

Spatio-temporal analysis of trajectories for safer construction sites

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Abstract

Purpose – The purpose of this paper is to improve the safety of construction workers by understanding their behaviors on construction sites using spatio-temporal (ST) trajectories.

Design/methodology/approach – A review of construction safety management literature and international occupational health and safety statistics shows that the major reasons for fatalities on construction sites are mobility-related issues, such as unsafe human behaviors, difficult site conditions, and workers falling from heights and striking against or being struck by moving objects. Consequently, literature has been reviewed to find possible technological solutions to track the mobility of construction workers to reduce fatalities. This examination has suggested that location acquisition systems, such as Global Positioning System (GPS), have been widely used for real-time monitoring and tracking of workers on construction sites for hazard prevention. However, the raw data captured from GPS devices are generally available as discrete points and do not hold enough information to understand the workers' mobility. As a solution, an application to transform raw GPS data into ST trajectories using different preprocessing algorithms is proposed for enhancing worker safety on construction sites.

Findings – The proposed system preprocesses raw GPS data for stay point detection, trajectory segmentation and intersection of multiple trajectories to find significant places and movements of workers on a construction site to enhance the information available to H&S managers for decision-making processes. In addition, it reduces the size of trajectory data for future analyses.

Originality/value – Application of location acquisition systems for construction safety management is very well addressed in the existing literature. However, a significant gap has been found: the usage of preprocessed ST trajectories is still missing in workers' safety monitoring scenarios in the area of construction management. To address this research gap, the proposed system uses preprocessed ST trajectories to monitor workers' movements on a construction site to identify potentially unsafe behaviors.

Keywords Construction, Health, Technology, Safety, Workers, Fatalities

Paper type Research paper

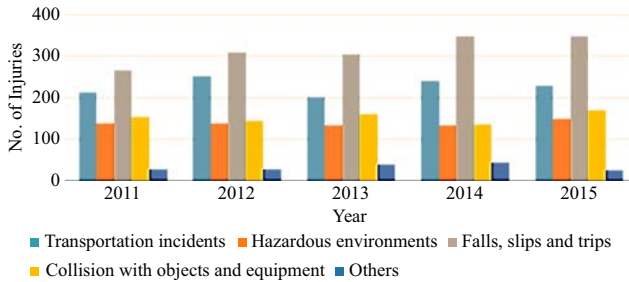
1. Introduction

International occupational health and safety statistics show that the construction industry experiences one of the highest accident rates among all industries (Stats.bls.gov., 2017). According to the National Census of Fatal Occupational Injuries conducted by the US Bureau of Labor Statistics in 2015, out of 4,836 fatal work injuries recorded, 19 percent were from the construction industry (Stats.bls.gov., 2017). The major reasons of fatalities were unsafe human behaviors, difficult site conditions, and workers falling from heights and striking against or being struck by moving objects. Despite numerous efforts to reduce fatalities on construction sites, such accidents continue to occur, as shown in Figure 1.

The advancements in location acquisition and mobile communication techniques based on Global System for Mobile Communications (GSM), Bluetooth, Wi-Fi and other wireless sensing

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Source: Stats.bls.gov. (2017)

Figure 1.
Fatal injuries in US
construction industry

technologies offers various opportunities to collect mobility data from construction sites for safety management (Neirotti *et al.*, 2014). With the help of Global Positioning System (GPS) equipped devices and vehicles, Radio Frequency Identification tag tracking and location-aware wireless sensors, possibilities to collect mobility data have increased significantly (Jin *et al.*, 2014). These technologies can generate huge amounts of data that contain time varying geographic positions of moving objects called trajectories (Patrourmpas and Sellis, 2017). Such trajectories captured from moving objects have unique features; they are in the form of streaming data, which means that data keeps on updating over time and includes spatial information (Patrourmpas and Sellis, 2017). Trajectories with such information are known as spatio-temporal (ST) trajectories. In recent years, it has become technically more convenient and economical to acquire ST trajectories of moving objects from a wider region in less time (Andrienko *et al.*, 2013). The analysis of such trajectories can lead to establish better understanding and knowledge discovery about moving objects (Miller and Han, 2009).

The trajectories of moving objects are continuous in nature in real-world scenarios (Šaltenis *et al.*, 2000). Because of data collection and storage devices limitations, continuous movements of moving objects are collected and stored in a discrete format, such as a sequence of GPS points having longitude, latitude and timestamp values. As the tracking time of GPS devices increases, the trajectory data in applications will gradually grow. Such huge amounts of data can sooner or later cause storage problems. Therefore, trajectory data reduction should be done before trajectory data management (Patrourmpas *et al.*, 2016). The primary aim of trajectory reduction is to decrease the computational complexity and reduce the time to query the trajectory data (Patrourmpas *et al.*, 2016). Once trajectory data are processed and reduced, they are ready to be saved in a trajectory database. Many applications managing mobility data require a semantic understanding of data as well, which is not possible to extract directly from raw GPS trajectories. This is because physical trajectories can easily be recorded using GPS devices but semantic interpretation of mobility data is still a big research challenge (Krisnadhi *et al.*, 2016). In general, a trajectory is the path that is followed by a moving object in space as a function of time (Nardini *et al.*, 2018). It is acquired as a series of location points having time stamps, denoted as follows:

$$\{\langle x_1, y_1, t_1 \rangle, \langle x_2, y_2, t_2 \rangle, \dots, \langle x_N, y_N, t_N \rangle\}.$$

Here, x_i and y_i represent x and y geographical coordinates at time t_i , N is the total number of points in the trajectory data, and it is usually followed by a sampling interval. There are many approaches to collecting trajectory data. They can be based on the change in time, location, event or various combinations of these. As trajectory data holds multi-faceted characteristics, these are used to analyze and understand mobility (Zheng *et al.*, 2017). Mobility-related characteristics include time (i.e. position of object mobility on the timescale),

position of the object in the geographical coordinate system, direction of the object, speed of the object, change in direction, acceleration (i.e. change in speed) and distance traveled. These characteristics can directly be computed from raw trajectories and are well-suited for applications that perform localization of objects in motion. However, most decision making applications require additional information with the trajectory data from the application context.

