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UMTrajNet: A spatiotemporal uncertainty modelling structure of human movement trajectories under complex indoor areas

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ABSTRACT

Movement uncertainty modeling is essential for reliable human mobility analytics, especially in indoor spaces with denied Global Navigation Satellite System (GNSS) signals and complex human motion modes. However, the performance of current uncertainty modelling approaches is hindered by the dynamic spatial–temporal correlations within the indoor human movement trajectory. To tackle these problems, this paper proposes a novel uncertainty modelling framework UMTrajNet to address indoor human movement reconstruction, movement uncertainty error prediction, and uncertainty region modelling. A spatiotemporal structure is designed by combining the Graph Convolutional Networks (GCN) network and the Long Short-Term Memory (LSTM) network, enabling adaptive learning the spatial and temporal features of human movement. An adaptive Euclidean distance method is employed to generate continuous uncertainty regions for the selected indoor trajectory based on extracted spatiotemporal features. By integrating GCN with LSTM, UMTrajNet effectively captures the complex spatial–temporal dependencies within the trajectory data thereby overcoming the limitations of traditional solely LSTM-based models in spatial context correlation modeling. Real-world experimental results indicate that the presented UMTrajNet significantly outperforms the state-of-the-art baseline models in uncertainty modelling across different datasets.

1. Introduction

The analysis of pedestrian trajectory data has emerged as a pivotal aspect of human mobility research, offering insights into spatiotemporal movements and social dynamics. Advances in Micro-Electro-Mechanical Systems (MEMS) sensors integrated in smart devices for the potential acquisition of human movement information, supporting a range of Location-Based Services (LBS) such as smart transportation, user habit analysis, epidemic prevention, and autonomous healthcare (Pal et al., 2018, Zhu et al., 2019, Liu et al., 2022a, Liu et al., 2022b, Shi et al., 2022). However, the complexity of urban scenarios and the heterogenous mobility data acquired from different devices introduce movement uncertainty, a significant challenge in trajectory data analysis. This uncertainty hampers the efficiency and accuracy of knowledge extraction from pedestrian trajectories (Downs et al., 2018, Shi et al., 2021). Recently, addressing movement uncertainty in large trajectory datasets across varied application scenarios has gained increasing attention, particularly for the human mobility mining, reliable positioning and navigation, and spatial querying (Pfoser and Jensen 1999, Weng et al., 2025, Yu, Chen et al. 2021).

Movement uncertainty in pedestrian trajectories traditionally considers two main sources: sampling error and measurement error. The sampling error is originated from inconsistent location points and varying sampling rates, leaving gaps in motion information (Zheng, Zheng et al. 2012). Measurement error is attributed to the data acquisition process, influenced by positioning methods, environmental factors, and devices differences (Gu et al., 2024, Zheng 2015). Traditional methods utilize the definition of a Space-Time Prism (STP) to estimate the Potential Path Area (PPA) according to the human trajectory (Miller 1991, Kwan 1998). However, these methods, often based on assumptions of constant speed, have limitations, leading to overestimated PPA in real-world applications (Downs and Horner 2014, Xia et al., 2018). To refine uncertainty estimation, adaptive speed control criteria and alternative methods like the Approximate Upper Bound (AUB) model

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based on the calculation of maximum movement range have been developed, but these approaches still struggle to fully capture the complex nature of pedestrian movement and the variability in data quality (Furtado et al., 2018, Zhou et al., 2018).

Recent advancements in movement uncertainty modeling have leveraged learning-based methods, particularly the Long Short-Term Memory (LSTM) related methods, to handle the intricacies of pedestrian movement in both outdoor and indoor environments. In these approaches, the LSTM model is employed to represent the complex temporal dependencies inherent in pedestrian trajectories. The framework typically involves using a series of position points, observed over a period of time, as input to model the spatiotemporal relationship and predict the uncertainty in pedestrian movement. This contrasts with earlier methods that often relied on static assumptions about movement speeds or distances. By incorporating a diverse set of features extracted from pedestrian movement data, including both measurement and sampling errors, these LSTM-based models offer a more dynamic and nuanced understanding of trajectory uncertainty. For instance, in urban environments, the model accounts for varying conditions such as signal occlusions and pedestrian movement patterns, thereby enhancing the accuracy of trajectory uncertainty predictions (Liu et al., 2021, Yu, Shi et al. 2022). The use of Bi-directional LSTM networks further refines this approach, providing a more comprehensive analysis by considering both past and future states in the data sequence. This sophisticated treatment of trajectory data represents a significant leap forward in the field, demonstrating improved robustness and precision in predicting movement uncertainty across diverse and complex urban scenes.

While the recent LSTM-based models have marked a significant advancement in understanding pedestrian movement uncertainty, they are not without limitations. A notable shortcoming is their relatively inadequate ability to capture spatial correlations effectively. While LSTMs are highly proficient in modeling temporal dependencies, they often struggle to adequately represent the spatial relationships that are crucial in pedestrian trajectory modeling. This limitation becomes particularly problematic in complex urban or indoor environments, where the spatial context, such as the proximity to landmarks, obstacles, or the specific layout of the environment, plays a significant role in shaping movement patterns. For instance, in dense urban areas or intricate indoor spaces, pedestrian movement is heavily influenced by factors such as narrow passageways, sharp turns, or proximity to walls and furniture. These spatial nuances are difficult for LSTMs to capture, as they are primarily designed to process sequential data without inherently accounting for the geometric or topological relationships between different spatial locations. Consequently, relying solely on component that capture temporal correlation can lead to suboptimal predictions in environments where spatial dependencies are as critical as temporal ones. This gap in spatial dependency modeling can lead to suboptimal predictions and analyses, underscoring the necessity for new models that can more comprehensively understand both the temporal and spatial dimensions of pedestrian movement. The development of such models would represent a significant step forward, offering the potential to more accurately reflect the intricacies of human mobility in varied and complex environments, thus paving the way for more precise and reliable movement uncertainty analysis.

Consequently, viewing the mentioned difficulties, this paper proposed a robust structure for modelling the uncertainty of human movement trajectory among complex indoor spaces by utilizing a spatiotemporal deep-learning network. The proposed model "UMTrajNet" can accurately characterize trajectory correlation features in both temporal and spatial perspectives, especially considering the spatial interconnectivity of pedestrian movement and presenting more accurate modelling of pedestrian movement uncertainty. Also, the changeable motion and handheld methods of mobile devices in the moving period are detected and normalized into an enhanced dataset with ground-truth reference for improving the performance of final uncertainty region modelling. The main contributions of this paper include:

(1) This work introduces a novel spatiotemporal framework UMTrajNet for movement uncertainty modelling. By integrating Graph Convolutional Networks (GCN) to model spatial dependencies and LSTM networks to represent temporal relationships, UMTrajNet overcomes the limitations of traditional LSTM-based models, which are inherently limited in their ability to represent complex spatial correlations within trajectory data. This integration allows UMTrajNet to more accurately model the intricate spatial relationships present in indoor environments, such as proximity to obstacles and the geometric layout of spaces, thereby significantly improving the precision and robustness of uncertainty modeling in human mobility analytics.
(2) An enhanced dataset for uncertainty prediction is collected and processed under different large-scale indoor scenarios, where a large number of pedestrian walking routes are incorporated to increase the generalization ability of the proposed deep-learning model. This dataset includes both measurement and sampling errors, enabling the collection of detailed pedestrian motion and handheld information, thereby improving the precision of overall uncertainty modeling of human trajectory.
(3) This study applies the Euclidean distance to represent measurement errors originating from heterogenous positioning sources on each selected location point of the acquired trajectory. The Euclidean coefficient is adaptively adjusted based on the training output. The overall uncertainty area is generated by accounting for both sampling and measurement errors influenced by changing human motion and handheld patterns.

The structure of the paper is organized as follows: Section 2 describes the problem statement, key definitions, and proposed UMTrajNet model of this study. Section 3 gives the experiment results, to verify the effectiveness and robustness of the involved chosen method. Section 4 presents the novelties and limitations of our work. Section 5 describes conclusions of this study together with the potential applications of our method.

