BULGARIAN ACADEMY OF SCIENCES

CYBERNETICS AND INFORMATION TECHNOLOGIES • Volume **24**, No 4
Sofia • 2024 Print ISSN: 1311-9702; Online ISSN: 1314-4081
DOI: 10.2478/cait-2024-0033

Deep Learning-Based Travel Time Estimation in Hiking with Consideration of Individual Walking Ability

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***Abstract*:** *Hiking is popular, but mountain accidents are serious problems. Accurately predicting hiking travel time is an essential factor in preventing mountain accidents. However, it is challenging to accurately reflect individual hiking ability and the effects of fatigue in travel time estimation. Therefore, this study proposes a deep learning model, "HikingTTE", for estimating arrival times when hiking. HikingTTE estimates hiking travel time by considering complex factors such as individual hiking ability, changes in walking pace, terrain, and elevation. The proposed model achieved significantly higher accuracy than existing hiking travel time estimation methods based on the relation between slope and speed. Furthermore, HikingTTE demonstrated higher accuracy in predicting hiking arrival times than a deep learning model originally developed to estimate taxi arrival times. The source code of HikingTTE is available on github for future development of the travel time estimation task.*

***Keywords*:** *Travel Time Estimation* (*TTE*), *Deep Learning, Mountain hiking, Hiking Ability Estimation* (*HAE*), *GPS Trajectory Analysis* (*GPS_TA*).

1. Introduction

Hiking is a popular activity worldwide [1-2]. In the United States, 175.8 million people aged six and older participated in outdoor activities in 2023, with 20% engaging in hiking [3]. Hiking is an accessible sport that can be enjoyed even by beginners and is popular among a wide range of age groups.

On the other hand, mountain accidents are a significant problem [4-5]. In Yosemite National Park, approximately 3.3 million people visited in 2021, during which 214 search and rescue operations were conducted, resulting in 9 fatalities [6]. In Japan, a record high of 3126 mountain accidents was reported in 2023, the highest number since national records began in 1961 [7]. The primary causes of these mountain incidents include losing the way, slipping, falls, fatigue, and illness [7]. To prevent such mountain accidents, planning a realistic route in advance and responding appropriately to unexpected delays or accidents by either turning back or preparing for a bivouac is essential.

To plan a hiking route, it is essential to check hiking maps in advance, identify trails suited to an individual's skill level and preferences, and estimate travel times accordingly [8-11]. AllTrails [12] provides information on over 450,000 trails and includes estimated completion times required to complete each trail. Additionally, it offers a function that allows users to refer to past hikers' GPS trajectories and travel times, which can aid in personal trip planning. By reviewing one's past hiking records, hikers can roughly estimate their hiking ability by comparing the estimated hiking time for each trail with their actual travel times.

On the other hand, estimating accurate travel times requires adjustments based on the individual characteristics of the hiker. These adjustments are influenced by various factors, including the hiker's experience level, physical stamina, equipment, group size, weather, and season. Factors such as reduced speed due to fatigue and increased travel time from breaks must also be considered. Moreover, conditions change constantly during a hike, necessitating real-time adjustments to estimated travel times. An estimation of accurate travel times demands substantial experience and knowledge. Experienced hikers can roughly estimate their walking pace from past hiking records. However, for beginners with limited or no prior records, accurately estimating their travel time is challenging.

In this study, we propose a travel time estimation method for hiking that considers the hiking ability of individuals using GPS trajectory data. Specifically, we apply deep learning-based travel time estimation techniques, originally developed in the field of transportation systems, to predict hiking travel time based on hikers' GPS trajectories.

Furthermore, in Travel Time Estimation (TTE) tasks, releasing code in an accessible form is important to further promote the development of deep learning methods. However, even in the transportation field, the release of code for TTE tasks remains limited. Therefore, by publicly releasing the implementation of our proposed model, we aim to advance hiking TTE, contribute to the technological development of the entire TTE field, and support future research and practical applications.

In summary, the contributions of this study are as follows:

1. This study is the first to apply deep learning methods to the task of hiking travel time estimation. As a result, it achieved higher accuracy than existing methods for hiking time estimation, demonstrating the effectiveness of deep learning-based approaches for this task.

2. To address the unique challenge of individual variation in hiking speeds, we integrated a slope-speed function using a modified Lorentz function into the deep learning model, developing a proposed model, "HikingTTE", that accounts for individual hiking abilities.

To advance the development of hiking TTE models in the future, we have made the proposed HikingTTE publicly available on GitHub.

Implementations of TTE tasks are rarely made public, and this is the first time a TTE model applicable to hiking tasks has been released.

The remainder of this paper is organized as follows: Section 2 reviews existing methods for hiking speed estimation and travel time estimation in the field of transportation systems. Section 3 provides details on the hiking logs used in this study and the hiking travel time estimation task. Section 4 presents the proposed method. Section 5 compares the proposed method with existing methods. Section 6 discusses the proposed methodology and Section 7 concludes the study.

The code for the HikingTTE is available on GitHub at the following link: **https://github.com/tarutaru2048/HikingTTE**

2. Related works

2.1. Existing walking speed estimation methods

2.1.1. Naismith's rule

Naismith's rule [13] is one of the methods for estimating travel time for hiking. Naismith proposed an empirical formula for estimating walking pace: "an hour for every three miles on the map, with an additional hour for every 2000 feet of ascent". This rule is simple, allowing quick calculations during a hike. However, it only considers uphill sections and does not account for downhill slopes.

2.1.2. Tobler's walking model

Tobler's walking model [14] represents the relation between the walking speed and the slope using an exponential function. Specifically, it is expressed by the following equation

$$W = 6e^{-3.5|S+0.05|},\ S = \frac{dx}{dh}, \tag{1}$$

where W represents walking speed (km/h) and S represents slope (%). When the slope S is –0.05 (–5%), W reaches its maximum value of 6 km/h. Although this model can be applied to downhill slopes as well, its exponential formula tends to underestimate speed on steep slopes.

