TRIPS: A System for Translating Raw Indoor Positioning Data into Visual Mobility Semantics

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ABSTRACT

The rapid accumulation of indoor positioning data is increasingly booming the interest in indoor mobility analyses. As a fundamental analysis, it is highly relevant to translate raw indoor positioning data into mobility semantics that describe what, where and when in a more concise and semantics-oriented way. Such a translation is challenging as multiple data sources are involved, raw indoor positioning data is of low quality, and translation results are hard to assess. We demonstrate a system *TRIPS* that streamlines the entire translation process by three functional components. The Configurator provides a standard but concise means to configure multiple input sources, including the indoor positioning data, indoor space information, and relevant contexts. The Translator cleans the indoor positioning data and exports reliable mobility semantics without manual interventions. The Viewer offers a suite of flexible operations to trace the input, output and intermediate data involved in the translation. Data analysts can interact with TRIPS to obtain the desired mobility semantics in a visual and convenient way.

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1. INTRODUCTION

Multiple studies [4, 5] disclose that people spend nearly 90% of their lives indoors. Thanks to the advances of wireless infrastructures [3] and smartphones, indoor human movements have been increasingly datafied as indoor positioning data in environments like office buildings, shopping malls, airports, and so on. Such data enables a number of applications, e.g., indoor behavior prediction [6], popular indoor location discovery [8] and in-store marketing [2]

The indoor positioning data in our investigation contains a set of *raw* positioning records as shown in the left part of Table 1. Each such raw record captures the object location as a geometric point at a timestamp. However, such locations feature inherently errors and such timestamps are discrete. As a result, the data is nonintuitive and lacks necessary semantics for data users. For example, a data analyst for a shopping mall needs to know if a shopper has stayed in a shop for a period of time sufficiently long for a real purchase. In such a case, it is insufficient to only look at the raw positioning records; some richer and more comprehensible annotations are needed as semantics. To this end, the analyst can configure the related *contexts* that help to determine the annotations. In particular, she may specify the regions for all shops (e.g., a Nike Store) in the mall and define a pattern of mobility event that someone stays in one or multiple shops. Given such contexts, the raw data can be translated into a high-level representation that is more concise and readable. An example is given in the right part of Table 1.

Table 1: Raw Indoor Positioning Data vs. Mobility Semantics

Raw Positioning Records	Mobility Semantics
$o_i, (5.1, 12.7, 3F)$, *1:02:05pm*	o_i:
$o_i, (6.5, 11.8, 3F)$, *1:02:12pm*	(*stay*, *Adidas*, *1:02:05-1:18:15pm*)
....	(*pass-by*, *Nike*, *1:18:16-1:20:13pm*)
$o_i, (13.6, 4.2, 2F)$, *1:24:05pm*	(*stay*, *Cashier*, *1:20:14-1:24:05pm*)

In this example, a shopper o_i's mobility behaviors are described by a sequence of triplets called *mobility semantics*. Each triplet includes an event annotation (mobility event *stay* or *pass-by*), a spatial annotation (a semantic region like *Nike* Store) and a temporal annotation (time period). In our definition, a *mobility event* refers to a generic movement pattern of some particular interest, and a *semantic region* refers to a region associated with some practical semantics. The annotations in the mobility semantics are closely related to the contexts specified by the data analyst. As a result, the mobility semantics disclose a shopper's preference to the analyst, which can, for example, enable her to make better recommendations to the shopper. Also, the mobility semantics are very concise to process as they use a more condensed form compared to the raw positioning records. Therefore, it is very useful and beneficial to translate the raw indoor positioning data into mobility semantics for the purpose of indoor mobility analysis.

Nevertheless, such a translation faces multiple challenges. First, such a translation involves the data from multi-sources, including the indoor positioning data, indoor space information and relevant indoor contexts. It is a laborious task to set up those data sources for a specific data analysis. Second, such a translation relies heavily on the quality of the raw indoor positioning data that, however, is uncertain and discrete in nature due to the limitations of indoor positioning [3]. Considerable efforts are needed to improve the data quality before the proper mobility semantics can be determined from the data. Third, the translation result needs to be assessed properly. It is useful to compare the resultant mobility semantics to the corresponding raw positioning records. However, such a comparison is difficult due to the large gap between these two kinds of representations (see Table 1). To address these challenges, a con-

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venient and integrated toolkit is needed to facilitate the translation from the raw indoor positioning data to the mobility semantics.