Other than location-related characteristics of trajectories, there exists an important characteristic of mobility data: the variety of travel means by which mobility has taken place (Adey, 2017). This is of special interest in domains such as urban planning, as selection of a location and a travel mean may be interconnected. For example, to analyze trajectories of a person going from home to office in a city, it is necessary to have some information about the city and its infrastructure, such as information about shops and restaurants, etc. Such data would help to visualize the trajectories of a person going to office in more detail in terms of the point of interest locations rather than just by the geographical coordinates of the location. The process of supplementing the GPS trajectories with such additional data is known as the semantic enrichment process (Shen and Cheng, 2017). This additional data categorizing stops and moves and distinguishing different types of moves is known as annotation, which is attached to a trajectory either to some of its parts or as a whole (Yan *et al.*, 2013). An annotation value is simply an attribute value that can be “on-tram” or “on-bus,” a possible value for TransportationMeans annotation in case of the scenario of a person going to an office. An example of semantically enriched trajectory could be the following (Yan *et al.*, 2013):

(Begin, home, 8am, -) → (move, road, 8am-8:30am, walk) → (move, road, 8:30am-9am, on-tram) → (stop, office, 9am-5pm, work) → (move, road, 5pm-5:30 pm, on-tram) → (move, road, 5:30pm-6:00 pm, walk) → (End, home, 6:00 pm, -)

The above example includes generic movement characteristics (e.g. stops and moves), application- specific geographical objects (e.g. office and work) and additional behavioral context (e.g. work) (Mousavi, 2016). Once trajectories are annotated and stored in a trajectory database, it can be used to detect and analyze trends and behaviors of moving objects.

The paper is organized as follows: in Section 2, the research method is discussed and the existing applications of ST trajectories are presented. Section 3 is based on the preprocessing of raw trajectories using different algorithms for worker safety on a construction site application. Section 4 presents the discussion of the presented work and the conclusion is presented in Section 5.

2. Background

A literature review is initially done to methodically collect information to recognize and understand the problem domain. At first, a review of construction safety management literature and international occupational health and safety statistics shows that the major reasons for fatalities on construction sites are unsafe human behaviors, difficult site conditions, and workers falling from heights and striking against or being struck by moving objects (Hsiao, 2016; Stats.bls.gov., 2017). Existing research shows that these reasons can be reduced if the mobility of workers and machineries is continuously monitored on construction sites for their behaviors (Guo *et al.*, 2017). This capability of monitoring construction sites in real-time for decision support systems will lead to the development of an intelligent job site. Based on this literature, the below-mentioned competency questions have been formulated to enable intelligent monitoring of construction sites for building supervisors and H&S managers. Second, literature is also reviewed to find possible technological solutions to monitor mobility of construction workers. This examination has suggested that location acquisition systems, such as GPS, have been used widely for

real-time monitoring and tracking of workers on construction sites for hazard prevention and safety management. However, the raw data captured from the GPS device are generally available as discrete points and do not hold enough information to understand the workers' mobility. As a solution, an application to transform raw GPS data into ST trajectories using different preprocessing algorithms is proposed in order to address the competency questions that have been formulated through the literature review to reduce fatalities on construction sites.

Competency questions related mobility:

- What are the stay points of workers or machineries on a construction site?
- Which types of movements are done by the workers?
- Which and how many workers or machineries are close to other workers or machineries?
- How many workers are present in a specified area?
- What is the closest point-pair distance between two workers or machineries?

In order to answer the questions as mentioned in "Selected competency questions", the existing literature is reviewed for existing applications based on ST trajectories. However, before using ST trajectories in applications, it should be processed according to the applications' requirements. Trajectory data processing deals with the algorithms for trajectory reconstruction. For an initial preprocessing, research has been done to clean the data by removing the noise and outliers and then compressing it. Noise in trajectories is a small distortion that has the potential to affect speed, acceleration and the travel distance estimates. However, its impact can be reduced by smoothing techniques (Marketos *et al.*, 2008). Marketos *et al.* (2008) proposed an online approach to filter outliers in a trajectory data by taking the maximum allowed speed of the moving object as a reference point. In addition, Jun *et al.* (2006) proposed a modified version of Kalman filter to control the outliers in GPS data with a more effective technique. Their algorithm demonstrates superior results as compared to other data smoothing techniques, and it can be used for the real time data smoothing. There have also been many research efforts made on the data compression methods of a trajectory data. For instance, Meratnia and de By proposed an algorithm that considers both temporal and spatial parameters in order to compress trajectories (Meratnia and Deby, 2004). In their proposed technique, distance and speed thresholds have been used for data compression. Choosing proper thresholds is totally dependent on the application, and having a clear understanding of an object in motion will help in the selection of appropriate thresholds. Their proposed algorithms can be used for an offline as well as for an online data reduction. After data compression, segmentation is another important step to understand mobility data. Buchin *et al.* (2011) proposed a framework to segment a trajectory based on ST criteria. Segmentation is achieved in such a way that each generated segment is made homogenous and it should fulfill the ST criteria. These criteria include location, speed, heading, velocity, curvature and shape. Under any of these criteria or any combination of these criteria, trajectory segmentation can be achieved in an efficient and optimal way.

After preprocessing of GPS trajectories data, it can be used in variety of applications, as data acquired from GPS devices lack in semantic information for the behavior analysis of a moving object. These GPS trajectories can be further annotated using tools and techniques offered by data mining and machine learning concepts. However, this will require training data. Trajectories resulting from annotation processes have been used in various applications, such as urban indoor activity detection and wild life monitoring (Hu *et al.*, 2013; Urbano and Cagnacci, 2014). Such applications will help to understand the factors behind

the movement of moving objects, and these factors can be dependent on each other (Noël *et al.*, 2015). In Vandecasteele *et al.* (2014), a prototype was developed for a maritime surveillance system for better understanding the vessel trajectories. A major contribution of the proposed system was to offer a reliable way to model semantic trajectories as well as semantic events. Geospatial trajectories have also been enriched with domain knowledge and contextual information to construct trajectory data-ware houses in order to support business intelligence processes in any organization (Brisaboa *et al.*, 2017). These data-ware houses are used to offer context-aware services such as recommender systems or digital assistance, providing higher level of personalization to people for traveling (Li *et al.*, 2017). Once trajectories data set is processed and maintained, hidden patterns can also be extracted. Moreover, this can not only benefit the exploration of important aspects of semantic trajectories, but can also help to automate the processes of clustering the trajectories based on the stored information using machine learning techniques (Lv *et al.*, 2012). Table I presents the summary of ST applications that have been discussed above.