2. Key definitions and problem statements

2.1. Problem statement

This study hope to model the pedestrian movement uncertainty by jointly considering the spatial and temporal correlations of a series of input features, including walking speed, step-length, heading, location increment, heading increment, time and distance indexes. The key terms of uncertainty modelling of human movement trajectories are defined as follows:

Definition 1. STP points from human trajectories: An STP is a two-dimensional geo-spatial location point associated with different sampling timestamp, represented as $STP_i = (x,y,t)$. Here, (x, y) denotes the geo-spatial coordinates, and t represents the corresponding timestamp. These points are obtained using various positioning techniques.

Definition 2. Ground-Truth Trajectory: Denoted as GT, is a sequence of STPs, represented as $GT = \{GT.STP_1, GT.STP_2, \cdots, GT.STP_n\}$. It models a set of reference locations for a pedestrian. In this work, the GT is obtained by integrating a SLAM (Simultaneous Localization and Mapping) system with an open street map. This approach provides a centimeter-level reference trajectory for uncertainty error reference.

Definition 3. Reference trajectory RT calculated by heterogenous positioning sources: This paper also uses human motion detection under GNSS-denied spaces to generate the continuous human trajectory. A constructed human motion-assisted indoor trajectory RT is defined as the set of related STPs acquired from the human trajectory vector $RT = \{STP_1, .STP_2, \ldots, .STP_n\}$ calculated by multiple positioning and sensing sources that applied under GNSS-denied areas, where $RT.STP_n$ is reconstructed location points from different sources, and $GT.STP_n$ provides accuracy movement trajectory points for $RT.STP_n$. The details of the trajectory reconstruction method are given in Section 2.2.1.

Problem of movement uncertainty: Given a reference movement trajectory RT and the related ground-truth movement trajectory GT, the purpose of uncertainty modeling is to generate the mapping relationships and corresponding parameters M from RT to $Dis(GT.P_i, RT.P_i)$, i.e., $M : RTDis(GT.P_i, RT.P_i)$, where $Dis(GT.P_i, RT.P_i)$ is the spatial distance between $GT.P_i$ and $RT.P_i$. The uncertain region of a reference trajectory RT is modeled based on the prediction of sampling and measurement errors using error circles with $RT.P_i$ as center and the predicted measurement error $Dis(GT.P_i, RT.P_i)$ as radius.

2.2. Proposed UMTrajNet model

Previous studies (Yu et al., 2023) have demonstrated that the movement uncertainties of RT are highly temporally dependent, which means that the deviation between the GT and RT at the current position is the sum of accumulated deviations of preceding steps. Besides temporal dependency, a key factor which is long overlooked by previous works is the spatial dependency of the RT's movement uncertainties. This is derived from the intuition that the deviation at the current step will also be affected by the step's location concerning the previous steps. For example, the geometry of the path taken by a pedestrian, such as turns and angles between consecutive steps, can affect the uncertainty of the trajectory. Sharp turns or sudden changes in direction might introduce more uncertainty than straight paths due to potential errors in capturing the exact turning point.

Consequently, to jointly model the spatial and temporal dependency of the movement uncertainties, a novel spatiotemporal learning-based structure is presented by combining the networks of LSTM and GCN. The outputs from the spatial and temporal dependency learning components are further concatenated and fed to an attention structure (Vaswani, et al., 2017), which is to conquer the challenges of current model that only consider one dimensional features of human movement data. Our framework is designed to process sensor-level data, which is often noisy, high-dimensional, and temporally dependent. To handle these characteristics, we integrated CNNs for spatial features extraction, LSTMs for temporal features extraction, and Transformer components contains self-attention module, leveraging the strengths of each while mitigating their individual limitations.

2.2.1. Trajectory reconstruction

Different from the outdoor trajectories that consist of sensor-originated locations based on stable sampling error and constant measurement error, the performance of acquired indoor trajectories is affected by changing sampling and measurement errors. Besides, reference points are normally difficult to acquire under indoor areas, and the accuracy of indoor trajectory is constrained by complex human walking routes and handheld modes, which exist challenges to present the spatiotemporal relationship of acquired indoor movement trajectories.

This paper models the indoor movement trajectory as a graph including the un-continuous location points and related movement characteristics, as shown in Fig. 1:

In Fig. 1, between two different STP points, we extract the human gait-length (L) and heading (θ) as the motion features, and consider changing sampling internals. The reference position information is provided by local devices including Quick Response (QR) code, Bluetooth Low Energy (BLE) node, Wi-Fi Access Points (APs) et al.

To generate the training dataset, we also need to know the position and attitude of the smartphone, we define 4 different handheld modes in the procedure of human trajectory graph: reading, calling, swaying, and pocket. To classify these kinds of smartphone attitudes, the Bi-LSTM network (Yu et al., 2023) is applied for pattern detection, and then the coordinates of different handheld modes are converted into navigation coordinates. Fig. 2 depicts 4 different smartphone handheld patterns:

After detection of handheld patterns, the overall indoor human movement trajectory is reconstructed as follows using the gathered motion features between different STP points:

$$STP_i(L_i, \theta_i) = R_{01} + \sum_{i=1}^{n} [L_i coscos(\theta_i) L_i sinsin(\theta_i)] \tag{1}$$

where R_{01} indicates the first reference STP from human movement trajectory.L_i and θ_i indicate the calculated gait-length and heading features among two adjacent STPs (Yu et al., 2023). After offsetting the two reference points for one selected trajectory, the above equation (1) is formulated as an optimization problem, and the optimal step-length and heading vectors are obtained:

$$\xi(L_i, \theta_i) = (\boldsymbol{z} - STP_i(L_i, \theta_i))^T \boldsymbol{\rho}^{-1} (\boldsymbol{z} - STP_i(L_i, \theta_i)) \tag{2}$$

where $\boldsymbol{\rho}$ represents the covariance matrix of extracted features, $\boldsymbol{Z}$ indicates the observed reference location measurement for trajectory

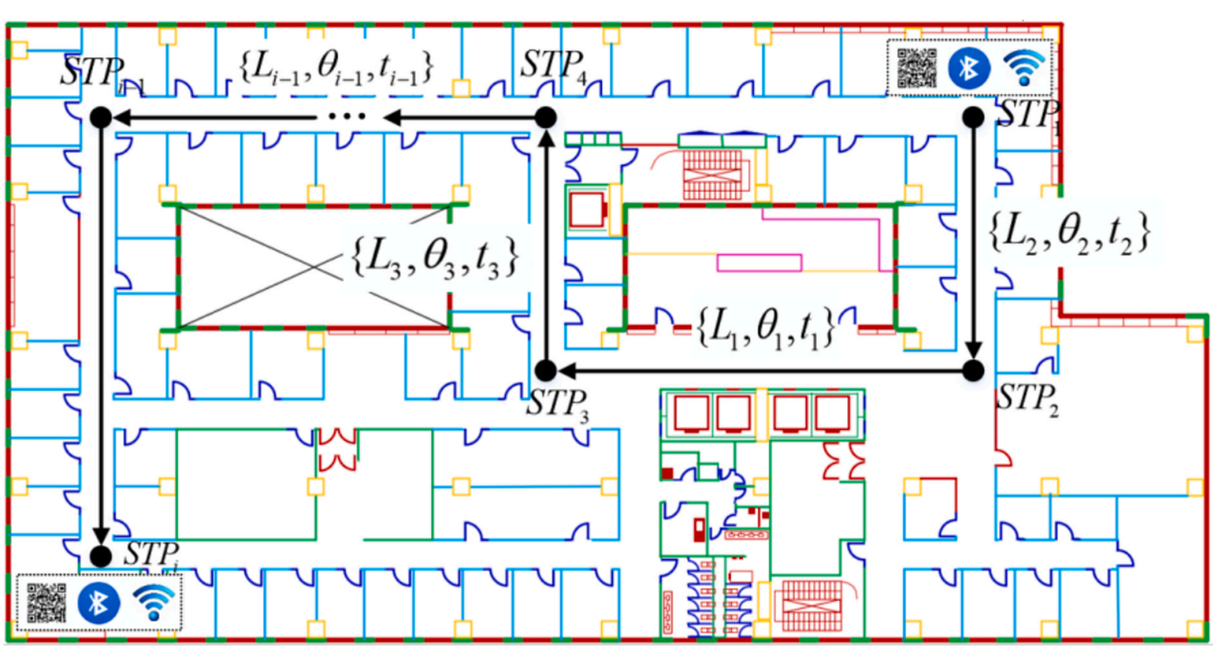

Fig. 1. Graph of Indoor Human Trajectory.