2.1.3. Campbell's walking model

Campbell's walking model [15] represents the relation between the walking speed and the slope using a modified Lorentz function. Specifically, it is expressed by the equation

$$r = c\left(\frac{1}{\pi b\left(1+\left(\frac{s+a}{b}\right)^2\right)}\right) + d + es, \tag{2}$$

where r represents the walking speed (m/s), s represents the slope (degrees), and a, b, c, d, and e are model parameters.

To create this model, GPS trajectory data from 1955 hikers recorded on 20 trails near Salt Lake City and Los Angeles were used. Additionally, to account for individual variations in walking speed, 39 separate models were created, each representing a different percentile (every 2.5th percentile). For example, in the 50th percentile model, the parameters are as follows: $a = -1.4579$, $b = 22.0787$,

$c = 76.3271$, $d = 0.0525$, $e = 3.2002 \times 10^{-4}$. This results in a walking speed of 4.133 km/h at a 0° slope and 1.707 km/h at a 30° slope. The Lorentz function has the advantage of not excessively underestimating speed on steep slopes, compared to exponential functions. However, determining which percentile model to use requires prior knowledge of the individual hiker's characteristics.

2.1.4. Wood's walking model

Wood's walking model [16] considers not only the slope of ascent in the walking direction (walking slope) but also the effects of hill slope and obstruction level. The walking slope angle refers to the slope relative to the direction in which the hiker is walking. In contrast, a hill slope is the slope of the terrain itself, uniquely defined at specific points on the terrain. The model was developed using 7636 trajectory logs of hikers from hikr.org [17]. Elevation and slope were derived from a Digital Elevation Model (DEM). Additionally, the obstruction level was calculated based on the elevation difference between the Digital Surface Model (DSM) and the Digital Terrain Model (DTM). Using this data, a model to predict walking speed was developed based on a Generalized Linear Model (GLM). Specifically, the model is represented by the equation

$$v = \exp(a + b\varphi + c\theta + d\theta^2). \quad (3)$$

Here, v represents the walking speed (km/h), φ represents the hill slope (degrees), and θ represents the walking slope (degrees). The parameters a, b, c, and d are adjusted based on the level of obstruction. It was reported that adding hill slope and obstruction level improved the accuracy of walking speed predictions. However, like Tobler's model, this exponential formula tends to excessively underestimate speed on steep slopes.

All these existing methods are models that estimate walking speed based on slope. Therefore, these models do not effectively consider slower speeds due to fatigue or additional travel time from breaks. In Campbell's walking model and Wood's walking model, break times are excluded during data preprocessing, meaning hikers need to consider break times separately when using these models.

2.2. Travel Time Estimation technology in the Transportation system

In the transportation field, the task of travel time estimation is a crucial issue, and various studies have been conducted to address this challenge. In 2015 Wang et al. [18] proposed a simple baseline based on the idea that "big data beats algorithms" using the origin and destination as inputs and estimating travel time by calculating the weighted average of historical trajectories along nearby routes. Recent advancements in deep learning have enabled methods that achieve higher accuracy than this baseline. Furthermore, advanced algorithms such as deep learning methods have complex internal structures within the model, and sharing research ideas solely through equations and proofs is insufficient; therefore, the release of code in an accessible form is increasingly important [19]. Based on this, we introduce below the TTE methods whose implementation codes are publicly available.

DeepTTE [20] is a model that takes GPS trajectory logs and attributes information as inputs and learns both local path and entire path travel time estimations simultaneously. Although the final goal is to predict the overall travel time, the accuracy of the entire travel time estimation was improved by simultaneously learning the travel times of the local path. As a result, travel time prediction with DeepTTE achieved higher accuracy than Wang et al.'s [18] baseline, decision tree-based methods, and multilayer perceptron.

Gct-TTE [21] is a transformer-based model that utilizes GPS sequences, weather data, map patches, and road graphs as inputs. It accepts multiple data modalities as inputs and uses dedicated feature extraction algorithms for each modality. As a result, Gct-TTE outperformed several state-of-the-art models, including DeepTTE, on the MAE and RMSE metrics.

On the other hand, it is difficult to use the road graph information, which Gct-TTE uses as input, for hiking tasks. Gct-TTE is constructed based on the assumption of complex networks such as urban road networks; however, hiking trails are usually composed of simple single paths or narrow trails, lacking the complex network structures that Gct-TTE aims to capture through road graphs. As a result, it is considered that there is little benefit from feature extraction using graph information in hiking trails. For these reasons, DeepTTE, which predicts Travel Time Estimation based on GPS trajectories and attribute information, is a more suitable choice for hiking tasks. Therefore, in this study, we position DeepTTE as the baseline for Travel Time Estimation tasks in hiking and aim to construct an approach that additionally considers hiking-specific factors. Specifically, by referring to Travel Time Estimation methods developed in the transportation field and adding an architecture to consider the hiking-specific "hiking ability," we enable travel time estimation that considers individual hiking abilities.

3. Preliminary

In this study, we use "Hiking GPS Trajectory" and "Hiking Attribute Information" to estimate arrival times for hiking.

3.1. Hiking GPS trajectory

Location data in hiking is stored in GPX format, an XML-based format used to store location data recorded by GPS devices. A GPX file includes latitude, longitude, elevation, and timestamp data, organized sequentially. Location data can also be saved in GPX format using hiking apps like AllTrails [12], Yamap [22], and Yamareco [23].

The goal of this study is to estimate the time required to complete a hike based on recorded GPX logs. We define the hiking log as follows:

- P: GPS trajectory,
- $p_1, p_2, \ldots, p_T$: Individual data points.