Application of ST trajectories for different systems is very well addressed in the existing literature as shown in Table I. However, a significant gap is found: the usage of preprocessed ST trajectories is still missing in workers' safety monitoring scenarios in the area of construction management. To address this research gap, a prototype system is proposed that processes ST trajectories based on the data processing algorithms that are selected from the existing literature to monitor workers' movements on a construction site to identify potential unsafe behaviors in order to reduce fatalities.

3. Construction workers safety monitoring application

After an extensive review of applications, it is concluded that, ST trajectories can also be used to track workers on construction sites. For this, a prototype system application is discussed to achieve the goal of visualizing trajectory data for safety management of workers (Arslan *et al.*, 2017). Building supervisor and H&S manager are the two roles that have been identified from the literature for managing construction sites (Arslan *et al.*, 2014). These roles have been taken into account for the development of a prototype system as mentioned in Figure 2. The prototype system application focuses on the following:

- (1) capturing GPS data values from construction workers' handheld devices on a construction site;
- (2) aggregating and saving the collected GPS data values on a cloud server having a centralized database management system configured;
- (3) transforming GPS data values into raw trajectories, executing data processing algorithms on a raw trajectory data to extract the movements of workers and reducing the trajectory data before storing for future analysis, once data processing tasks are completed; and
- (4) presenting trajectories visualizations to building supervisors and H&S managers for an effective construction site monitoring and ensuring safety at work.

The prototype system uses document oriented databases, such as MongoDB, for data storage and R platform for processing the GPS data. The MongoDB server is used because it provides open-source cloud based solutions, stores massive data sets efficiently and requires simple configurations with a programming platform. Whereas, the R platform is used because open source solution offers integrations with JSON based databases such as MongoDB and provides packages to support ST data for its processing and visualizations.

The prototype system can be divided into three main layers: GPS data acquisition, processing the GPS data and generation of its visualizations. The data acquisition layer

Use cases	Detecting semantic outliers from moving objects (Chakri <i>et al.</i> , 2017)	Semantic trajectory compression for representing urban movements (Richter <i>et al.</i> , 2012)	Compressing trajectory data by exploiting the semantic embedding of movement in a geographical context (Schmid <i>et al.</i> , 2009)	A geo-ontology design pattern for semantic trajectories (Hu <i>et al.</i> , 2013)	Semantic middleware for trajectories to enable annotating trajectories (Yan <i>et al.</i> , 2011)	Automated semantic trajectory annotation with indoor point-of-interest visits in urban areas (Wagner <i>et al.</i> , 2013)	Application of life trajectories for the modeling and analytics of human mobility in the urban context (Noel <i>et al.</i> , 2015)
Building indoor/outdoor Data set	Outdoor	Outdoor	Outdoor	Outdoor	Outdoor	Indoor	Outdoor
	Data set of school buses	Everyday trajectories reflecting movement between regularly visited places of four persons	Data contains geometric representation of the path contains 115 points in space-time (115 tuples of (x, y, t) . It further comprises 52 events, i.e., 52 intersections and stops along the way	An individual's trajectory data recorded by a handheld GPS receiver and an animal tracking data retrieved from the MoveBank, an online database	(1) 3 million GPS records of two Lausanne taxis, collected over 5 months (2) 2 million GPS records of 17,241 private cars tracked in Milan during one week; (3) a GPS trace of 2-hour drive of a private car in Seattle	Data from 132 mobile devices containing the trajectory id and fields of latitude, longitude, altitude, accuracy, speed, and timestamp	Data of fifty people to assess the model
Findings	Extracted semantic trajectories to understand the	Proposed algorithm compresses trajectory data with a higher compression	STC algorithm achieves a high compression rate. Instead of the 115	Proposed design pattern is used to semantically annotate trajectory data of navigation and wildlife monitoring	A framework is proposed to support semantic enrichment of trajectories exploiting both the geometric properties of the stream and the	Proposed an algorithm for the automated detection of visited	Proposed model allows a better understanding the reasons why and

(continued)

Table I. Applications of ST trajectories

Table I.

unusual behaviors	rate (89.53%) and drastically reduces the amount of data to be stored	original points, it ends up with only 6 items, which corresponds to a compression rate of 94.78%	background geographic and application data	points-of-interest. It extracts the actual visited points-of-interest well in terms of precision for the challenging urban indoor activity detection	circumstances in which people are moving, whether they depend on external or internal factors	
Key components/ technologies	Weka-STPM toolkit	GPS	Web Ontology Language (OWL)	Java 6 platform, PostgreSQL 8.4 with spatial extension PostGIS 1.5.1	PhoneGap platform	
Use cases	Maritime surveillance system based on semantic events (Vandecasteele <i>et al.</i> , 2014)	Semantic trajectories in Mobile Workforce Management (MWM) applications (Brisaboa <i>et al.</i> , 2017)	Personalized Route Guidance System (PaRE) to provide higher-quality navigation directions (Li <i>et al.</i> , 2017)	Efficient frequent sequence mining on taxi trip records using road network shortcuts (Zhang, 2014)	Extraction of hidden shared structure among human trajectories (Chen <i>et al.</i> , 2013)	Discovering semantic trajectory data model to define important aspects of semantic trajectories (Lv <i>et al.</i> , 2012)
Building indoor/ outdoor	Outdoor and indoor	Outdoor	Outdoor	Outdoor	Outdoor	
Data set	More than one million vessels positions with attributes such as the unique	A trajectory data set of people traveling by car in Milan	Real trajectory data set from Planet.gpx, which contains the GPS traces uploaded by	17,558 taxi trip records in New York City over a month's period	A data set of trajectories of tourists moving in Rome to visit participants	

(continued)

identification number of the vessel, the position, speed and rate of turn	mobile device and the GIS	(Italy), during one week. The data set contains track of 16,946 cars and 48,906 trajectories for a total of 1,806,293 points	OpenStreetMap users within 7.5 years	China over a month's period	the main city attractions	for nearly two months
Findings	A prototype is developed to allow the maritime operator to better understand changes in the velocity of a vessel by analyzing semantic trajectories and semantic events	Supporting business processes by collecting the information captured by the sensors of the mobile devices and analyzing and annotating the trajectory high-level activities using context information	Proposed system can reduce the number of navigation directions by more than 60% while still providing enough information for user to follow the route	"Pathlet Dictionary" is introduced to represent spatial regularities in a trajectory data set and presented an effective algorithm to learn pathlet dictionaries from large collections of trajectories	More semantics are added to raw trajectory data for real applications such as; tourism and animal behavior	Hierarchical clustering algorithm is proposed to extract visit points from the GPS trajectories, and then these visit points can be clustered to form physical places
Key components/ technologies	Triple store, Semantic Web Rules Language (SWRL), ST Inference engine	MWM system, OpenStreetMap and Android mobile devices	OpenStreetMap and Java platform			
						Spatial databases (PostgreSQL, PostGIS) and ArcGIS

Table I.