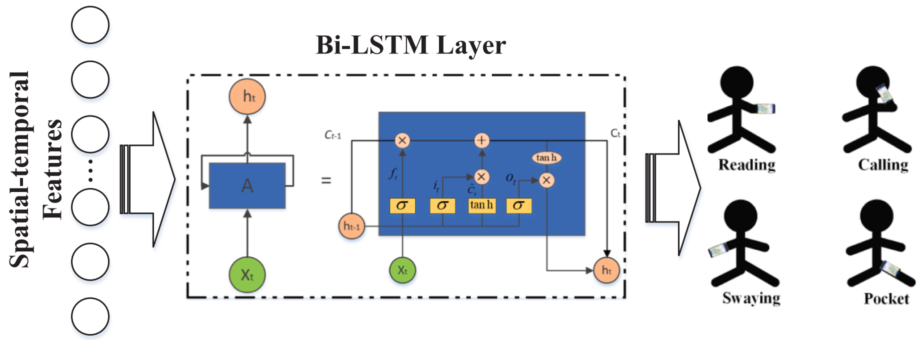

Fig. 2. Detection of Different Handheld Patterns.

optimization.

Especially, to generate the GT trajectory points, a lidar-scanning based system and positioning algorithm is applied for calculating centimeter-level reference trajectories (Bao et al., 2022). Overall, each vector in the created dataset contains the following information:

$$Vector_{train} = \left\{x_{G/O}, y_{G/O}, L, \theta, x_r, y_r\right\} \tag{3}$$

where $x_{G/O}$ and $y_{G/O}$ indicate the GT position vectors, L and θ indicate the gait-length and heading features, x_r and y_r are the raw trajectory with sampling and measurement errors.

A feature tuple is then constructed by concatenating the features of k consecutive steps:

$$Feat_i = \{x_{t-k+1}, x_{t-k+2}, \cdots, x_t\} \tag{4}$$

Which will be fed into the model for feature learning and predicting the step-wise movement uncertainty error and uncertainty region.

2.2.2. Features extraction and modelling

This part introduces typical features that can be extracted from reconstructed human movement trajectories for uncertainty modeling, which considers both sampling error and measurement error for generating an accurate mapping relationship between uncertainty error and extracted motion features of human movement trajectory:

1) Calculated gait-length and heading pairs (θ_i,L_i) between two adjacent STP points $STP_i(L_i, \theta_i)$ calculated by (Yu et al., 2022).
2) Actual sampling interval $\Delta\kappa_i$ among two adjacent detected gaits and related updated STP points $STP_i(L_i, \theta_i)$.
3) Cumulated gait amount $step(i)$ under time period of present STP point realized by the gait detection methods in (Yu et al., 2021).
4) Cumulated human movement velocity v_i among two related STP points $STP_i(L_i, \theta_i)$:

$$v_i = \frac{L_i}{\Delta\kappa_i} \tag{5}$$

5) Present cumulated distance based on previous time periods:

$$Dis_{cum}(i) = \sum_{i=1}^{k} L_i \tag{6}$$

6) Distance index calculated by current cumulated distance and overall distance (Shi et al., 2022):

$$PI_d(i) = \frac{\sum_{i=1}^{k} L_i}{\sum_{i=1}^{n} L_i} \tag{7}$$

where n represents the amount of recorded gaits from the whole human movement trajectory, k represents the cumulated amount of steps on the present timestamp.

7) Time index calculated based on the accumulated time period and overall length of time (Shi et al., 2022):

$$PI_t(i) = T(i)/T_{total} \tag{8}$$

where T_{total} indicates the overall length of time required by human movement trajectory,$T(i)$ indicates the accumulated length of current time period.

8) Step index calculated based on the accumulated steps and overall steps from trajectory (Shi et al., 2022):

$$PI_s(i) = step(i)/step_{total} \tag{9}$$

where $step_{total}$ is the recorded steps acquired from human movement trajectory,$step(i)$ is the cumulated step number at current timestamp.

9) Calculated heading difference $\Delta\theta_i$ acquired from different STP points:

$$\Delta\theta_i = \theta_i - \theta_{i-1} \tag{10}$$

10) Calculated overall heading deviation based on the heading from initial moment:

$$\Delta\theta_i = \sum_{i=1}^{k} (\theta_i - \theta_1) \tag{11}$$

Above generated features are modeled as the input vector of the proposed UMTrajNet, which can comprehensively describe the mapping relationship between sampling and measurement errors and uncertainty parameters.

In summary, our developed uncertainty modeling structure UMTrajNet will fully consider both sampling and measurement errors from human movement trajectory. The model addresses sampling error by incorporating the calculated coordinate update interval among related STP points and a collected input vector under related period. Additionally, it tackles measurement error by utilizing various features extracted from the trajectory.

2.2.3. Spatiotemporal network for movement uncertainty modelling

Human indoor movement trajectories exhibit more complex spatial and temporal relationships than outdoor trajectories with stable sampling and measurement errors, making its uncertainty error modelling more challenging. In this work, we design a spatiotemporal network that self-learns the complex human motion features from spatial and time dimensions simultaneously. As explained previously, our proposed spatiotemporal network is composed of three interrelated modules, which are described in Fig. 3.

Temporal Dependency Modelling with LSTM: The LSTM backbone is used for feature learning by modelling the temporal dependency of the movement uncertainty between consecutive steps.

Specifically, we define the constructed feature in Formula 12 is used as the state at each time point where t is the number of time steps. The LSTM contains a cell state C_t and a hidden state H_t. At each time step t, the LSTM takes input x_t (as defined in Section 2.2.2) and previous hidden state H_{t-1}, then updates the states as (Shi et al., 2022):

$$\begin{aligned} i_t &= \sigma(W_{xi}x_t + W_{hi}H_{t-1} + W_{ci}C_{t-1} + b_i), \\ f_t &= \sigma\left(W_{xf}x_t + W_{hf}H_{t-1} + W_{cf}C_{t-1} + b_f\right), \\ C_t &= f_t \odot C_{t-1} + i_t \odot tanh(W_{xc}x_t + W_{hc}H_{t-1} + b_c), \\ o_t &= \sigma(W_{xo}x_t + W_{ho}H_{t-1} + W_{co}C_t + b_o), \\ H_t &= o_t \odot tanh(C_t) \end{aligned} \tag{12}$$

where σ is the sigmoid function, and $\odot$ denotes element-wise multiplication. The LSTM could learn time series relationships and model the temporal dynamics in the sequence.

Spatial Dependency Modelling with GCN: A graph neural network component is employed to learn the spatial dependency by representing the *RT.STP* as nodes and their relationships as edges within a graph structure, which allows the network to capture and learn the intricate spatial correlations between different points in the trajectory, enhancing the overall accuracy of the uncertainty prediction. Specifically, we define the spatial information as a graph $G = (V, A)$, where V is the feature (as defined in Section 2.2.2) of nodes, i.e., the positions, and $A \in R^{n\times n}$ is the set of edges for describing the relationship between the positions in each time step.