Each hiking log consists of T data points. Additionally, we include the cumulative distance from the starting point, the walking slope angle, and the terrain slope angle as additional information for each data point. The walking slope angle refers to the slope in the walking direction, and the terrain slope refers to the slope of the terrain itself. It has been suggested that the walking slope angle and terrain slope are related to walking speed [24]. We include the cumulative distance because it is a factor that directly affects TTE. In this study, the cumulative distance and walking slope angle were calculated from the differences in latitude, longitude, and elevation, and the terrain slope was obtained from DEM data. Therefore, the i-th data point of a hiking GPS trajectory contains the following information:

- $p_i.\mathrm{lat}$: latitude
- $p_i.\mathrm{lng}$: longitude
- $p_i.\mathrm{ele}$: elevation
- $p_i.\mathrm{dist}$: cumulative distance from the starting point
- $p_i.\mathrm{ws}$: walking slope angle
- $p_i.\mathrm{ts}$: terrain slope angle
- $p_i.\mathrm{time}$: travel time from the starting point to this point

3.2. Hiking attribute information

Hiking attribute information represents characteristics of the entire hiking log. The following information, which can be extracted from the hiking GPS trajectory, is added to each log:

- $\mathrm{ele}_{\mathrm{max}}$: maximum elevation point
- $\mathrm{ele}_{\mathrm{min}}$: minimum elevation point
- $\mathrm{D}+$: cumulative ascent
- $\mathrm{D}-$: cumulative descent
- $\mathrm{dist}_{\mathrm{total}}$: total distance of the log
- $\mathrm{time}_{\mathrm{total}}$: total time of the log

Collectively, these six attributes characterizing the entire log are referred to as Attr. These hiking attributes are useful indicators for understanding the overall profile of a hike and are essential data for estimating its difficulty level. For example, courses with higher cumulative ascent and total distance are expected to be more physically demanding for hikers, while lower values indicate less physical strain. Considering these attributes is expected to enable more accurate predictions.

3.3. Problem definition

This study aims to estimate the travel time to complete a section of the hiking route using the Hiking GPS trajectory P and Hiking attribute information Attr. The GPS trajectory is divided into a front segment of $X\%$ and a back segment of $(100-X)\%$. In the front $X\%$ of the log, arrival time information $p_i.\,time$ at each point is used to extract hiker-specific characteristics. The goal is to predict the travel time required for the back $(100-X)\%$ using the characteristics extracted from the front $X\%$ and the trajectory information in the back segment. The front segment of the GPS trajectory is denoted as $P_{\mathrm{front}} = \{p_1, p_2, \dots, p_x\}$, and the back segment as $P_{\mathrm{back}} = \{p_{x+1}, p_{x+2}, \dots, p_T\}$.

This problem setting reflects the situation where a hiker estimates the remaining time on a route based on their prior walking record. In hiking, if a hiker falls behind schedule, they may need to turn back or choose an escape route. Therefore, it is essential to adjust estimated arrival times based on their walking record, providing more accurate predictions. Extracting characteristics from the first $X\%$ of the hiking record allows indirect consideration of factors like experience, physical condition, equipment, group size, weather, and season that impact hiking speed. Even if these factors cannot be directly measured, they can be inferred from the hiking record in the first $X\%$.

The model proposed in this study incorporates hiking ability by extracting it from the first $X\%$ of the GPS trajectory log, then uses this ability to estimate the travel time required to complete the remaining $(100 - X)\%$ of the route. The next section details the architecture of the proposed model.

4. Proposed method

In this study, we develop a travel time estimation model, HikingTTE, which incorporates hiking ability by utilizing a slope-speed function and the multitask learning approach. An overview of the model architecture is shown in Fig. 1. This model consists of three main components. The first is the Hiking Ability Estimation Component, which estimates the hiker's walking ability. The second is the Spatio-Temporal Component, responsible for extracting spatio-temporal features. The third is the Multi-Task Learning Component, which performs multitask learning.

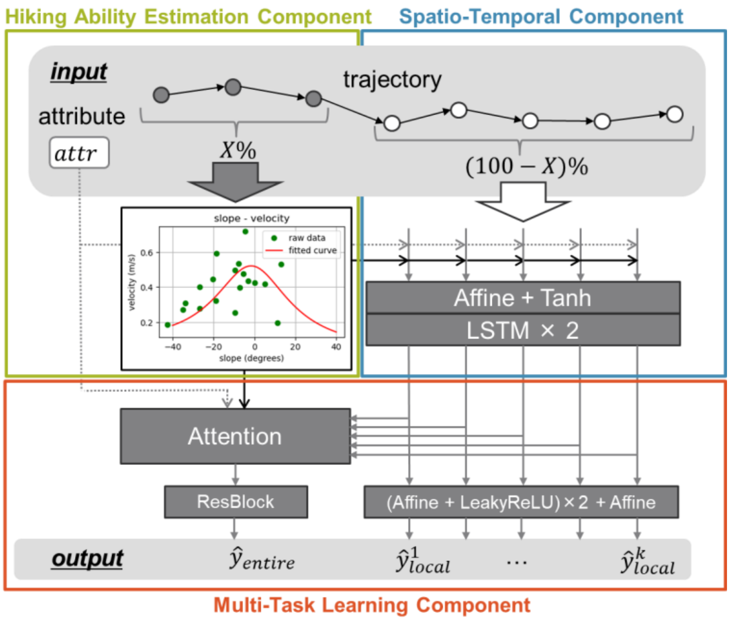

Fig. 1. Overview of model architecture: HikingTTE

4.1. Hiking ability estimation component

The Hiking ability estimation component estimates individual hiking ability. Campbell, Dennison and Thompson [15] used a modified Lorentz function, shown in (2), to model the relationship between slope and walking speed. This study also assumes that slope and walking speed can be represented by a modified Lorentz function and estimates individual hiking characteristics from the first $X\%$ of the GPS trajectory log (P_{front}). We concatenate the attribute representation attr with the output h_{att} of the attention mechanism. Then, through three layers of fully connected layers with residual connections, we output the target $\hat{y}_{\text{entire}}$. This mechanism enables travel time prediction that considers both attribute information and location information.