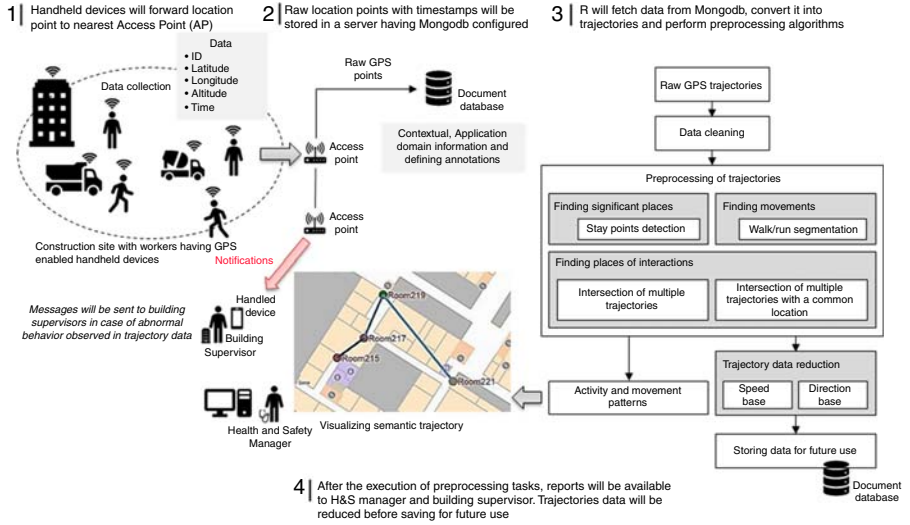


Figure 2. Preprocessing ST trajectories for safety management on construction sites

consists of smartphones that send GPS data of workers at a defined interval. A single GPS data record consists of a worker identification (ID), timestamp, altitude, latitude and longitude values. An application programming interface is designed to acquire GPS data from the workers' smart phone through wireless access points, aggregating and then storing it in a MongoDB server that is configured on a cloud. A data connection is established between a MongoDB and R studio to process the trajectories data. Mentioned below are the tasks that R studio will execute after retrieving data from a MongoDB server.

3.1 Data cleaning

Data cleaning is the first step that R will perform on data retrieved from a MongoDB. Real-life trajectories captured from GPS devices usually suffer from noise, and to improve data quality, noise should be reduced. There can be various reasons for having noisy GPS trajectories; however, sampling and measurement maladjustments, sensor battery outages and signal losses are some of them (Zheng *et al.*, 2009). For noise reduction, there exist mean and median filters, which are the most simplified forms of filters for smoothing GPS data. For this research, a median filter is used because of its robustness characteristic; whereas, a mean filter is not recommended because it is highly sensitive to outliers (Zheng *et al.*, 2009). In a median filter, for a measured point z_i , the estimate of the unknown value is the median of z_i and its $n-1$ predecessors in time. The median filter is based on the sliding window mechanism covering n temporally adjacent values of z_i as shown in the following equation:

$$\hat{x}_i = \text{median}\{z_{i-n+1}, z_{i-n+2}, z_{i-n+3}, \dots, z_{i-1}, z_i\}.$$

A median filter for our data cleaning is also chosen because of the high sampling rate of our GPS data, which makes a median filter a good option. Though, if the sampling rate of GPS data is too low, then a median filter is not recommended and advanced filters such as the Kalman filter can be considered for noise reduction. Figure 3 shows the actual and the filtered trajectory of a worker.

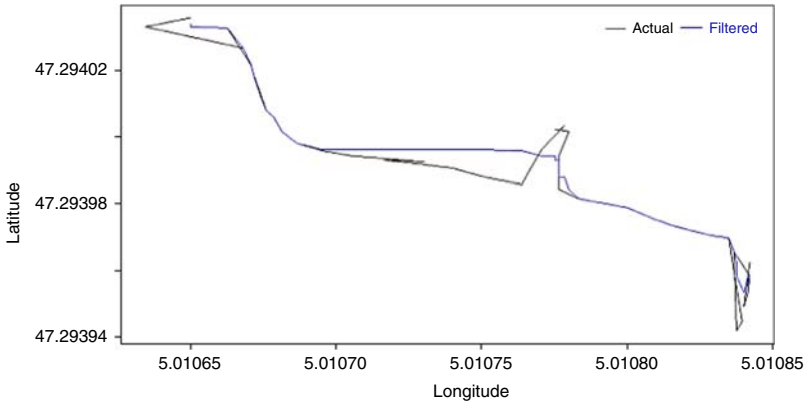


Figure 3.
Actual and filtered
trajectory of a worker

3.2 Stay points detection

After cleaning the GPS trajectories, our data processing algorithms in the R environment will calculate the stay points of workers using Algorithm 1. Stay points are the geographic location points where an individual has spent a significant time within a certain distance. The calculation of stay points depends on two parameters: the distance threshold (D_{thresh}) and the time threshold (T_{thresh}). The values of both these parameters are application dependent and set manually in an algorithm. Zheng *et al.* (2009) proposed an algorithm for finding stay points in trajectories. A single stay point s can be treated as a virtual location point characterized by a set of successive GPS points $Z = \{z_m, z_{m+1}, z_{m+2}, \dots, z_n\}$, $\forall m < i \leq n$, $\text{Distance}(z_m, z_i) \leq D_{thresh}$ and $|z_n.T - z_m.T| \geq T_{thresh}$. Formally, conditioned by Z , D_{thresh} and T_{thresh} a stay point $s = (\text{Latitude}, \text{Longitude}, \text{arrivaltime}, \text{leavingtime})$, where:

$$s.\text{latitude} = \sum_{i=m}^n \frac{z_i.\text{Latitude}}{|Z|},$$

$$s.\text{longitude} = \sum_{i=m}^n \frac{z_i.\text{Longitude}}{|Z|}.$$

For our application, we need to find the locations on a construction site where workers have spent more time than required. Calculating such stay points will help building supervisors and H&S manager to monitor their level of mobility and safety plans that can be implemented accordingly (see Figure 4):