For training the GCN, a contingency matrix is needed for delimitating the spatial relationship between the nodes (i.e., locations of timesteps). However, due to the complexity and randomness of each timestep's location, a trainable matrix A is introduced, whose weights can be updated during the model training and hence can delimitate the spatial contingency of trajectories with various geometry. The output $H^{l+1} \in R^{n\times f}$ of the $l-th$ layer of our GCN is computed as:

$$H^{l+1} = \sigma\left(\widehat{A}\, V^l W^l\right), \tag{13}$$

where,$\widehat{A} = \widetilde{D}^{-1/2}\widetilde{A}\widetilde{D}^{-1/2}$, $\widetilde{A} = A + I_n$, $\widetilde{D}ii = \sum_j \widetilde{A}ij$,$W^l$ is the weight matrix,σ is the activation function. By stacking multiple graph convolution layers, the network can aggregate spatial features from a node's wider neighborhood. The graph structure provides an explicit model for capturing interactions between spatial entities.

Fusion Model with Attention: The extracted spatial and temporal features are concatenated and further fed into a feature fusion module for joint feature learning and final movement uncertainty prediction. The attention mechanism is employed to fuse the features in a learnable way. Denote the combined features as $X_c \in R^{n\times(d_1+d_2)}$, where N is the number of spatial units and d_1 and d_2 are the feature dimension of the outputs. The self-attention mechanism learns a soft alignment between each pair of spatial and temporal features, capturing the relevance between them. Mathematically, the output of self-attention mechanism Z is computed as:

$$Z = SoftMAX\left(\frac{QK^T}{\sqrt{d_k}}\right)V, \tag{14}$$

where $Q = X_cW^Q$, $K = X_cW^K$, $V = X_cW^V$, W^Q, W^K, W^V are the learnable parameters of the query, key and value, and d_k is the dimension of the key vectors. After model training, the final output Z is taken as the predicted stepwise movement uncertainty $Dis(x_iy_i)$.

Uncertainty Area Modelling: After the uncertainty error prediction, the adaptive Euclidean distance is applied for the presentation of predicted uncertainty error under each step period. The uncertainty area is generated using the location of each step (x_i, y_i) and value of predicted uncertainty error $Dis(x_iy_i)$:

$$(x - x_i)^2 + (y - y_i)^2 = Dis(x_iy_i)^2, \tag{15}$$

where the uncertainty area between adjacent step points (x_i, y_i) and $(x_{i\text{-}1}, y_{i\text{-}1})$ is generated as the union of two adjacent uncertainty circles.

3. Experiments

Comprehensive experiments are designed in this part to evaluate the accuracy and robustness of presented UMTrajNet-based uncertainty modeling framework using both self-generated datasets, and public datasets. Furthermore, the performance of presented UMTrajNet structure is estimated and compared with the state-of-the-art uncertainty modelling methods.

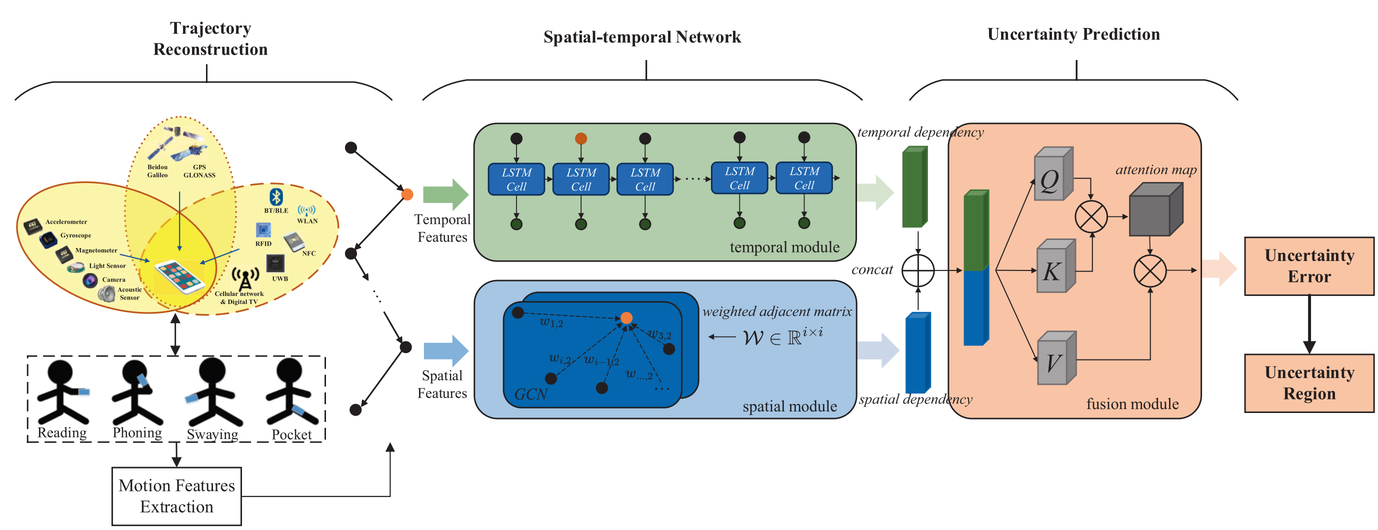

Fig. 3. Framework of the proposed spatiotemporal network UMTrajNet for uncertainty modelling of human movement trajectory.

3.1. Experimental dataset collection

The dataset used in this work were acquired in three different large buildings, one is a large-scale shopping mall recommended by IPIN-2018 competition track3, one is a multi-floor library recommended by IPIN-2020 competition track3, and the last is a large-scale office building. In addition, to improve the diversity of generated dataset, the testers use two lidars-assisted SLAM systems to provide centimeter-level ground-truth location points, and the smartphone is held under different attitude patterns, which is described in Fig. 4:

The statistics of the final generated datasets used in this paper are summarized as:

The final dataset comprises 111 trajectories, containing 24,245 sampling points with an average sampling frequency of 0.56 s. The average trajectory length is 112.97 m, and the maximum speed is 4.94 m/s and an average speed is 1.10 m/s. Specific details are presented in Table 1. Additionally, the produced dataset includes both optimized trajectories and ground-truth references. Examples of several selected trajectories are shown in Fig. 5. For cross-validation purposes, 70 % of dataset is randomly selected for model training and 30 % of dataset is used for verification. Additionally, referencing previous work (Shi et al., 2022), the Z-score is used to normalize the input features.

For comparison and unless specified otherwise, the following setup was used in all case studies. Both the proposed UMTrajNet and the baseline models were developed using Python and TensorFlow. In terms of deep learning approaches, the models underwent training for 400 epochs, with batches of 64 and the learning rate is selected as 0.001 using Adam optimizer. All experiments were conducted on servers installed with an Intel(R) Xeon(R) E5-2660 v4 CPU and an nVidia Tesla P100 GPU.

Fig. 4. SLAM System for Dataset Generation.

3.2. Baseline models and evaluation metrics

This paper proposes a novel spatiotemporal network that considers the merits of both GCN module and LSTM module, and can autonomously learn the relationship from a trajectory segment from the spatial and temporal perspectives. The proposed UMTrajNet can realize accurate uncertainty error prediction and uncertainty region modelling, especially for human indoor trajectories with complex spatial and temporal correlation features.

To comprehensively evaluate the performance of existing uncertainty modelling algorithms, three primary metrics are calculated and presented as the accuracy indexes of presented UMTrajNet framework and compared against the existing models. **(1) Mean Absolute Error (MAE):** It estimates the average distance between GT.STP points and RT. STP points. This metric serves as an indicator of the preciseness of the uncertainty estimations produced by different models, where a lower MAE signifies a higher accuracy in predicting the spatial deviation of pedestrian movements. **(2) Coverage Ratio (Completeness):** The coverage ratio quantifies the proportion of the GT trajectories that are encompassed within the uncertain regions. A higher coverage ratio indicates a more comprehensive encapsulation of the GT trajectory points within the modeled uncertain areas, thus reflecting a model's effectiveness in capturing the extent of movement uncertainty. **(3) Density of Covered Points**: The density metric assesses the concentration of GT trajectory points within the uncertainty regions relative to the area of these regions. This density is computed as the ratio of the count of covered trajectory points to the spatial area of the uncertain region. A high density implies that the region is not only covering many points but is also compact, thereby enhancing the model's precision in defining movement uncertainty.