There exist few solutions [10–12] for interpretating raw GPS trajectories. A trajectory reconstruction manager [10] transforms raw GPS data into application-dependent movement features for data warehouse use. It does not support specifying any context except for the parameters necessary for feature extraction, namely temporal and spatial gaps, maximum speed, maximum noise duration, and tolerance distance in a stop. A semantic trajectory annotation platform [12] allows users to acquire third-party geographic artifacts to enrich their contexts. However, the platform only offers two mobility patterns suitable for geographic objects, i.e., stop and move. Concentrating on road network traffics, STMaker [11] summarizes a segment of raw trajectory by a short text according to a given context. The existing solutions are unable to capture complex indoor topology of distinct entities (e.g., doors, walls and floors), which is the key to cleaning the raw indoor positioning data. Besides, the existing solutions provide no proper mechanism for assessing the result. The manager in [10] and the platform in [12] both lack a graphical interface for users to visually compare the input positioning sequence and output semantic representation. Although STMaker [11] can render GPS trajectories on a digital map, it cannot visualize its output texts for the assessment purpose. Consequently, the existing solutions are functionally insufficient for translating raw indoor positioning data into mobility semantics.

This work demonstrates a system *TRIPS* that Translates Raw Indoor Positioning data into mobility Semantics. It features the following highlights:

- It provides a standard but concise means to configure multiple input sources, including raw indoor positioning data, indoor space information and relevant contexts.
- It incorporates a translator that is able to clean raw indoor positioning data and translate the data into reliable mobility semantics without manual interventions.
- It offers a suite of flexible interactions to visually trace the input, output and intermediate data involved in the translation, making it intuitive to assess the translation result.

2. SYSTEM DESIGN

As illustrated in Figure 1, TRIPS consists of two frontend components and one backend component.

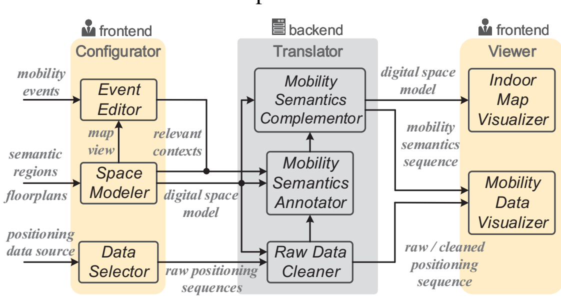

Figure 1: System Architecture

The Configurator takes charge of the configuration of the input data involved in the translation.

1) The *Data Selector* module accepts the indoor positioning data from multi-sources (e.g., text files, database tables, and streams APIs), and offers users a set of configurable and combinable rules to select the (device) positioning sequences of particular interest. Typical rules include device ID pattern, spatial range, temporal range, positioning frequency, and periodic pattern. For example, one can select the positioning sequences that last for more than one hour and appear on the ground floor in the target indoor space.

2) The *Space Modeler* module allows users to extract the target indoor space's physical information and the contexts of the semantic regions. It offers multiple drawing operations that can be applied to an input floorplan image to obtain the physical information. It also supports loading and assigning the semantic tags to the drawn shapes for creating semantic regions. The extracted information is recorded in the *digital space model* (DSM). It contains the semi-structured data that mainly describes the geometric attributes and topological relations for indoor entities, those for semantic regions, and the mapping between indoor entities and semantic regions.

3) The *Event Editor* module helps users work out the training data for the model that identifies the mobility events in the translation. It allows users to define mobility event patterns, and designate each defined pattern the corresponding positioning sequence segments on the map view. The designated data segments will be used to train a learning-based model for identifying the user-defined event patterns from other positioning sequences.