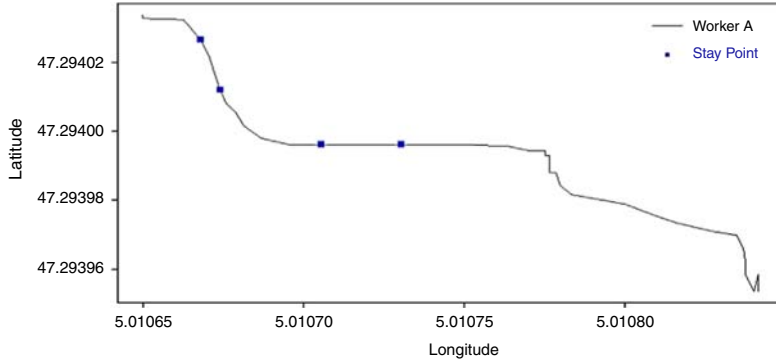
Algorithm 1. Stay Points Detection

Input: GPS Trajectory(G) $\leftarrow \{G_{lab}, G_{low}, G_i\}$, Distance Threshold (D_{thresh}), Time Threshold (T_{thresh})

Output: Stay points (S) $\leftarrow \{S_{lab}, S_{arrv}, S_{leav}\}$

1. $i \leftarrow 0$, Total number of GPS points (G_{num}) = $|G|$
2. While ($i < G_{num}$)
3. {
4. $j \leftarrow i+1$
5. While ($j < G_{num}$)
6. {
7. Distance $\leftarrow \text{distHaversine}(\{G_{lon}[j], G_{lat}[j]\}, \{G_{lon}[i], G_{lat}[i]\})$
8. If (Distance $> D_{thresh}$)

Figure 4.
Stay points detection
in a worker's
trajectory



```

9.      {
10.     deltaT ← Gt[i+1] - Gt[i]
11.     If (deltaT ≥ Tthresh)
12.     {
13.       Mlon ← mean (Glon[i], Glon[i+1])
14.       Mlat ← mean (Glat[i], Glat[i+1])
15.       Sarrv ← Gt[i]
16.       Sleav ← Gt[i+1]
17.     }
18.     i = j; break;
19.   }
20.   j ← j+1
21. }
22. }

```

For an average latitude and longitude of the collection Z , $s_{arrivaltime} = z_m \cdot T$ and $s_{leavingtime} = z_n \cdot T$ represent a worker's arrival and leaving times on a stay point (s). Algorithm 1 first checks if the distance between a point under consideration and its successors in a trajectory is larger than a specified threshold. Then it calculates the time interval between a point and the last successor that is within the distance threshold. If the time span is larger than a given threshold, a stay point will be detected in a trajectory. For our application, we have set D_{thresh} to 5 meters and T_{thresh} to 20 meters for stay point detection. There are four stay points detected in a worker A's trajectory as shown in Figure 4. However, the number of stay points can be increased or decreased as it is totally dependent on the values of the distance threshold (D_{thresh}) and the time threshold (T_{thresh}).

3.3 Segmentation of a trajectory

For our application, we need to segment trajectories for finding the types of movements that are being made by the workers on a construction site. Segmentation is the process of dividing a trajectory into various segments to reduce the computational complexity but increase the opportunities to mine richer knowledge (Zheng, 2015). Segmentation can be done based on: time interval, shape of a trajectory and semantic meaning of location points in a trajectory (Zheng, 2015; Potamias *et al.*, 2006)—since construction sites are very dynamic in nature and it is very important to monitor the type of movements a worker makes on a site. Quick movements in the workers' trajectory data will alert the building supervisors and H&S manager highlighting abnormal situation occurring on a construction site.

Based on our application requirement, we have used a segmentation method that is based on semantics. Zheng *et al.* (2008) proposed a walk-based segmentation method. Their proposed algorithm calculates walk points and run points based on the point's speed and acceleration as shown in Algorithm 2. The trajectory can then be divided into alternate walk and run segments as shown in Figure 5:

Algorithm 2. Trajectory data segmentation based on speed

Input: GPS Trajectory(G) $\leftarrow\{G_{lat}, G_{lon}, G_t\}$, Minimum Speed (S_{min}), Maximum Speed (S_{max})

Output: Run Segment(R) $\leftarrow\{R_{lat}, R_{lon}, R_t\}$, Walk Segment(W) $\leftarrow\{W_{lat}, W_{lon}, W_t\}$

1. $i \leftarrow 0$, Total number of GPS points (G_{num}) $\leftarrow |G|$
2. While ($i < G_{num}$)
3. {
4. Distance $\leftarrow \text{distHaversine}(\{G_{lon}[j], G_{lat}[j]\}, \{G_{lon}[i], G_{lat}[i]\})$
5. DeltaT $\leftarrow \text{Append}((G_t[j] - G_t[i]) * 60)$
6. Speed $\leftarrow \text{Append}(\text{Speed}, \text{Distance}[i] / \text{DeltaT}[i])$
7. If ($(\text{Speed}[i] \geq S_{min}) \ \& \ (\text{Speed}[i] \leq S_{max})$)
8. {
9. $W_{lon} \leftarrow \text{Append}(W_{lon}, G_{lon}[j])$
10. $W_{lat} \leftarrow \text{Append}(W_{lat}, G_{lat}[j])$
11. $W_t \leftarrow \text{Append}(W_t, G_t[j])$
12. }
13. Else
14. {
15. $R_{lon} \leftarrow \text{Append}(R_{lon}, G_{lon}[j])$
16. $R_{lat} \leftarrow \text{Append}(R_{lat}, G_{lat}[j])$
17. $R_t \leftarrow \text{Append}(R_t, G_t[j])$
18. }
19. $z \leftarrow z + 1$
20. $i \leftarrow j$
21. $j \leftarrow j + 1$
22. }

4. Intersection of two trajectories or intersection between trajectories and a location

It is important for our application to calculate the worker movements that have been made collectively. Such understanding will depict how many workers are working on a same