For the baseline models selection, we divide the existing uncertainty modelling algorithms into learning-based methods and physical methods. For the learning-based methods, we include Attention-Bi-LSTM (Wei et al., 2021), Bi-LSTM (Yu et al., 2023), Attention-LSTM (Li et al., 2019), LSTM (Liu et al., 2022), Transformer (Franco et al., 2023), TimesNet (Wu et al., 2022), and GMAN (Zheng et al., 2014) for comparison. One thing to note is that typical spatiotemporal models require a predefined adjacency matrix to represent spatial relationships. However, such explicit graph structures do not exist in our task. Therefore, we adopt a fully connected graph to represent potential interactions among trajectory points. Although some models were originally designed for other tasks like trajectory prediction, we have adapted them for the uncertainty prediction task by reframing the problem as step-wise spatial error regression. This enables the models to leverage their spatiotemporal modeling capabilities to estimate the deviation between reconstructed and ground-truth trajectories. For the physical uncertainty modelling methods, we include UB (Liu, 2022), AUB (Furtado et al., 2018), and BAEE (Shi et al., 2021) models in terms of Coverage Ratio and Density metrics for evaluation since the physical models cannot directly predict the values of uncertainty error.

Together, these metrics facilitate a comprehensive evaluation of the models' performance, highlighting their capacity to balance between the coverage and precision of uncertain regions in pedestrian trajectory analysis.

3.3. Model performance evaluation

Table 2 presents the comparative performance of all evaluated models in terms of Mean Absolute Error (MAE), a key metric for assessing the accuracy of pedestrian trajectory uncertainty prediction. Our proposed model, UMTrajNet, achieves the lowest average MAE of 0.420, demonstrating its superior capability in capturing both spatial and temporal dependencies in indoor movement data. This result confirms that UMTrajNet outperforms not only traditional deep learning methods but also recent spatiotemporal modeling approaches in uncertainty estimation.

Table 1
The statistics of the generated dataset.

Number of trajectories	Total number of trajectory points	Average Trajectory Length	Maximum Speed	Average Speed	Average Sample interval
111	24,245	112.97	4.94	1.10	0.56

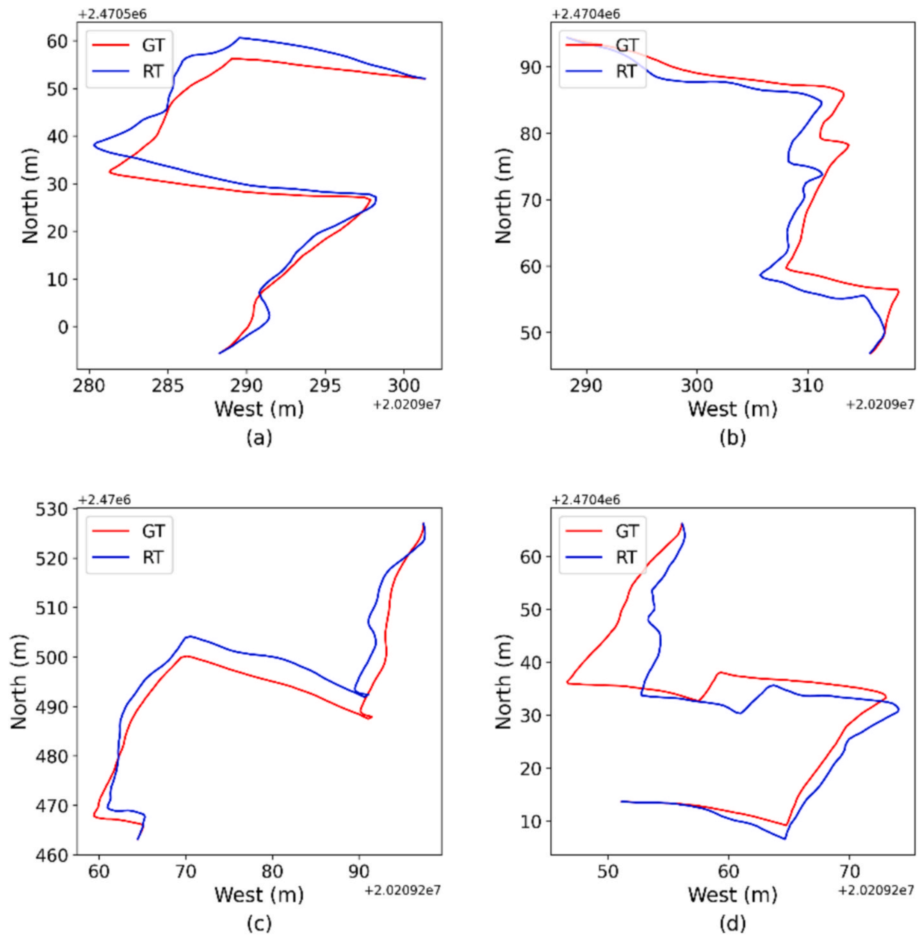

Fig. 5. Examples of the Referenced Trajectory (RT) and Ground-truth Trajectory (GT).

Table 2
The average MAE of respective models.

Model /Traj-index	UMTrajNet	AttentionBiLSTM	Bi-LSTM	AttentionLSTM	LSTM	Transformer	TimesNet	GMAN
MAE	0.42	0.52	0.52	0.55	0.56	0.89	0.54	0.68
T01_01	0.37	0.52	0.39	0.60	0.46	0.82	0.47	0.66
T03_01	0.29	0.37	0.44	0.46	0.47	0.69	0.44	0.58
T05_01	0.27	0.39	0.35	0.45	0.35	0.63	0.34	0.43
T07_01	0.47	0.64	0.58	0.69	0.66	0.95	0.56	0.74
T09_01	0.23	0.37	0.32	0.39	0.31	0.62	0.31	0.47
T11_01	0.48	0.59	0.6	0.69	0.72	1.15	0.64	1.02
T13_01	0.35	0.44	0.47	0.49	0.48	0.76	0.50	0.58
T15_01	0.31	0.59	0.39	0.63	0.40	0.69	0.43	0.57
T17_01	0.39	0.34	0.49	0.37	0.53	0.74	0.43	0.64
T19_01	0.41	0.51	0.46	0.53	0.52	0.93	0.50	0.81
T21_01	0.47	0.58	0.64	0.61	0.74	1.00	0.64	0.86
T23_01	0.72	0.78	0.87	0.81	0.83	0.92	0.80	0.75
T25_01	0.42	0.53	0.53	0.53	0.62	1.06	0.59	0.74
T27_01	0.57	0.67	0.86	0.77	0.90	1.12	0.83	0.84
T29_01	0.39	0.49	0.45	0.54	0.46	1.00	0.52	0.70
T31_01	0.44	0.70	0.64	0.63	0.60	0.92	0.51	0.82
T33_01	0.45	0.51	0.56	0.51	0.62	0.74	0.52	0.62
T35_01	0.37	0.53	0.46	0.56	0.53	0.80	0.48	0.65
T37_01	0.43	0.54	0.67	0.67	0.68	1.23	0.68	0.94

The AttentionBiLSTM and Bi-LSTM models attain MAE values of 0.519 and 0.522, respectively. While these models benefit from enhanced temporal modeling through attention mechanisms and bidirectional context, their lack of explicit spatial reasoning leads to limited performance improvements. Similarly, AttentionLSTM and LSTM produce MAEs of 0.552 and 0.563, highlighting the limitations of purely temporal models when applied to spatially complex indoor trajectories.

The Transformer model, despite its advanced capability in modeling long-range dependencies through self-attention mechanisms, yields a notably higher MAE of 0.89. This performance gap suggests that while Transformers excel in generic sequence modeling tasks, they may struggle to capture the fine-grained, structured spatial relationships required in indoor trajectory uncertainty estimation unless specifically adapted for spatially correlated data.