These fixed parameters use values from Campbell's 50th percentile model ($a = -1.4579$, $b = 22.0787$, $d = 0.0525$, $e = 3.2002 \times 10^{-4}$), and parameter c is estimated by fitting it to the hiking record in the first $X\%$ using the equation

$$r = c\left(\frac{1}{\pi \times 22.0787\left(1+\left(\frac{s-1.4579}{22.0787}\right)^2\right)}\right) + 0.0525 + 3.2002 \times 10^{-4} s. \tag{4}$$

The slope-speed function generated by this component is passed to the next Spatio-Temporal Component, and it is also used to calculate the estimated speeds $\hat{v}_{-30^\circ}$, $\hat{v}_{-20^\circ}, \hat{v}_{-10^\circ}, \hat{v}_{0^\circ}, \hat{v}_{10^\circ}, \hat{v}_{20^\circ}, \hat{v}_{30^\circ}$ at slopes of [–30°, –20°, –10°, 0°, 10°, 20°, 30°]. These estimated speeds for the seven slope patterns are then added to the attribute information Attr, providing the model with data on the hiker's walking speed ability at specific slopes.

4.2. Spatio-Temporal Component

The Spatio-Temporal Component takes the GPS trajectory log of the remaining $(100 - X)\%$ of the hiking route as input to learn spatio-temporal relationships. This study is based on the DeepTTE [20] architecture but excludes the GeoConv layer, instead using a simple LSTM [25] to extract spatio-temporal features. The GeoConv layer was designed to account for left-right turns on roads by convolving latitude and longitude data, but such considerations are unnecessary in hiking, where trails are generally single-track. Additionally, Wang et al. [26] noted that the GeoConv layer, due to its fixed kernel size, may fail to capture features smaller or larger than the kernel. For these reasons, this study uses a simple LSTM to extract spatio-temporal features.

First, the model takes the back segment of the GPS trajectory log, $P_{\text{back}} = \{p_{x+1}, p_{x+2}, \dots, p_T\}$, as input. Each data point p_i contains six attributes: latitude (lat), longitude (lng), elevation (ele), cumulative distance (dist), walking slope (ws), and terrain slope (ts). Next, Using the slope-speed function created in the Hiking Ability Estimation Component (Section 4.1), the estimated speed ($\hat{v}$) is added to each data point p_i as an additional attribute. As a result, each data point p_i now contains seven attributes, with the estimated speed $\hat{v}$ reflecting the hiker's walking ability. Utilizing this estimated speed is expected to enable more accurate predictions.

Second, the elevation ($p_i.\text{ele}$), latitude ($p_i.\text{lat}$), longitude ($p_i.\text{lng}$), and cumulative distance ($p_i.\text{dist}$) are each converted into a differential format relative to the previous data point, as $p_i.\text{ele}_{\text{diff}}$, $p_i.\text{lat}_{\text{diff}}$, $p_i.\text{lng}_{\text{diff}}$, $p_i.\text{dist}_{\text{diff}}$. This approach incorporates route information between data points, rather than the GPS data points themselves. Additionally, since elevation itself may impact walking speed, both the differential and original elevation values are retained. As a result, each data point contains eight attributes: elevation ($p_i.\text{ele}$), elevation difference

($p_i.\mathrm{ele}_{\mathrm{diff}}$), latitude difference ($p_i.\mathrm{lat}_{\mathrm{diff}}$), longitude difference ($p_i.\mathrm{lng}_{\mathrm{diff}}$), distance difference ($p_i.\mathrm{dist}_{\mathrm{diff}}$), walking slope ($p_i.\mathrm{ws}$), terrain slope ($p_i.\mathrm{ts}$), and estimated speed ($p_i.\hat{v}$).

Third, each data point $p_i = \{p_i.\mathrm{ele},\ p_i.\mathrm{ele}_{\mathrm{diff}},\ p_i.lat_{\mathrm{diff}},\ p_i.\mathrm{lng}_{\mathrm{diff}},\ p_i.\mathrm{dist}_{\mathrm{diff}},\ p_i.\mathrm{ws},\ p_i.\mathrm{ts},\ p_i.\hat{v}\}$ is normalized, then transformed by a learned weight matrix W_{loc} and activated with the tanh function to create a 16-dimensional spatial representation loc (the next equation)

(5) $$\mathrm{loc}_i = \tanh(W_{\mathrm{loc}} \cdot p_i).$$

Finally, the spatial representation loc is concatenated with the normalized attribute information Attr. The attribute information $\mathrm{Attr} = \{\mathrm{ele}_{\max},\ \mathrm{ele}_{\min},\ D+,\ D-, \mathrm{dist}_{\mathrm{total}}\ ,\ \hat{v}_{-30^\circ}, \hat{v}_{-20^\circ}, \hat{v}_{-10^\circ}, \hat{v}_{0^\circ}, \hat{v}_{10^\circ}, \hat{v}_{20^\circ}, \hat{v}_{30^\circ}\}$ consists of 12 elements. The concatenated data is then input to a two-layer LSTM (Equation (6)). LSTM (Long Short-Term Memory) [25] is a type of recurrent neural network designed to capture long-term dependencies in time-series data, using three gate mechanisms: input gate, forget gate, and output gate to regulate information flow,

(6) $$h = \sigma_{\mathrm{lstm}}(W_h \cdot [\mathrm{loc},\ \mathrm{Attr}]).$$

The LSTM is composed of two layers, producing a final hidden state h. The hidden state h has 128 dimensions. Each hidden state h_i corresponds to the location information representation loc_i of a segment of the hiking log. This mechanism enables the model to account for spatio-temporal relationships within the hiking log.

4.3. Multi-task learning component

The multi-task learning component simultaneously predicts the travel time for both the local path and the entire path. Multi-task learning, as proposed in DeepTTE [20], involves learning both local path and entire path travel times simultaneously to enhance the prediction accuracy for each during training. In DeepTTE's taxi transportation task, the primary objective is to predict the travel time for the entire path; however, incorporating local path predictions enhances the accuracy of the entire path estimation. Following this approach, our study also incorporates multi-task learning from DeepTTE.

