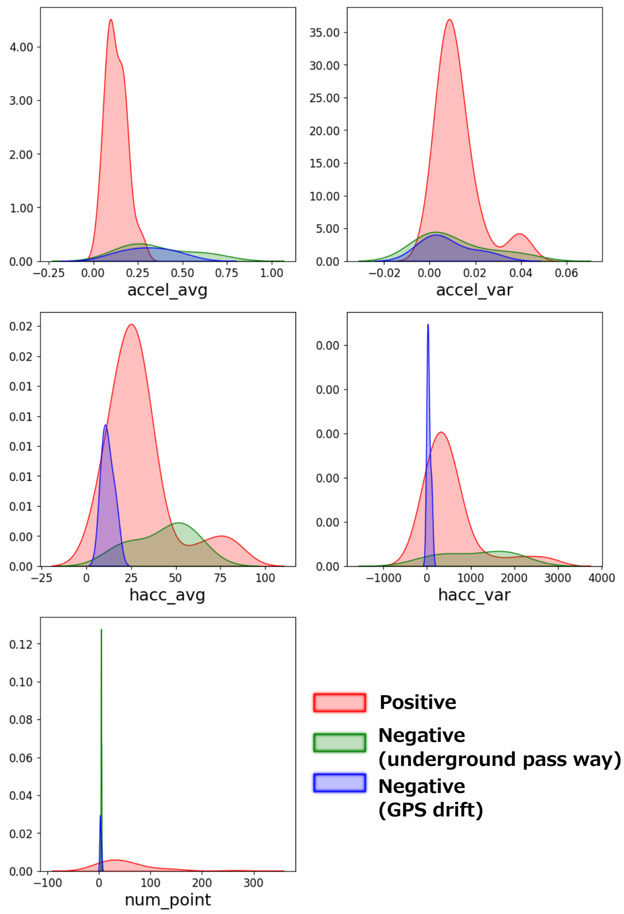

Figure 4. Density distributions of each feature across three cluster classes: valid indoor stays (red), underground passage noise (green), and GPS drift noise (blue). None of the individual features—$accel\_avg$, $accel\_var$, $hacc\_avg$, $hacc\_var$, or num_point—exhibits sufficient class separation on its own, highlighting the need for multi-feature classification.

Features	Accuracy	F-Measure
$(accel\_avg, accel\_var)$	0.83	0.88
$(accel\_avg, hacc\_avg)$	0.71	0.80
$(accel\_avg, hacc\_var)$	0.69	0.78
$(accel\_avg, num\_point)$	0.80	0.86
$(accel\_var, hacc\_avg)$	0.60	0.72
$(accel\_var, hacc\_var)$	0.60	0.71
$(accel\_var, num\_point)$	0.86	0.90
$(hacc\_avg, num\_point)$	0.86	0.90
$(accel\_var, num\_point)$	0.94 (Best)	0.96 (Best)
All features except $hacc\_var$	0.77	0.85

Table 1. Classification performance of decision tree models using different combinations of feature pairs and a full-feature configuration (excluding $hacc\_var$). Each model was evaluated using leave-one-out cross-validation (LOOCV). The pair $(accel\_var, num\_point)$ achieved the highest accuracy and F_1-score, indicating that motion variability and cluster duration together provide the most reliable basis for distinguishing valid indoor stays from noise.

4.3 Comparison with Alternative Clustering Methods

This study conducted a qualitative comparison between our proposed GPS accuracy clustering and two widely used baseline methods: HDBSCAN (Campello et al., 2015) and Stay Point Detection (Li et al., 2008). Both have been applied in trajectory analysis, but their effectiveness in identifying story-relevant geofence zones—especially in complex urban tourism settings—remains limited.

As shown in Figure 5, the methods produce notably different clustering outcomes. HDBSCAN (left) tends to form overly large clusters that often merge distinct spatial experiences, such as entering a building versus pausing nearby. This is due to its reliance on local point density, which can cause semantically different regions to be absorbed into a single cluster. Such overgeneralization reduces its utility for distinguishing nuanced tourist behaviours. On the other hand, Stay Point Detection (right) identifies clusters only when the user remains stationary beyond a certain duration. While this is effective for detecting brief stops, it often fails to capture extended indoor stays, especially in large buildings where users may move slowly or continuously. Consequently, key indoor locations relevant to storytelling may be missed entirely. By comparison, our GPS accuracy clustering approach can identify indoor zones based on degraded signal quality rather than strict immobility, allowing it to detect meaningful stays. Furthermore, it supports spatially coherent merging and better aligns with *enclosure-* and *viewpoint-geofence* distinctions.

In summary, while HDBSCAN and Stay Point Detection serve general clustering purposes, they are suboptimal for urban storytelling applications. Our method offers better spatial granularity and interpretability, making it more suitable for real-world deployment in location-based narrative systems.

Figure 5. Comparison of clustering results using HDBSCAN (left) and Stay Point Detection (right) on GPS trajectories. HDBSCAN tends to produce overly large clusters, while Stay Point Detection misses clusters in large indoor areas.

5. Conclusions

This study proposed a data-driven framework for geofence design in smart tourism, distinguishing between enclosure- and viewpoint-based storytelling experiences. By combining GPS accuracy clustering with motion sensor data-based noise filtering, the method enables context-sensitive detection of meaningful spatial engagement zones. Field experiments in Akita City demonstrated high classification accuracy, highlighting the approach's practical potential. Building on these findings, future work will focus on developing a practical workflow for determining the specific parameters of *enclosure- and viewpoint-geofences* based on sensor data patterns. Additionally, we aim to demonstrate the effectiveness of the data-driven geofencing approach from a service design perspective, evaluating how it enhances the delivery of location-based storytelling in real-world tourism applications.

Acknowledgements

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