We further evaluate TimesNet and GMAN, two recent transformer-based models developed for sequence forecasting and spatiotemporal representation learning. TimesNet, while outperforming the vanilla Transformer, still performs worse than UMTrajNet due to its implicit treatment of spatial dependencies, which is ineffective in environments with complex indoor topologies. GMAN, which incorporates a spatio-temporal attention mechanism, achieves an MAE of 0.68, demonstrating improved spatial reasoning over conventional Transformer architectures. However, its overall performance remains limited because it fails to effectively capture dynamic and localized spatial variations.

After the uncertainty error prediction, the adaptive Euclidean distance is applied for the presentation of predicted uncertainty error under each step period. The uncertainty area is built using the location of each step and value of predicted uncertainty error, described in Fig. 6:

We have compared our proposed spatiotemporal uncertainty prediction model with existing learn-based methods, and then the designed uncertainty model is compared with physical uncertainty modelling methods including UB (Liu, 2022), AUB (Furtado et al., 2018), and BAEE (Shi et al., 2021) models in terms of Coverage Ratio and Density metrics, as shown in Table 3. With a Coverage Ratio of 95.6 %, UMTrajNet slightly trails behind BAEE's 96.2 % but outperforms AUB's 90.1 %. UB presents a perfect Coverage Ratio at 100 %, serving as the benchmark.

Table 3
The average coverage ratio and density of respective models.

Models	UMTrajNet	BAEE	AUB	UB
Coverage Ratio	95.6 %	96.2 %	90.1 %	100 %
Density	0.218	0.151	0.191	0.013

Although UMTrajNet doesn't top the list, it demonstrates a high level of completeness in capturing ground-truth trajectories. In terms of Density, UMTrajNet significantly outshines all with 0.218, compared to BAEE's 0.151, AUB's 0.191, and UB's 0.013. The Density metric, indicating the precision of the uncertain region, is crucial because it balances the need for a model not only to cover ground-truth points (as UB does with a broader scope) but also to do so efficiently without overestimating the area—something UMTrajNet excels at. The generated uncertainty region using different uncertainty modeling approaches is described in Fig. 7.

It can be found from Fig. 7 that the proposed UMTrajNet's performance highlights a strong balance between coverage and density, suggesting it is effective at creating uncertain regions that are comprehensive and precise. While UB covers all ground-truth points, its low density indicates a lack of precision, potentially leading to overestimated uncertain areas. UMTrajNet manages to maintain a high level of preciseness without sacrificing coverage, which is indicative of its robustness in uncertainty modeling, crucial for practical applications where both metrics are significant.

The essence of UMTrajNet's superiority lies in its holistic approach to modeling uncertainty by adeptly synthesizing spatial and temporal data. This allows for nuanced representation of pedestrian movement, addressing the limitations found in models that focus on temporal aspects alone, such as LSTM and its variants, or on spatial features, as in the case of Ablation_Spatial. The integration of both dimensions endows UMTrajNet with the agility to accurately delineate the uncertainty regions, thereby ensuring that the trajectories are covered comprehensively, as the Coverage Ratio suggests, and with significant precision, as evidenced by the high Density metric. When pitted against models such

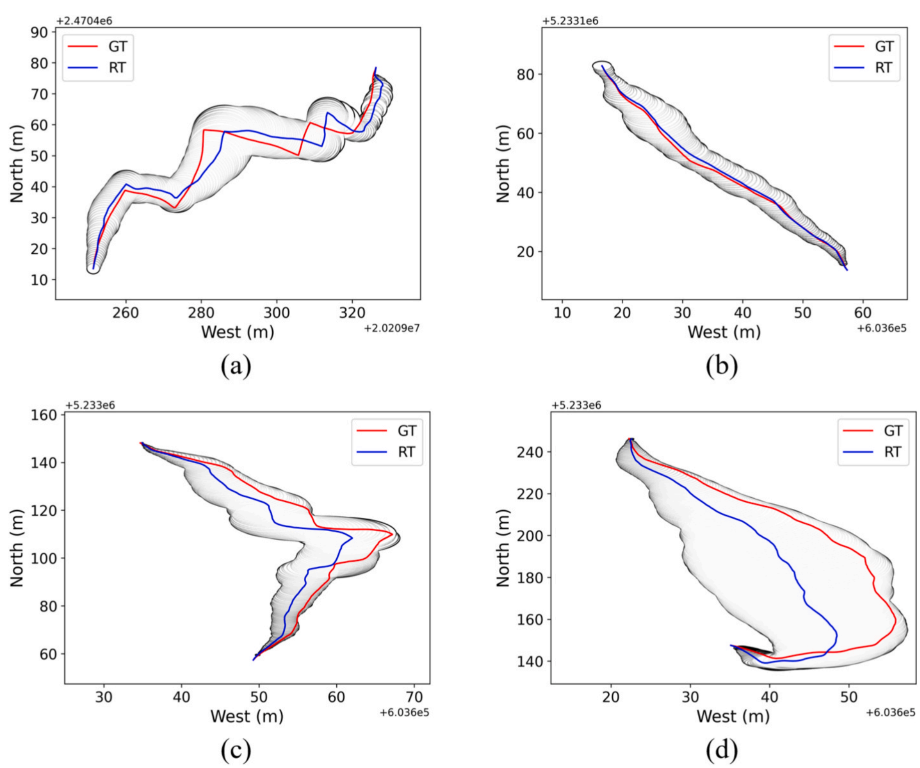

Fig. 6. Generated uncertainty regions of selected trajectory.

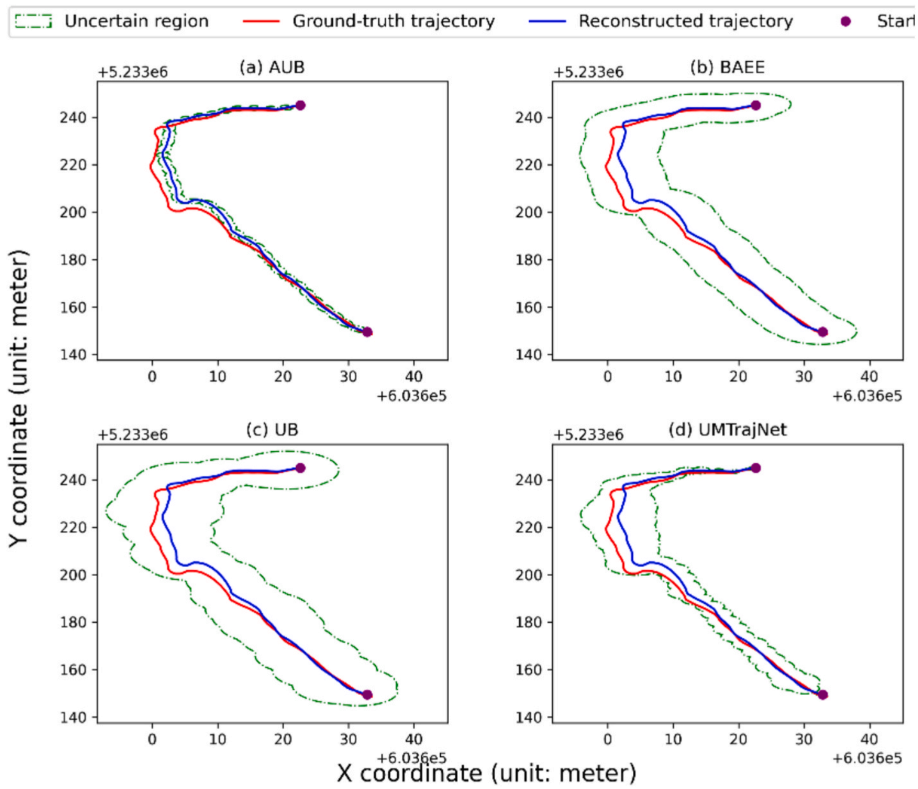

Fig. 7. Generated uncertainty region using different models.

as UB, which assumes a simpler elliptical uncertain region based on maximum speed and moving time, and its more sophisticated counterparts AUB and BAEE that introduce bounds and metrics to refine the uncertainty estimation, UMTrajNet offers a more dynamic and granular approach. It eschews overly conservative or generalized assumptions in favor of an adaptive model that reflects the complexity and variability of real-world pedestrian movements.