Local path travel time estimation module. The local path travel time estimation module takes the hidden state h, output from the Spatio-Temporal Component, as input and performs a nonlinear transformation. As shown in Fig. 1, this nonlinear transformation consists of two layers of (Affine + LeakyReLU), followed by a linear transformation, resulting in the final local path travel time predictions $\hat{y}_{\mathrm{local}} = \{\hat{y}^{x+1}_{\mathrm{local}}, \hat{y}^{x+2}_{\mathrm{local}}, \dots, \hat{y}^{T}_{\mathrm{local}}\}$. Each prediction $\hat{y}^{i}_{\mathrm{local}}$ corresponds to the GPS data point p_i and represents the model's estimate of the time required to complete that local path.

Entire path travel time estimation module. The entire path travel time estimation module utilizes an Attention mechanism, taking the attribute information and the hidden state h from the Spatio-Temporal Component as input to calculate the entire path travel time. An overview of the model is shown in Fig. 2. First, we perform a nonlinear transformation on the attribute information, matching its dimensionality with the hidden states h. Then, using the nonlinearly transformed attribute information as the Query, and the hidden states h as the Key and Value, we compute the weighted sum h_{att} via the attention mechanism (the next equations); here, σ_{att} represents the nonlinear transformation layer:

(7) $$z_i = \langle \sigma_{\text{att}}(\text{attr}), h_i \rangle,$$

(8) $$\alpha_i = \frac{\exp(z_i)}{\sum \exp(z_j)},$$

(9) $$h_{\text{att}} = \sum_{i=x+1}^{T} \alpha_i \times h_i.$$

This mechanism allows us to consider the importance of different local paths in the hiking log.

Subsequently, we predict the final travel time through fully connected layers and residual connections (the next equations; here, W_{att} W_l, and W_y are learnable weights, and h_l is the hidden state in the residual connection layer),

(10) $$h_l = W_{\text{att}} \times [\text{attr}, h_{\text{att}}],$$

(11) $$h_{l+1} = \text{LeakyReLU}(W_l \times h_l) + h_l,$$

(12) $$\hat{y}_{\text{entire}} = W_y + h_n.$$

We concatenate the attribute representation attr with the output h_{att} of the attention mechanism. Then, through three layers of fully connected layers with residual connections, we output the target $\hat{y}_{\text{entire}}$. This mechanism enables travel time estimation that considers both attribute information and location information.

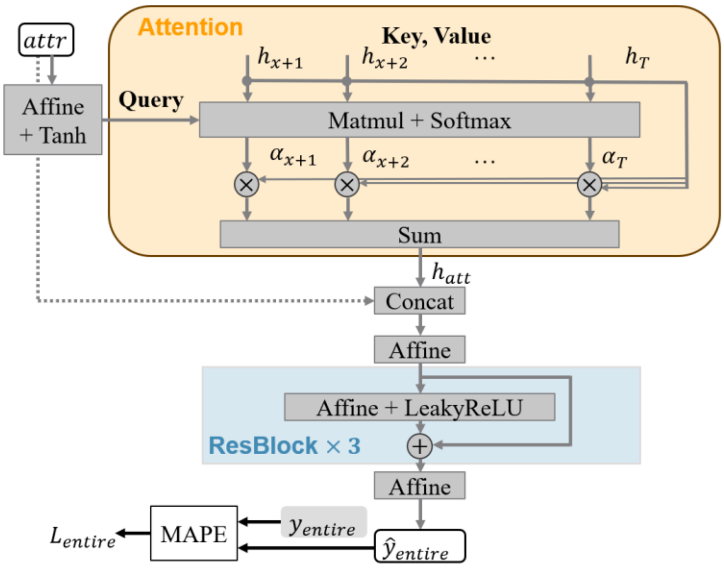

Fig. 2. Overview of Entire path travel time estimation module

Model Training. During the training phase, we use a weighted loss combining the MAPE loss (L_{local}) for local path predictions and the MAPE loss (L_{entire}) for the entire travel time prediction. The loss for local path predictions is calculated by the equation

(13) $$L_{\text{local}} = \frac{1}{\text{length}(P_{\text{back}})} \sum_{i=x+1}^{T} \left| \frac{\hat{y}_{\text{local}}^i - y_{\text{local}}^i}{y_{\text{local}}^i + \epsilon} \right|.$$

Here, ϵ is a constant used to prevent the MAPE loss from becoming too large and destabilizing the training. Additionally, the loss for the entire path is expressed by the equation

(14) $$L_{\text{entire}} = \left| \frac{\hat{y}_{\text{entire}} - y_{\text{entire}}}{y_{\text{entire}}} \right|.$$

By weighting L_{local} and L_{entire}, we proceed with training to minimize the equation

(15) $$\alpha \times L_{\text{local}} + (1 - \alpha) \times L_{\text{entire}}.$$

Here, α is a weighting coefficient that takes a value between 0 and 1. Since the final goal is to minimize L_{entire} the evaluation is conducted using MAPE, MAE, and MSE between the predicted entire travel time ($\hat{y}_{\text{entire}}$) and the actual entire travel time (y_{entire}).

5. Experiment

In this section, we present the results of experiments conducted using real historical GPS trajectories of hikers. In the experiments, we first conduct a preliminary experiment where we do not use the hiker's walking performance (i.e., $X = 0\%$) to compare existing hiking arrival time estimation methods with our proposed method. Then, as the main experiment, we evaluate the prediction accuracy when using historical hiker information, comparing it against a baseline.

5.1. Dataset

In this study, we used the dataset "GPS recorded hikes from hikr.org" [27], which is publicly available on Kaggle. This dataset consists of approximately 12,000 hiking logs collected from GPS trajectories of hikers posted on hikr.org [17]. Each hiking log contains information for each GPS point p_i, including latitude (lat), longitude (lng), elevation (ele), and timestamp (time).

5.1.1. Preprocessing of the hikr.org dataset

First, since the dataset contains missing values, we performed the following steps on each hiking log to eliminate them.