The Translator constructs a sequence of mobility semantics for each individual positioning sequence.

1) The *Raw Data Cleaner* module reads the positioning sequence selected by the Data Selector, and eliminates the data errors by considering the indoor mobility constraints captured in the DSM.

2) The *(Mobility Semantics) Annotator* module reads the cleaned sequence from the Raw Data Cleaner, and extracts a sequence of mobility semantics by matching proper annotations according to the relevant contexts (i.e., semantic regions and mobility events).

3) The *(Mobility Semantics) Complementor* module handles the discontinuity of the original mobility semantics sequence generated by the Annotator. It infers the missing mobility semantics of the sequence by referring to other generated mobility semantics sequences and the spatial information captured by the DSM.

The Viewer provides an interface for browsing and comparing different mobility data sequences involved in the translation.

1) The *Indoor Map Visualizer* shows an interactive map view with necessary tooltips. It allows a switch between different floors.

2) The *Mobility Data Visualizer* renders on the map view the data sequences involved in the translation, namely the raw or cleaned positioning sequence, the mobility semantics sequence, and the ground truth positioning sequence.

3. KEY TECHNIQUES

Creating DSM from Floorplan Image. As introduced in Section 2, the DSM serves as a very useful data structure in the system. On the one hand, it captures the geometric properties and topological relations of unique *entities* (e.g., doors, walls, rooms, and staircases) in the indoor space, which enables the spatial computations for cleaning the positioning records in the Raw Data Cleaner. On the other hand, it records the user-defined semantic regions and their connectivity information, which helps the Annotator make annotations and the Complementor infer the missing mobility semantics. To obtain the DSM, it is essential to extract entity information from the target indoor space. Our previous work Vita [7] has supported parsing indoor entities from industry-standard digital building information files (e.g., CAD or IFC format). However, in many applications, the only information provided is a floorplan image without any meta-data. In such a case, we need a semi-automatic tool to assist creating the DSM.

To this end, we design a drawing tool in Space Modeler as shown in Figure 2. By using the tool, the analysts can easily create the DSM in three steps. (1) Import the floorplan image to the canvas. (2) Trace the floorplan image by drawing and combining the geometric elements (e.g., polygons, polylines and circles) to form the indoor entities (e.g., doors, rooms). Multiple features are available to facilitate the drawing, such as keyboard shortcuts, redo/undo, auto-adjust hint, edit-mode of free transformation/resizing/moving, and layer/group control. (3) Load and attach the semantic tags to the drawn entities through the semantic tab (bottom right corner in Figure 2). Users can customize and apply different styles to differentiate the indoor entities with different semantic tags.

Figure 2: Drawing Tool for Creating DSM in Space Modeler

Once the three steps are done, the system reads the drawn indoor entities' geometric properties and semantic tags, and computes the topological relations between the entities and those between the semantic regions. All aforementioned information is stored in the DSM in JSON format, which is flexible to parse and manipulate.

Three-Layer Translation Framework. A big challenge to obtain mobility semantics is that the raw indoor positioning data is uncertain and discrete, without any semantics. To address this issue, we design a three-layer framework that is able to progressively improve the data quality when generating reliable mobility semantics. As shown in Figure 3, the framework takes each individual positioning sequence as input and generates the corresponding mobility semantics sequence. The data is processed through three functional layers, each equipped with the applicable techniques to facilitate the data processing.

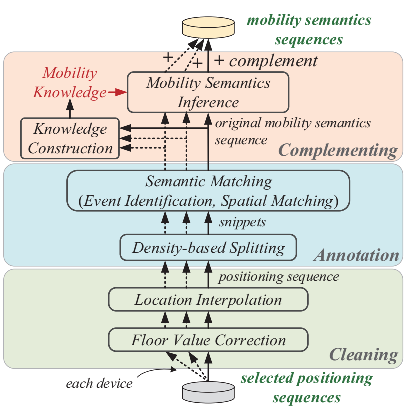

Figure 3: Three-Layer Translation Framework

The *Cleaning* layer identifies and repairs the distinct raw data errors that result from the indoor positioning. Considering the speed constraint that people cannot move too fast indoors, the invalid positioning records are identified by checking the speeds between consecutive positioning records based on the *minimum indoor walking distance* [13]. An invalid positioning record is repaired in two steps. A *floor value correction* fixes an error in that record's floor value. If the speed constraint violation still occurs after the correction, a *location interpolation* is performed by deriving the possible locations at the time of that record based on the indoor geometrical and topological information captured by the DSM.