In environments where accuracy and efficiency translate directly to improved functionality and user experience, such as in smart city planning, intelligent transport systems, and location-based services, UMTrajNet's precision and reliability present significant benefits. The model's nuanced consideration of both spatial and temporal factors, leading to higher density and strong coverage, underscores its potential to inform and enhance a variety of applications. Thus, the UMTrajNet model is not merely an incremental improvement over existing models, but a transformative step towards more sophisticated and practical movement uncertainty modeling.

3.4. Sensitivity analysis of designed UMTrajNet framework

Sensitivity analysis of parameters is crucial for understanding how changes in model hyperparameters affect the performance of presented UMTrajNet framework for uncertainty modeling of human movement trajectories. By examining these effects, we can optimize the model to achieve better accuracy in predicting trajectory uncertainty and ensure its robustness across diverse indoor environments. We investigated two essential hyperparameters of UMTrajNet framework in this analysis:

- N-steps: This parameter refers to the count of previous locations considered when predicting deviations at the current location.
- Hidden-dimension: This parameter defines the output size of the combined spatial and temporal modules.

We fine-tuned these hyperparameters within specified ranges, with n_steps set between 2 and 10, and hidden_dimen is set between 16 and 46. The performance of each configuration was measured using the Mean Absolute Error (MAE), as detailed in Section 3.2 of our study.

As shown in Fig. 8, adjustments to these hyperparameters significantly impacted the MAE, which varied between 0.31 and 0.55. Notably, an increment in the n_steps consistently led to improved performance, as indicated by a reduction in MAE. This suggests that the model benefits from incorporating a broader context of past data. Additionally, the hidden feature dimension also impacts the MAE, with optimal performance observed in the mid-range of the tested dimensions.

The sensitivity analysis results not only demonstrate the robustness of proposed UMTrajNet-based uncertainty modelling structure but also highlight its superior performance in comparison to other methods, even with short historical data used, referencing Table 2. The robustness and superior performance of our model stem from its innovative design, which integrates GCN and LSTM networks and considers both spatial and temporal dependencies effectively. The GCN module models spatial

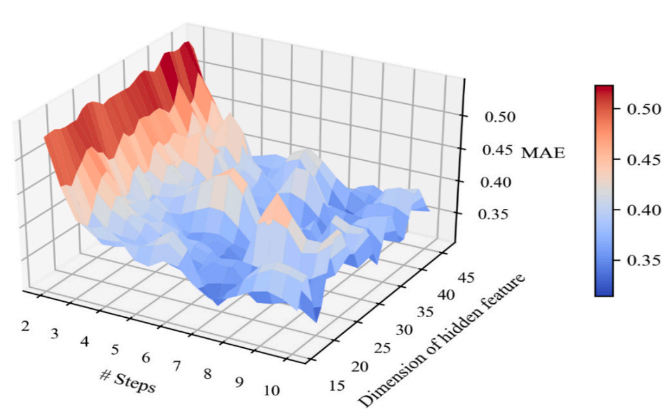

Fig. 8. Analysis of Hyperparameter Sensitivity: Variations in Model Performance Across Different Hyperparameter Settings.

relationships between different locations, while the LSTM module handles temporal sequences and long-term dependencies. The flexibility in hyperparameter settings, such as n-steps and hidden-dimension, enables the model to adapt to varying contexts, ensuring accurate predictions even with limited historical data. These features collectively allow our model to outperform traditional methods, making it particularly effective for modeling the uncertainty of human movement trajectories under complex indoor scenarios. The model's ability to adapt to varying hyperparameter settings underscores its potential for advanced uncertainty modeling of indoor human movement trajectories.

3.5. Ablation study of model components

To further investigate the contribution of each key module in the proposed UMTrajNet framework, we conducted an ablation study. Three ablated variants were designed:

- **UMTrajNet w/o Spatial**: Disabling the GCN module for spatial dependency modeling.
- **UMTrajNet w/o Temporal**: Disabling the LSTM module for temporal dependency modeling.
- **UMTrajNet w/o Fusion**: Replacing the attention-based fusion module with MLP.

The average uncertainty prediction errors (MAE) for each variant are reported in Fig. 9.

As shown in Fig. 9, the complete UMTrajNet model achieves the lowest average prediction error compared to its ablated variants. Removing the spatial modeling component (GCN) or the temporal modeling component (LSTM) individually results in a moderate increase in error, reflecting the necessity of both spatial and temporal feature learning for accurate uncertainty prediction. Notably, removing the fusion module causes a significant error increase, emphasizing the critical role of the attention-based feature fusion in integrating spatiotemporal information effectively. These results confirm that each module contributes synergistically to the overall performance of UMTrajNet.

3.6. Runtime analysis

To provide a comprehensive evaluation of the proposed framework, we measured the total training time and average inference time per sample across the proposed UMTrajNet and baselines. The results are summarized in Fig. 10.

Specifically, UMTrajNet achieved a total training time of approximately 1152 s and an average inference time of 89.1 ms per sample, indicating a reasonable trade-off between computational cost and modeling accuracy. Compared to the baselines, although LSTM demonstrated slightly lower training and inference times, it did so at the expense of reduced uncertainty modeling performance. Attention-BiLSTM, while offering enhanced feature extraction, exhibited longer training and inference times. The Transformer model, known for capturing long-range dependencies, incurred the highest computational overhead among all methods.

Considering that the average data sampling interval in our dataset is 0.56 s, the inference latency of UMTrajNet remains substantially lower than the data acquisition rate. This ensures that the proposed framework can support near real-time uncertainty estimation without introducing noticeable delays, making it well-suited for real-world indoor trajectory analysis tasks. Overall, the results demonstrate that UMTrajNet achieves an effective balance between performance and efficiency, offering a practical and scalable solution for complex indoor human movement uncertainty modeling.

4. Discussion

This section presents an in-depth analysis of the benefits and limitations of our proposed spatiotemporal network, along with the associated uncertainty modeling framework for tracking human movement trajectories indoors.

4.1. Contributions of proposed uncertainty modelling structure

This paper introduces an innovative spatiotemporal deep learning network designed for predicting uncertainty errors and modeling uncertainty regions in complex indoor human movement trajectories. This approach aims to make significant contributions across various application domains:

Firstly, we develop an accurate method for modeling trajectory uncertainty errors using everyday mobile sensing data from public users. This method provides high-resolution uncertainty error predictions at each step, significantly benefiting human mobility analysis for instance pedestrian network modelling (Zhou et al. 2021), crowdsourced positioning database generation (Yu et al. 2021), and social media data analysis (Hwang and Jang 2017). Understanding the uncertainty in public trajectories is crucial for indoor location-based services (iLBS) and human mobility analytics.