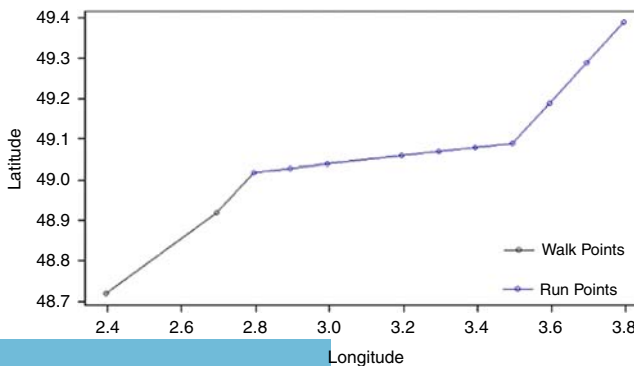


Figure 5. Segmentation of a worker's trajectory based on speed

activity and how many will be affected by the occurrence of any safety hazard in that particular location. As trajectories are traces in the form of chronologically ordered points, the distance from one worker's trajectory to another worker's trajectory or the distance between workers' trajectories and a common location can be found using the Haversine distance formula as mentioned below:

$$d = 2r \sin^{-1} \left(\sqrt{\sin^2 \frac{\theta_i - \theta_j}{2} + \cos \theta_i \cos \theta_j \sin^2 \frac{\varphi_i - \varphi_j}{2}} \right),$$

where r is the radius of the Earth, and θ and φ are the latitudes and longitudes of points i and j , respectively. This formula is used to find points of intersection in trajectories to visualize the assembly points within the area of interest as shown in Figures 6 and 7.

In addition, there can be some situations on construction sites where there is a need to find the closest point between the trajectories of two workers. For these scenarios also, the Haversine distance formula can be used, as shown in Figure 8.

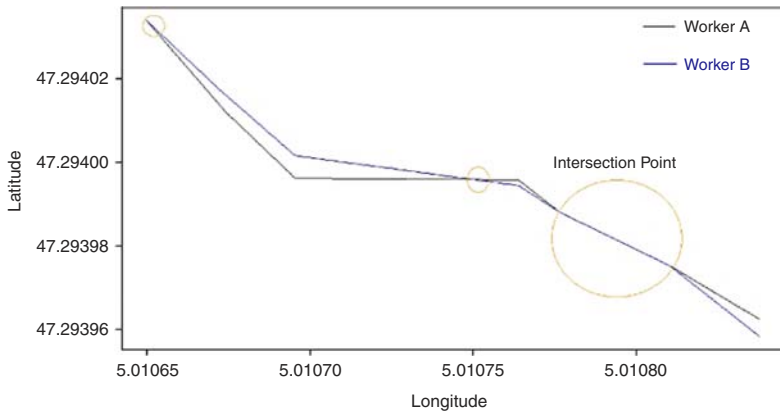


Figure 6.
Points of intersection
of two trajectories

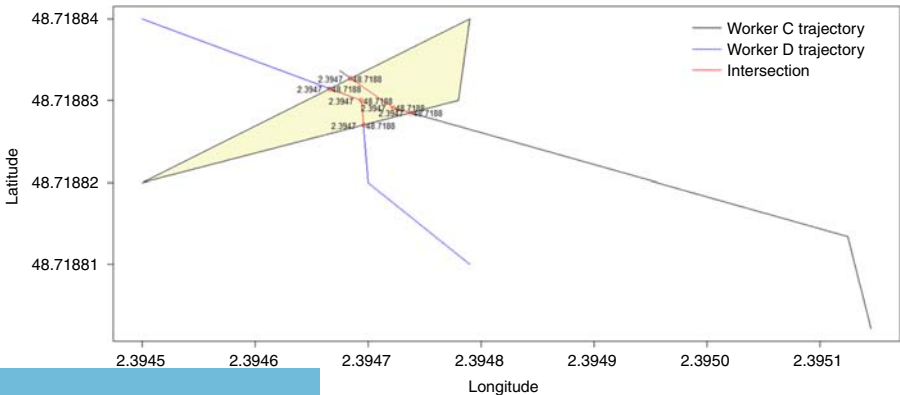


Figure 7.
Points of intersection
of two trajectories
in a location

4.1 Trajectory data reduction

Once data processing of trajectories is complete, it is now required to store these trajectories in a database for future use and analysis. Before storing, this data should be reduced in size. Potamias *et al.* discussed that a location point should be incorporated in a trajectory as long as it shows any change in the trajectory path (Zheng *et al.*, 2008). As long as the location of an incoming GPS point can be predicted from previous points, this location point can be discarded safely as it will provide very little information. Batched compression and online data reduction are two methods to reduce the size of a trajectory (Zheng, 2015). Batch compression algorithms produce higher quality results when compared to online compression algorithms. For our application, we have used a batched compression technique, as our data has already been captured for a specific duration, and its volume is kept limited for a deeper understanding. The most common form of batch compression algorithm for data with higher sampling rate is the uniform sampling algorithm, which is based on an on-line generalization mechanism. The main idea behind line-generalization is to retain a fraction of the spatiotemporal data in the original trajectory without taking into account the redundancy of data points (Zheng, 2015; Potamias *et al.*, 2006). It keeps every i th data point (3rd, 6th, 9th, etc.) and discards the remaining points. As a result, in the future, reduced trajectories can be reconstructed that will be an approximation of an original trajectories with a coarser granularity. Figures 9 and 10 show the actual and reduced versions of a trajectory using a uniform sampling algorithm.

In addition to the line-generalization reduction approach, changes in speed and direction can also be used to decide whether a particular trajectory point should be included in a reduced trajectory or not (Zheng, 2015). For our case, the threshold-guided sampling approach is used, which has been proposed by Potamias *et al.* (Potamias *et al.*, 2006). A safe zone is created based on the speed threshold, which is an allowable level of change in the speed of a worker. If the incoming location point resides within the safe zone that is created by computing previous trajectory point's speed and a speed threshold under consideration, then it means that this particular point will not be providing much information in a trajectory and hence can be discarded without compromising the accuracy of information in the trajectory data. The same approach has been used to form a safe zone for a change in a direction scenario (see Figure 10). By changing the speed or a direction angle, more points will be deleted or added in a trajectory data.