The *Annotation* layer extracts a sequence of mobility semantics from a cleaned positioning sequence. In particular, a *density-based splitting* obtains a number of data snippets by clustering positioning records with respect to their spatio-temporal attributes. A *semantic matching* matches each snippet to a set of mobility semantics by making annotations as follows. The event and temporal annotations are made by a learning-based identification model, for which the training mobility event data is collected through the Event Editor. The feature extraction considers the information of positioning location variance, traveling distance and speed, covering range, number of turns, etc. The spatial annotation is made by matching the semantic regions in the DSM created by the Space Modeler.

The *Complementing* layer recovers the missing mobility semantics between two consecutive yet temporally far apart mobility semantics to make the output sequence complete. A *knowledge construction* aggregates the mobility semantics already annotated to build the prior mobility knowledge that captures the transition probabilities between semantic regions. Next, by a maximum a posteriori estimation, a *mobility semantics inference* utilizes the mobility knowledge to infer the most-likely mobility semantics between two semantic regions involved in the intermediate result. As a result, each original mobility semantics sequence is complemented.

The core techniques of the framework are online published [1].

Visualization of Mobility Data Sequences. To assess the translation result, multiple sources of mobility data sequences involved in the process need to be rendered on the map simultaneously. The data includes the raw and cleaned positioning sequences, the ground truth trajectory, and the mobility semantics sequence. They have different representations and characteristics, making it hard to process them in a unified way. To improve the efficiency of the mobility data visualization, we implement the following important features in the Viewer.

Figure 4: Visualization of Different Mobility Data Sequences

Abstraction of Different Mobility Data. We abstract each data sequence as a timeline of *entries*, each consists of a display point and a time range. The display point is used to render the corresponding entry on the map view, being represented as a geometric point at a certain floor. The time range determines the entry's coverage of the timeline. We differentiate two cases. If the entry represents a positioning record from a positioning sequence, its display point and time range are the location and timestamp in that record, respectively. If the entry represents a mobility semantics, its display point is selected from the positioning location(s) in the mobility semantics's corresponding raw record(s) [1], and its time range uses the temporal annotation directly. As shown in Figure 4, the Mobility Data Visualizer in the Viewer can render the entries abstracted from the positioning records or mobility semantics in a generic way.

Map View and Timeline Control. As shown in Figure 4, we provide both map view (center) and timeline (right side) to browse the data sequences. The map view is flexible to click, drag and zoom in/out. For the timeline, we use the mobility semantics as the primary navigator as it is the most concise compared to other data

[1]The system selects the temporally middle or the spatially central positioning location according to the user configuration.