Secondly, our spatiotemporal model thoroughly considers complex spatial and temporal features by utilizing extended movement trajectory data, rather than relying solely on data from two consecutive time points. This approach achieves higher accuracy in uncertainty error

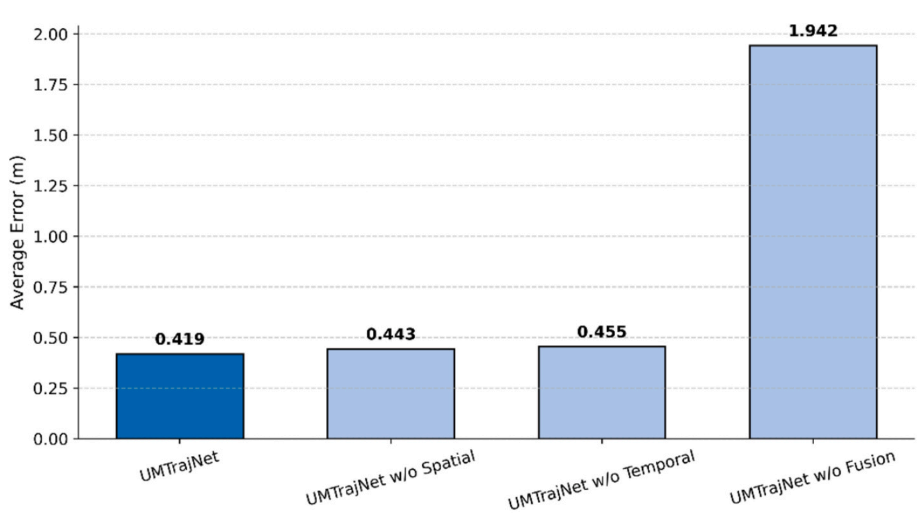

Fig. 9. Comparison of average uncertainty prediction errors among the full UMTrajNet model and its ablated variants.

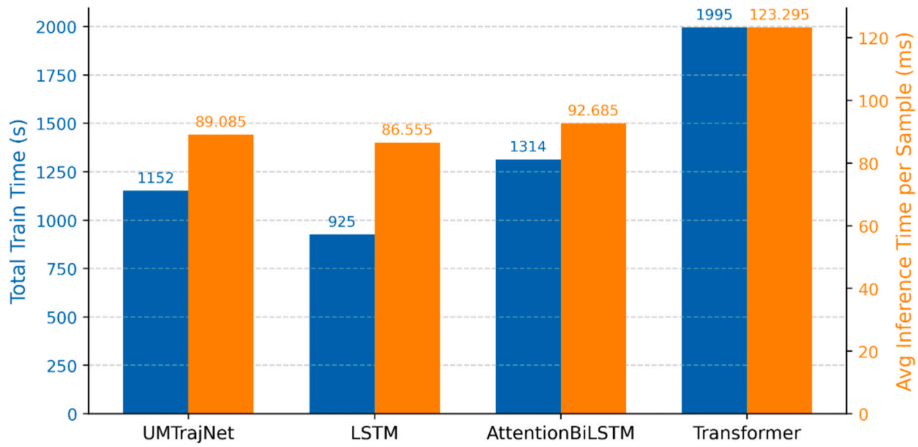

Fig. 10. Time cost comparison of different methods.

prediction compared to traditional models, outperforming existing methods.

Thirdly, from a theoretical perspective, this work represents an advanced attempt to model the PPA of indoor trajectories, accounting for both variable sampling and measurement errors. Traditional methods typically address only constant sampling or measurement errors. Our approach achieves superior completeness and density metrics compared to three conventional algorithms, using an enhanced dataset from diverse real-world scenarios. This advancement supports reliable urban navigation services, including motion and behavior analysis (Ridel et al. 2018), COVID-19 contact tracing indoors (Munzert et al. 2021), and smart health monitoring and sports rehabilitation (Gogate et al. 2016). In case of pandemic prevention, uncertainty modeling can enhance the accuracy of human tracking and predicting crowd movements, which is crucial for identifying potential virus transmission paths. In the realm of smart healthcare, pedestrian movement uncertainty analysis can be utilized to optimize the layout and resource management of hospitals and medical facilities, which can help predict peak times of patient flow, thereby optimizing staff allocation and resource distribution, ultimately improving the efficiency and quality of healthcare services.

4.2. Limitations of proposed uncertainty modelling structure

Admittedly, the presented spatiotemporal network-based uncertainty modelling framework for indoor human movement uncertainty also has certain limitations when applied to complex urban environments:

Firstly, the uncertainty of indoor human movement trajectory involves different dimensions, (x, y, and z axes), which follow different spatial and temporal error distributions related to specific urban scenes. Beyond modelling uncertainty errors using Euclidean distance, more comprehensive error distributions can be considered to model the complex uncertainty errors for human movement trajectory. In addition, the discontinuous trajectories can also affect the precision of the generated uncertainty region, necessitating further exploration of modeling methods based on points and lines to better capture real movement trajectories.

Secondly, the accuracy of uncertainty modelling is influenced by learned movement features. Enhancing the training dataset with additional trajectory-related attributes is crucial for improving prediction precision. Moreover, the labeling precision of the training data impacts model performance, as obtaining ground-truth trajectories indoors is challenging due to the absence of GNSS signals. In such scenarios, exploring small sample learning and unsupervised learning can help better capture uncertainty-related human movement characteristics and optimize the model accordingly.

Thirdly, indoor environments offer diverse locations with abundant radio signals and artificial field data, which can pose challenges for movement detection and uncertainty modelling. Future frameworks for uncertainty prediction should consider integrating these rich features from various indoor locations to enhance prediction performance by providing more comprehensive observations. Additionally, features extracted from different sources can be combined using advanced algorithms to model more input features and their interrelationships, thereby improving uncertainty region prediction.

Finally, the performance of human movement uncertainty modeling is highly related to the complexity of indoor environments. This paper has collected dataset under typical indoor scenes for instance shopping mall, library, office building, while the other less structured scenarios such as underground parking, tunnels, metro station are not involved. The human walking modes and features are sometimes different with typical indoor scenes when under less structured scenarios, so there are higher requirements for the spatial and temporal correlation capabilities of uncertainty model and also more features needs to be extracted to comprehensively describe the uncertainty error under these cases.

5. Conclusion

Previous uncertainty modeling techniques often struggle with several key issues: they are compromised by the discontinuous nature of human movement trajectories, fail to adequately capture the intricate spatial relationships and navigation paths within indoor environments, and are limited in their ability to handle the dynamic spatiotemporal characteristics of human movement. To address these gaps, this study introduces an innovative framework for uncertainty modeling, specifically designed to overcome the limitations of existing approaches.

Our framework includes three main contributions: 1) The integration of GCN and LSTM networks, forming a robust spatiotemporal uncertainty modeling framework. This design enables the model to capture both spatial dependencies—such as the influence of landmarks and spatial layouts—and temporal dynamics, which are crucial for accurately modeling human movement in complex environments; 2) By moving beyond the conventional uncertainty modeling approaches of relying solely on adjacent locational points, our UMTrajNet framework leverages entire segments of trajectories to extract more comprehensive spatiotemporal features; 3) Proposed UMTrajNet incorporates extensive datasets that account for the sampling and measurement errors associated with discontinuous trajectories and the diverse motion and device-handling modes encountered in real-world scenarios. This design not only addresses the specific gaps left by previous works but also significantly enhances the accuracy and reliability of uncertainty modeling in human mobility analytics.

Overall, the proposed UMTrajNet innovatively integrates GCN and

LSTM modules, which effectively captures both spatial and temporal dependencies, leading to more accurate uncertainty modeling. This advancement significantly enhances the modeling of human movement trajectories in complex indoor environments, providing valuable insights and tools for improving human mobility analytics, smart indoor navigation, and location-based services. Also, there are some limitations focus on the current UMTrajNet. Firstly, there are many different kinds of measurement errors originated from heterogenous positioning and sensing sources, therefore, more comprehensive input features need to be extracted to improve the generalizability of proposed UMTrajNet. Secondly, environmental factors are also very important in the procedure of uncertainty modeling such as directions of road network, height and location of surrounding buildings, which are not considered in the current model. Our future work is to further improve the accuracy and generalizability of the current uncertainty modeling framework for human movement trajectories by considering heterogenous measurement errors and environmental factors, providing a robust solution for uncertainty analysis of dynamic human movement trajectories under complex urban scenarios.

CRediT authorship contribution statement

Qiao Wan: Investigation, Formal analysis, Conceptualization. **Mengyi He:** Resources, Methodology, Investigation. **Zhewei Liu:** Software, Methodology. **Shuyu Zhang:** Software, Methodology. **Liang Chen:** Supervision, Project administration. **Ruizhi Chen:** Supervision, Project administration. **Yue Yu:** Writing – original draft, Visualization, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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