1. Remove points containing missing values.
2. Exclude hiking logs with fewer than 50 data points.
3. Identify invalid data (data where speed exceeds 5 m/s = 18 km/h or the interval between data points exceeds 1200 s):
    a. If a segment with at least 50 consecutive valid points exists, extract and use that segment,
    b. If not, exclude that hiking log.

As a result of these operations, we obtained 8538 hiking logs. Then, we calculated and added the time difference $\text{time}_{\text{diff}}$ between each point p_i and the previous one. Next, we calculated the total travel time $\text{time}_{\text{total}}$ from the time difference between the first and last data points of the GPS trajectory. The $\text{time}_{\text{total}}$ is the target we ultimately aim to estimate in this study.

Next, to create the attribute information of the logs, we extracted the maximum elevation ele_{max} and minimum elevation ele_{min} from the elevation data of the hiking logs. Additionally, we calculated the cumulative ascent *D*+ and cumulative descent *D*– from the elevation differences between each point.

5.1.2. Addition of slopes

The walking slope angle ws (degrees) was calculated from the horizontal distance and elevation difference between each point in the log. For obtaining the terrain slope angle ts (degrees), we used NASADEM [28] for regions below 60° latitude and ArcticDEM Mosaic [29] for regions above 60° latitude. These datasets are freely available, highly accurate, and widely used in numerous studies [30-33].

Ultimately, each log P contains attribute information $\mathrm{Attr} = \{\mathrm{ele}_{\mathrm{max}}, \mathrm{ele}_{\mathrm{min}}, D+, D-, \mathrm{dist}_{\mathrm{total}}, \mathrm{time}_{\mathrm{total}}\}$ and each data point $p_i = \{\mathrm{lat}, \mathrm{lng}, \mathrm{ele}, \mathrm{dist}, \mathrm{ws}, \mathrm{ts}, \mathrm{time}\}$. The GPS trajectory is handled in the form of differences from the previous data point, as explained in Section 4.2. The final goal is to estimate the travel time $\mathrm{time}_{\mathrm{total}}$ of the entire path. Note that the travel time of local path $p_i.\mathrm{time}$ is used only during training.

5.2. Model training

To train the model, we split the dataset into training data, validation data, and test data. We allocated 80% of the data as training data and 20% as test data, with 5% of the training data used as validation data. Using MAPE as the loss function, we trained the model by weighting the losses of local path travel time estimation and entire travel time estimation as described in Section 4.3. We used Adam [34] as the optimizer with a learning rate of 0.001 and trained the model for 1000 epochs. As hyperparameters, we selected a batch size of 64 and a weighting coefficient $\alpha = 0.5$ for the losses of the local travel time prediction L_{local} and the entire travel time prediction L_{entire}.

5.3. Evaluation

We used MAE (Mean Absolute Error), MSE (Mean Squared Error), and MAPE (Mean Absolute Percentage Error) as evaluation metrics. Additionally, we tracked validation loss on the validation data over the course of 1000 training epochs. Specifically, we recorded the validation loss at each epoch, computed a moving average of the loss with a filter size of 50 epochs, and selected the model at the point where this moving average was minimized as the final model. Since we saved the model weights every 10 epochs, we selected the weights closest to the epoch where the moving average was minimized. We then calculated MAPE, MAE, and MSE on the test data to compare our proposed method with existing methods.

5.4. Preliminary experiment

In the preliminary experiment, we perform the task of estimating the travel time of the entire GPS trajectory. In this preliminary experiment, we first examine whether deep learning methods are effective for travel time estimation in hiking. Therefore, we compare a model that excludes the “Hiking Ability Estimation Component” from our proposed method with existing hiking speed estimation methods. Excluding the “Hiking Ability Estimation Component” means setting the front segment ratio $X = 0\%$ of the GPS trajectory P, not creating the slope-speed function, and not using the estimated speed $\hat{v}$ information. We compared our method with four existing hiking travel time estimation models: Naismith's Rule [13], Tobler's hiking model [14], Campbell's hiking model [15], and Wood's hiking model [16].

Naismith's Rule. By fitting Naismith's Rule to the relation between walking slope angle ws (degrees) and speed v (m/s) we can express it with the following equation:

(16) $$v = \frac{4828.02}{3600(1+\tan(\mathrm{ws})\times 7.92)}.$$

Therefore, we calculated the travel time for each local path using the walking slope ws and estimated the total travel time by summing them. However, since Naismith's Rule cannot handle downhill slopes, we set $\mathrm{ws} = 0$ when $\mathrm{ws} < 0$.

Tobler's Hiking model. Since Tobler's hiking function is expressed by (1), we calculated the travel time for each segment from the walking slope ws and estimated the total travel time. However, Tobler's hiking function has the drawback of underestimating speed when the slope is large. Therefore, when the absolute value of the slope exceeds 80% (38.66°), we set $\mathrm{ws} = 38.66°$. This value was selected by comparing the MAPE when applying different slope (%) limits to the training data and choosing the value with the smallest MAPE.

Campbell's Hiking model. Campbell's hiking model is given by (2), and since it has different model parameters a, b, c, d, and e for each percentile of hiking speed, we estimated the parameters using the training data. In constructing the model, Campbell performed the following steps: (1) excluding invalid data, (2) correcting for variability in individual logs, and (3) aggregating across the entire dataset.

1. For the invalid data exclusion step, like Campbell, [15], we excluded points where the movement speed was less than 0.2 m/s, considering them as breaks, and points where the speed was 5 m/s or higher, as they might not hiking. Additionally, we excluded data points with a slope of 30° during model construction due to the small number of such points.

2. To correct for variation in individual walking speed, Campbell, Dennison and Thompson [15] calculated the median speed at every 1-degree slope interval for each individual log and used this value as the hiking speed at that slope for that log. However, since the dataset used in this study has fewer data points compared to Campbell's dataset, we aggregated data at every 2-degree slope interval.