Here, the purpose of the reduction is only to remove the redundant or insignificant points from the original trajectory because storing larger trajectory data is problematic, as it can quickly overwhelm the available data storage capacity. However, discarding

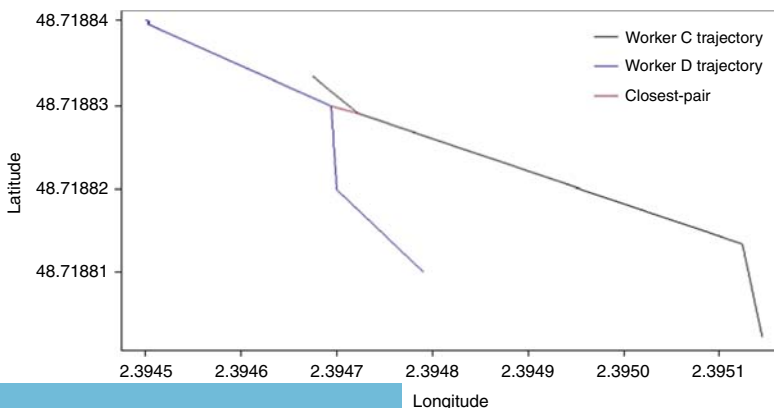


Figure 8.
Calculating a closest
point between
two trajectories

Figure 9.
Actual and reduced
worker trajectory

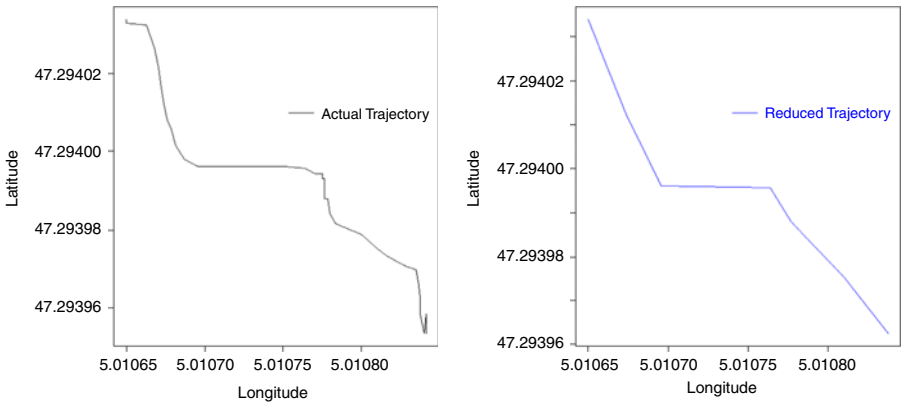
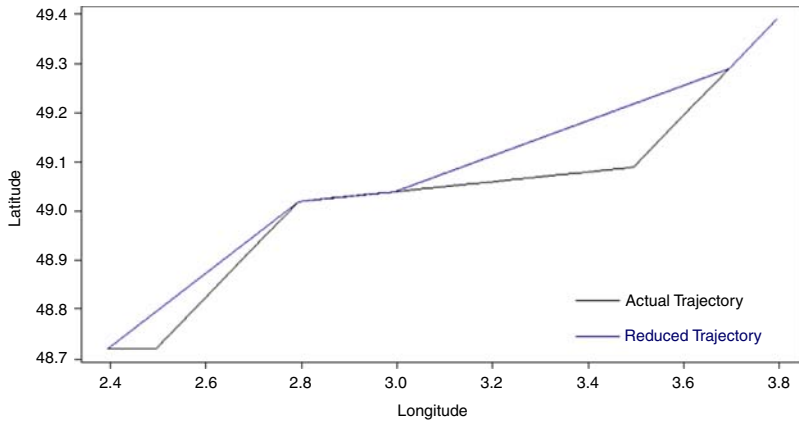


Figure 10.
Reduction based on a
speed 0–3.5 meter
per second



trajectory points randomly, uniformly or based on any criteria (as mentioned above) would cause information loss. Thus, for safety-related critical applications, advanced trajectory reduction techniques (Muckell *et al.*, 2011; Muckell *et al.*, 2014) should be used, which will reduce the storage requirements while maintaining an acceptable degree of error in the reduced trajectory data. In addition, this error threshold is totally dependent on the type of application in order to balance the tradeoff between storage size and accuracy of trajectories.

5. Discussion

The application based on ST trajectories as discussed in Section 3 consists of different data processing algorithms that attempt to contribute to improving the workers' safety on construction sites. The system application utilizes GPS data from the construction site to understand mobilities of workers as well as machineries in order to analyze potential safety hazards on construction sites. The prototype system visualizations address the competency questions as shown in Table II. This derived safety information will assist building supervisors and H&S managers in monitoring, controlling and implementing evacuation plans efficiently. Each algorithm opens up a possibility to understand and explore different types of mobility that occur on the sites more deeply. This information can then be shared

Competency questions related mobility	Derived safety information from a proposed system's visualizations
What are the stay points of workers or machineries on a construction site?	Calculating the stay points as shown in Figure 4 will indicate the occurrence of an unexpected situation on a site if the duration of stay is greater or less than the required
Which type of movements are done by the workers?	Segmenting the trajectories into walk and run points in a given time duration as shown in Figure 5 will indicate the occurrence of unexpected situation on a construction site
Which and how many workers or machineries are close to other workers or machineries?	It will help to visualize that how many workers and which machineries are engaged for a certain project activity so that safety plans can be made accordingly (shown in Figure 6)
How many workers are present in a specified area?	Parallel movements of workers in a specified location as shown in Figure 7 will indicate that how many workers will be affected on the occurrence of any safety hazard in that particular location
What is the closest point-pair distance between two workers or machineries?	Hazardous situations that occur on construction sites can be due to an excessive proximity between different workers, between a worker and an equipment or a dangerous material on site, as workers often carry out their work in a dynamic and complex manner. Calculating closed-pair distances as shown in Figure 8 will help to visualize the worker's level of protection from the dangerous material or machinery as well as it shows the risk of injuring other workers with the equipment used in the activity

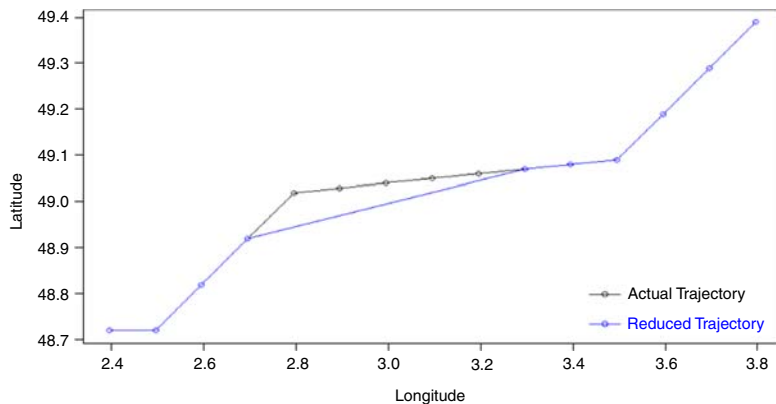
Table II.
Prototype system
addressing the
selected competency
questions

among various construction project stakeholders to improve existing work practices and to ensure safe construction operations, hence reducing the occurrences of fatal accidents.