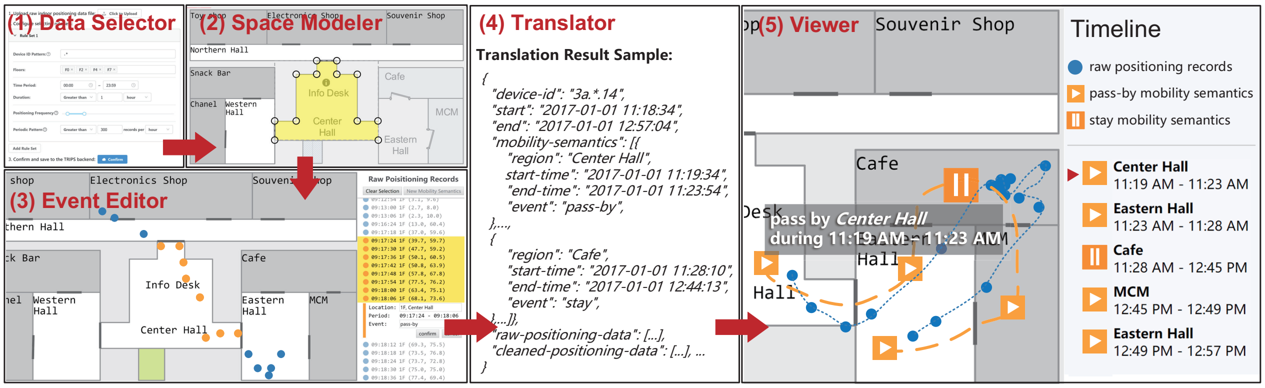

Figure 5: Example of TRIPS's Workflow in the Shopping Mall Scenario

sources. When clicking a mobility semantics entry on the timeline, all relevant data entries covered by its time range will be displayed on map view synchronously. One can slide the timeline to play an animated, semantics-enriched movement for a selected device.

Visibility Control. On the left side of the interface in Figure 4, a legend panel allows toggling the visibility of data from each source. It helps users focus on the parts of their interest when comparing data from different sources to assess the translation result.

4. DEMONSTRATION

The demonstration of TRIPS will be a detailed walk-through to show its convenience in constructing visual mobility semantics from raw indoor positioning data.

Environment. The system backend will be deployed on an Intel Xeon E5-2660 2.20GHz server remotely. The audience can interact with TRIPS in a web browser. We will use a dataset obtained from a Wi-Fi based positioning system in a 7-floor shopping mall in Hangzhou, China from 2017-01-01 to 2017-01-07. The device MAC addresses in the dataset are anonymized for privacy concern.

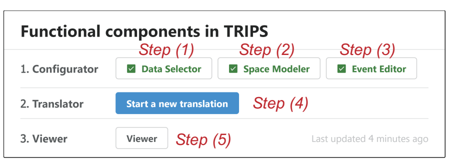

Figure 6: TRIPS's Main User Interface

System workflow. TRIPS's main user interface is illustrated in Figure 6. Its general workflow consists of five steps:
(1) Set up the indoor positioning data by using the Data Selector.
(2) Import or create the DSM by using the Space Modeler.
(3) Define the mobility event patterns and collect the corresponding training data by using the Event Editor.
(4) Submit the translation task to the Translator.
(5) Browse the translation result in the Viewer.

The data configurated in steps (2)-(3) will be stored in the backend for the reuse in other translation tasks in the same indoor space.

A walk-through. Figure 5 exemplifies a walk-through of TRIPS for constructing the shoppers' mobility semantics in a mall case.

In step (1), an analyst uploads the indoor positioning data and selects her desired positioning sequences (e.g., those that only appear during the mall's operating hours 10:00 AM - 10:00 PM).

In step (2), the analyst imports the floorplan image of the ground floor and draws the corresponding indoor entities, edits and assigns the semantic tags to the drawn entities to define a set of shops/sites she is interested in, and then saves the DSM file.

In step (3), the analyst defines the mobility event patterns and collects the training data as follows. To define a 'pass-by' pattern that somebody passes through a semantic region, she browses a set of randomly selected raw positioning sequences on the map view, and designates her defined pass-by pattern a set of corresponding positioning sequence segments (as depicted in Figure 5(3)). Such collected event data will be used as training data by the Translator to identify other pass-by events.

In step (4), the Translator accomplishes the translation task submitted by the analyst. As shown in the exported translation result file in Figure 5(4), a device *3a.*.14*'s indoor positioning records have been translated into a trace of mobility semantics, one of which indicates that some shopper has *passed by* the *Center Hall* during *11:19 AM - 11:23 AM*.

In step (5), the analyst opens the translation result file of *3a.*.14*, controls the map view or timeline to trace the mobility data sequences, and compares the mobility semantics to the corresponding raw positioning records. As a result, the analyst can know the translation effect very intuitively and will obtain a general idea of the shoppers' mobility behaviors in the mall.

A short video about the use of the prototype system is also available at TRIPS's project website [1].

5. ACKNOWLEDGMENTS

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