3. For aggregation over the entire dataset, Campbell, Dennison and Thompson [15] further grouped the previously calculated "median speed at each 2-degree slope interval" into 2.5 percentiles based on hiking speed, obtained the medians, and then fitted the relationship between slope and speed for each percentile to (2). In contrast, in this study, we aggregated and fitted data every 5 percentiles.

We created 19 different models at every 5th percentile and adopted the 50th percentile model as the median model for all logs. As a result, we obtained the parameters $a = -2.730$, $b = 17.33$, $c = 53.96$, $d = 0.1070$, $e = -1.041 \times 10^{-3}$ for (2).

Wood's Hiking Model. Wood's hiking model is given by (3) and has different parameters a, b, c, and d depending on the obstruction level. However, in this study, since DSM and DTM data required for calculating the obstruction level were not available, we used the same parameters. Additionally, since this study aims to estimate the total travel time including breaks, we did not exclude break times during the preprocessing of Wood's hiking model. Then, by training Wood's hiking model using a Generalized Linear Model (GLM) on the training data, we obtained the parameters $a = 1.4806,\ b = -0.0046,\ c = -0.0106,\ d = -0.0015$ for (3).

Furthermore, since Wood's hiking model, like Tobler's hiking function, tends to excessively underestimate speed when the slope is large, we set $\mathrm{ws} = 40$ when the absolute value of the slope exceeds 40°. This value was determined by applying Wood's hiking model to the training data with various slope limits, predicting the total travel time for the entire path, comparing the MAPE for each slope limit, and selecting the slope limit that resulted in the lowest MAPE.

The comparison results between these existing hiking TTE methods and our proposed method are shown in Table 1.

Table 1. Preliminary experimental results (Split ratio X = 0%)

Model	MAPE↓(%)	MAE↓(h)	MSE↓(h^2)
Proposed method	**15.62**	**0.475**	**0.704**
Naismith [13]	30.54	1.005	1.766
Tobler [14]	28.77	0.962	1.607
Campbell, Dennison and Thompson [15]	28.57	0.965	1.675
Wood et al.[16]	30.11	1.047	1.824

From Table 1, our proposed method outperformed the existing methods in all evaluation metrics. Among the existing hiking models, Campbell's method had the best MAPE, but our proposed method improved MAPE by 12.95 points compared to Campbell's method.

5.5. Main experiment

As demonstrated in Section 5.4, our proposed method achieved significantly higher accuracy than all existing hiking travel time estimation methods, including state-of-the-art approaches. In this experiment, we conduct further experiments on the task of estimating the time required to walk through the back segment $(100 - X)\%$ of the GPS trajectory, based on hiker characteristics extracted from the front segment $X\%$, which is the original task. As comparative methods, we compare DeepTTE, which was developed for Travel Time Estimation tasks in the transportation field, and the DeepTTE+Ave model, which modifies the data given to DeepTTE for this task.

DeepTTE. DeepTTE[20] is a deep learning model that estimates travel time from attribute information and GPS trajectories. In processing GPS trajectories, it convolves multiple GPS data points with a kernel size k to extract spatio-temporal features. Since it is a travel time estimation method developed in the transportation field, we cannot use this model as is for hiking travel time estimation. Therefore, to use it for hiking travel time estimation, we modified the data given as follows. First, as the GPS trajectory, we provided the model with the six elements $p_i = \{\mathrm{lat},\ \mathrm{lng},\ \mathrm{ele},\ \mathrm{dist},\ \mathrm{ws},\ \mathrm{ts}\}$ explained in Section 3.1. Also, as attribute information, we provided the model with $\mathrm{Attr} = \{\mathrm{ele}_{\mathrm{max}},\ \mathrm{ele}_{\mathrm{min}},\ D+,\ D-,\ \mathrm{dist}_{\mathrm{total}},\ \mathrm{time}_{\mathrm{total}}\}$ explained in Section 3.2.

DeepTTE + Ave. DeepTTE+Ave adds the average walking speed $\bar{v}$ and average walking slope angle $\overline{ws}$ of the front segment X% to the attribute information Attr of the DeepTTE. By adding these two pieces of information, we provide DeepTTE with the hiker's hiking ability information.

We trained each model for data split ratios $X = 5\%, 10\%, 20\%, 30\%, 40\%, 50\%, 60\%, 70\%, 80\%, 90\%$ and compared the accuracy of the proposed method with DeepTTE and DeepTTE+Ave. The results are shown in Table 2.

Table 2. Main experimental results

Split ratio X	Model	MAPE↓(%)	MAE↓(h)	MSE↓(h^2)
5%	Proposed method	**11.31**	**0.3804**	**0.4009**
	DeepTTE+Ave	11.46	0.3935	0.4544
	DeepTTE	15.85	0.4729	0.6645
10%	Proposed method	**10.48**	**0.3359**	**0.3007**
	DeepTTE+Ave	10.91	0.3501	0.3248
	DeepTTE	15.73	0.4424	0.5436
20%	Proposed method	**10.68**	**0.3022**	**0.2430**
	DeepTTE+Ave	10.99	0.3128	0.2561
	DeepTTE	16.29	0.4123	0.4979
30%	Proposed method	**10.23**	**0.2600**	**0.1900**
	DeepTTE+Ave	10.97	0.2781	0.2051
	DeepTTE	18.53	0.3959	0.4353
40%	Proposed method	**10.72**	**0.2371**	**0.1609**
	DeepTTE+Ave	10.98	0.2422	0.1645
	DeepTTE	18.60	0.3368	0.3492
50%	Proposed method	**10.86**	**0.1971**	**0.1084**
	DeepTTE+Ave	12.02	0.2163	0.1310
	DeepTTE	17.81	0.2745	0.2239
60%	Proposed method	**11.61**	**0.1702**	**0.0834**
	DeepTTE+Ave	11.56	0.1679	0.0803
	DeepTTE	18.05	0.2231	0.1516
70%	Proposed method	**13.05**	**0.1407**	0.0599
	DeepTTE+Ave	13.39	0.1439	**0.0589**
	DeepTTE	19.56	0.1812	0.0966
80%	Proposed method	**13.74**	**0.1004**	**0.0332**
	DeepTTE+Ave	15.34	0.1089	0.0371
	DeepTTE	22.04	0.1344	0.0544
90%	Proposed method	**16.63**	**0.0570**	**0.0113**
	DeepTTE+Ave	21.39	0.0707	0.0156
	DeepTTE	27.21	0.0823	0.0210

From Table 2, the proposed method achieved better MAPE and MAE than the baseline using DeepTTE in all data split ratios except $X = 60\%$. In terms of MSE, the proposed method was outperformed by DeepTTE+Ave at X=60% and X=70%, but the differences were minimal, at only 0.0031 and 0.001, respectively. On average, the proposed method improved MAPE by 0.97 percentage points [ma1]compared to DeepTTE+Ave.