However, there are some limitations of the discussed system application, as mentioned below:

- (1) The location data used for the proof of concept system application is not real-time data. Formerly collected Comma Separated Values files of a GPS device are used to understand mobility by processing raw trajectories. In addition, batch pre-processing algorithms have been implemented as discussed in Section 3 to understand the trajectories occurring on a site. However, batch or offline data processing methods are only recommended when we have to visualize behavior patterns from the existing data. But for the applications where the mobility data of people and objects are continuously updating and dynamic correlations between various trajectories are needed to be found, trajectories should be processed in real time. Real time trajectory processing solutions have the ability to process raw trajectory data within a controlled time window and generate processed trajectories in an online mode. In online processing, as soon as data is received, trajectory basic features such as speed, direction, and displacement, etc. are calculated (Zheng, 2015). Consequently, data filtering, smoothing and reduction techniques are applied before generating trajectory visualizations.
- (2) GPS technology is discussed to acquire workers' location data from a construction site. However, this technology is recommended only in an outdoor environment. Whereas, construction sites are composed of an outdoor as well as an indoor environment. Using GPS devices inside the building will introduce large measurement errors in trajectories because of interference effects. This impact will result in partial to total loss of signal tracking to capture workers' mobility. Therefore, the accuracy of the GPS device becomes questionable for critical aspects such as H&S management. Hence, it is important to consider using an alternative technology to collect indoor positioning data (Figure 11).

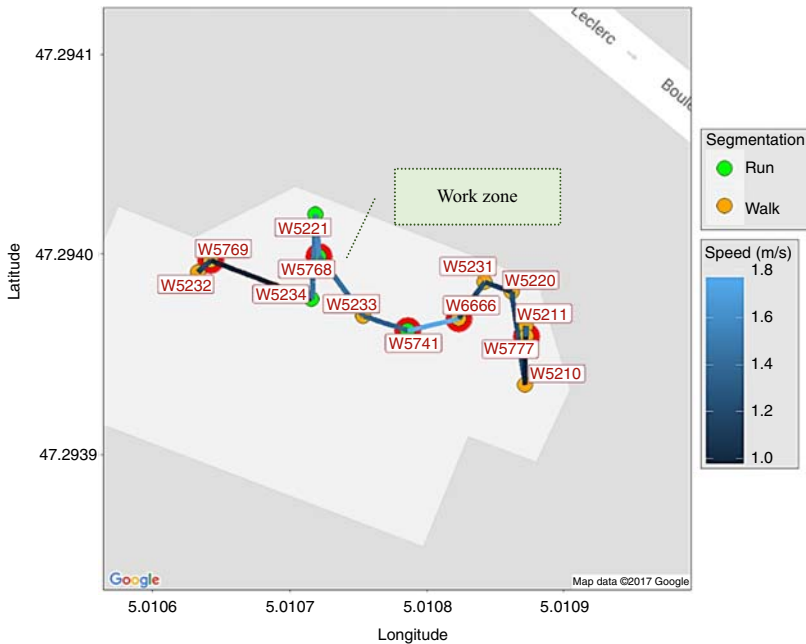
Figure 11.
Reduction based
on a direction
angle 10° – 20°



- (3) As the scope of the paper is limited to only preprocessing the ST trajectories, the generated visualizations are still incomplete to give a complete picture of mobility patterns of workers to building supervisors and H&S manager for decision making as contextual information and application domain knowledge are not incorporated. Other technologies such as Building Information Modeling can be used for visualizing the trajectories since it has been described as one of the most promising developments in the area of safety management (Cruz and Nicolle, 2006; Cruz, 2017). Another possible way to improve understanding of the generated visualizations is to enrich them with semantic information acquired from external data sources both private data such as construction site information describing the work zones and public data such as OpenStreetMap and Google Maps. For this, existing semantic enrichment techniques (Yan *et al.*, 2011) can be explored to construct semantically enriched trajectories which are: enrichment with semantic points that maps site location identification to pre-processed trajectory points; enrichment with semantic lines that rely on the speed-based segmentation approach (as discussed in Section 3) infers modes of transportation used in trajectory's episodes; and enrichment with a semantic region for mapping a complete trajectory on an actual construction site zone. Semantically enriched trajectories (see Figure 12 as an example) will provide an intuitive and readily understandable pre-processed visualization that will help H&S managers in making improved decisions for monitoring and controlling site activities by understanding workers' behaviors that ultimately attempts to contribute to reducing fatal accidents occurring on construction sites each year.

6. Conclusion

In this paper, we have presented the importance of preprocessing ST trajectories captured from construction sites. Once trajectory data is preprocessed correctly, it can be used in variety of applications for construction safety monitoring and management. A significant gap has been found in the literature, which is that the usage of preprocessed ST trajectory data is still missing in workers' safety monitoring scenarios in the area of construction management. To address this research gap, our paper has discussed a system application that uses preprocessed ST trajectories to monitor workers' movements on a construction site. GPS data acquired from workers' handheld devices has been used and it has then been processed using various algorithms aims to provide effective visualizations to building supervisors and H&S manager. However, our proposed application is in the development stage, lacking contextual and semantic information in the visualizations generated. Considering the preprocessing the



Notes: Visualizing a complete workers’ trajectory with semantic stay points in red colored circles (site identifications for, e.g. W5768 for a workzone), semantic lines (segmentation into run and walk points) and a semantic region

Figure 12.
Semantically
enriched trajectory

very first step to prepare the ST trajectories for semantic enrichment, making this processed data a base that can lead to improved understanding of mobility of workers on construction sites. In addition, using appropriate data and pattern mining algorithms and techniques on a processed trajectory data will help discover interesting patterns and rules and to extract unknown and nontrivial behaviors for decision-making processes.

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