6. Discussion

In this study, we developed a model called “HikingTTE” for TTE in hiking. This model can predict the estimated time required to complete a planned hiking trail. Furthermore, we added a mechanism that estimates the hiker’s hiking ability based on their walking performance from the starting point to the current location while on the trail. To the best of our knowledge, HikingTTE is the first Travel Time Estimation model that includes a mechanism to estimate individual hiking ability, and we expect it to become a new standard in hiking travel time estimation.

Compared to existing hiking travel time estimation models such as “Naismith’s Rule”, “Tobler’s Hiking Model”, “Campbell’s Hiking Model”, and “Wood’s Hiking Model”, our method significantly improves accuracy. Existing hiking travel time estimation models merely describe the relation between slope and speed and cannot consider individual hiking ability or the effects of fatigue during hiking. HikingTTE can consider individual hiking ability through the Hiking Ability Estimation Component and enables learning spatiotemporal dependencies via the Spatio-Temporal Component. Furthermore, by incorporating deep learning methods, it became possible to capture complex interrelationships among various features such as terrain, elevation, individual hiking ability, and changes in walking pace, not just the simple relation between slope and speed. This allows us to consider various factors that existing hiking travel time estimation models could not handle, achieving high-precision travel time estimation.

Moreover, “Campbell's Hiking Model” and “Wood’s Hiking Model” excluded break times during the data preprocessing stage. Therefore, when using these models, it was necessary to additionally account for break times. HikingTTE uses GPS trajectories that include breaks for training, and its predictions consider break times. Therefore, the predictions can be used directly as arrival times. Furthermore, the Kaggle dataset [27] used in this study consists of hiking logs from various regions worldwide obtained from hikr.org [17]. Therefore, the predictions by HikingTTE can be applied to hiking courses in general, regardless of specific trails.

However, the dataset used in this study does not include features such as age, gender, weather, and party size, which are considered to affect hiking speed. Although these features can be indirectly considered through the relation between slope and hiking speed from the front segment $X\%$ of the data, it is thought that using these data directly could further improve accuracy. If we were to add these data to HikingTTE, information such as “age”, “gender”, and “party size” could be additionally included in the attribute information Attr, and “weather” information could be added to the GPS trajectory p_i.

Additionally, as a method to estimate the hiker’s hiking ability, it is conceivable to reference their past hiking logs. However, the dataset used in this study had the limitation that there were few hiking records of the same user. Therefore, in this experimental setup, we estimated the hiker’s hiking ability using the front segment $X\%$ of the data. If the hiker’s past hiking logs are available, it would be possible to make even more accurate predictions by considering past hiking characteristics. Specifically, by utilizing past data, it would be possible not only to obtain estimated arrival times during hiking as in the current task but also to obtain estimated arrival times that reflect one's hiking ability before starting the hike. This would expand the applicability of the model, making it possible to use it when planning hikes.

Regarding changes in the prediction accuracy of the model when varying the split ratio X, several trends were observed. First, as X increased, the MAE (Mean Absolute Error) and MSE (Mean Squared Error) improved. This is because the prediction interval becomes shorter, naturally reducing the absolute error. On the other hand, MAPE is an indicator based on relative error, and even if the absolute error is small, MAPE tends to become larger when the prediction path is short. Therefore, as the value of the split ratio X increases, MAPE tends to become larger. In the proposed method, MAPE was 11.31% when $X = 5\%$ and accuracy improved in the range of X is from 10% up to 30%. This is because, at $X = 5\%$, the small number of data points makes it difficult to adequately consider individual hiking ability, whereas using data points of around X is from 10% up to 30% or more allows hiking characteristics to be more appropriately considered. Furthermore, when X reaches 40% or more, MAPE worsens again, but this is not because the individual's ability can no longer be estimated, but due to the characteristics of the MAPE evaluation metric.

7. Conclusion

In this study, we proposed "HikingTTE", a deep-learning model for Travel Time Estimation in hiking. Existing hiking Travel Time Estimation models primarily estimate walking speed from the slope and could not incorporate individual hiking ability or reductions in walking speed due to fatigue into their predictions. HikingTTE, proposed in this study, integrates a Hiking Ability Estimation Component using a modified Lorentz function into a deep learning-based Travel Time Estimation model, enabling comprehensive consideration of individual hiking ability, changes in walking pace, terrain, elevation, and more. As a result, our proposed method demonstrated a significant improvement over existing hiking travel time estimation models based on the relation between slope and speed, allowing us to provide hikers with more precise estimated arrival times. Moreover, compared to methods that apply DeepTTE – a taxi TTE method for a similar task – to hiking, our model achieved higher prediction accuracy. This study is the first to propose a deep learning-based hiking TTE model that considers individual hiking ability, and it is expected to become an important baseline in this field. Furthermore, by releasing HikingTTE as the first open-source resource for the hiking TTE task, we aim to contribute to the advancement of the entire field. Future challenges include adding additional features to the data that are considered to affect hiking ability, such as age, gender, weather, and party size, and incorporating the hiker's past hiking logs into the model.

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Received: 04.11.2024. Accepted: 14.11.2024. Fast-track.