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The Architecture of an Intelligent Digital Twin for a Cyber-Physical Route-Finding System in Smart Cities

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Abstract: Within an intelligent automated cyber-physical system, the realization of the autonomous mechanism for data collection, data integration, and data analysis plays a critical role in the design, development, operation, and maintenance of such a system. This construct is particularly vital for fault-tolerant route-finding systems that rely on the imprecise GPS location of the vehicles to properly operate, timely plan, and continuously produce informative feedback to the user. More essentially, the integration of digital twins with cyber-physical route-finding systems has been overlooked in intelligent transportation services with the capacity to construct the network routes solely from the locations of the operating vehicles. To address this limitation, the present study proposes a conceptual architecture that employs digital twin to autonomously maintain, update, and manage intelligent transportation systems. This virtual management simulation can improve the accuracy of time-of-arrival prediction based on auto-generated routes on which the vehicle's real-time location is mapped. To that end, first, an intelligent transportation system was developed based on two primary mechanisms: 1) an automated route finding process in which predictive data-driven models (i.e., regularized least-squares regression) can elicit the geometry and direction of the routes of the transportation network from the cloud of geotagged data points of the operating vehicles and 2) an intelligent mapping process capable of accurately locating the vehicles on the map whereby their arrival times to any point on the route can be estimated. Afterward, the digital representations of the physical entities (i.e., vehicles and routes) were simulated based on the auto-generated routes and the vehicles' locations in near-real-time. Finally, the feasibility and usability of the presented conceptual framework were evaluated through the comparison between the primary characteristics of the physical entities with their digital representations. The proposed architecture can be used by the vehicle-tracking applications dependent on geotagged data for digital mapping and location tracking of vehicles under a systematic comparison and simulation cyber-physical system.

Keywords: Autonomous Route Finding, Digital Twin, Smart Cities, Intelligent Cyber-Physical Systems, Regularized Least-Squares Regression

1. INTRODUCTION

The infrastructure of a smart city is founded upon a network of sensors and actuators embedded across the urban area, interacting with a multitude of wireless mobile devices (e.g., smartphones) under a responsive cloud-based network architecture [1]. Such a system requires an integrated cyber-physical infrastructure with various software platforms for securely processing massive amounts of information. Major physical infrastructures in cities, such as transportation systems, are part of a spatial-temporal, large-scale connected system that bridges humans and technology through numerous sensors [2]. Yet conventional transportation systems have not achieved full coordination and optimization due to a lack of widespread interconnection, intercommunication, and interoperability [2]. In this regard, recent advancements in information technologies, such as the Internet of Things (IoT), cloud computing, and Cyber-Physical Systems (CPS), have provided the opportunity to address emerging challenges that arise in urban traffic systems. Accordingly, various monitoring devices and sensors can be installed on roads and vehicles to largely collect and timely process traffic information so as to provide real-time status models of vehicles [3]. Particularly, cyber-physical systems with their integrated computational and physical components can be leveraged to collect such big data, elucidate latent patterns from the data, and generate information-rich feedbacks to the users, effectively and efficiently. In the context of CPS, a digital twin of the system can address the challenges pertaining to poor data management and low prediction accuracy of the system. In this regard, a digital twin is distinguished from other simulation approaches in that it can synchronize digital constructs based on real assets, actively record data from the real environment, and sufficiently simulate real-world mechanisms and operations [4]. Given these qualities, integrating the intelligent digital twin with cyber-physical route-finding systems can provide the means for better system management and lead to a robust realization of autonomous mechanisms within transportation systems.

Most of the transportation systems, particularly in the United States, benefit from easy and free accessibility to real-time Global Positioning System (GPS) data of public vehicles [5]. The embedded GPS devices in these "physical systems" send the location of the vehicles to a cloud server, which later can be publicly accessed through simple text-based queries, such as JSON. The retrieved data can be analyzed quickly using ubiquitous smartphones equipped with high-computing power and miniaturized high-density sensors [5]. Considering these capabilities, GPS data is widely utilized to estimate the arrival time of public vehicles, especially public buses [6–8]. However, these GPS-based systems are prone to several errors, such as location update delay or non-accurate location data. Notably, it would be challenging to estimate bus arrival time accurately due to traffic, dwell time at the bus stations and intersections, and unpredictable events, such as accidents or roadwork. On the other hand, not all the route information retrieved from public servers is accurate and up to date. In other words, although the server can provide various bus routes to the user, in most cases, the polygons representing these routes do not reflect their latest changes nor their correct directions. The accessibility to the precise geometries and directions of these routes is of utmost importance as most of the bus-arrival algorithms depend on the correct location and sequence of the constructing points [9].

As a response to this challenge, this study attempts to develop a digital twin of a transportation system by proposing an intelligent cyber-physical route-finding conceptual framework capable of automatically construct and evaluate routes with accurate direction and geometry and continuously estimate the arrival time of the buses on those routes. The cyber-physical part of this framework is built upon two chief constructs, an automated route-finding process by which the polygon representing the route can be accurately inferred and a bus-arrival time estimation system that can intelligently monitor all the operating vehicles on a specific route and provide the user with a relatively accurate arrival time of the next closest vehicle on that route. Such a system obtains real-time GPS data from an online server and stores them on a workstation. Once a sufficient number of points are collected for each route, the system uses a least-square regression algorithm [10,11] to approximate the polygon representing the route. Afterward, it leverages the Google Map matching Application Programming Interface (API), in real-time, to correct and verify the resultant route. This procedure ensures that the bus follows the logical path and has not left the route for a certain reason (e.g., gas filling). Finally, the retrieved route is discretized to small pieces upon which the location of the vehicle can be mapped, and the bus-arrival algorithm can be built. These automated route-construction and vehicle-mapping procedures will then be used to simulate and manage the physical entities of the systems. By implementing the proposed approach on an Android smartphone, a workstation, and a cloud server, the digital twins of the vehicles and the buses were constructed. Specific characteristics of these digital representations were compared with those obtained from their real-world entities to evaluate the performance of the cyber-physical system. The findings of this study can pave the way to establish a more efficient transportation system to improve the daily experience of city dwellers. The remainder of this paper is organized as follows. Section 2 introduces the background and motivation of this study. Section 3 outlines the overall architecture of the proposed approach. Section 4 elaborates on the results of the framework implementation. Finally, Section 5 presents the discussion and conclusion.

2. RESEARCH BACKGROUND

There is a great potential for CPS to address one of the main challenges of the people living in big cities, robust, reliable, and convenient transportation. The integration of big data analytics and high-density sensed data enables policy-makers to accurately elicit beneficial information from the urban environments, various entities, and citizens. Cyber-physical systems are a synthesis of digital content and cyber methods with physical processes in which embedded computers control the physical processes using feedback loops, and physical processes affect computations [12]. One application of CPS in the transportation area is to transmit the information of physical transportation objects to the cyber system to achieve information communication, system coordination, and optimal decision-making control of the transportation system through the interaction and feedback between the physical and cyber systems [2]. In this regard, the digital twin of a system can be regarded as a virtual representation of a physical asset in a CPS, capable of reflecting its static and dynamic characteristics [4]. Essentially, a digital twin of an asset must inherit all the functionalities that the asset is able to perform in the real world. An intelligent digital twin, therefore, can potentially implement different machine learning algorithms on available models and data to optimize a variety of operations in a transportation system.

The integration of GPS traces and smartphone applications for transit tracking systems has been among the new emerging real-time tracking technologies in the past few years [13–15]. The extensive research in the transit tracking systems and supporting applications is due to the availability of the all-embracing, ubiquitous smartphones, affordable and accurate GPS, fast internet speeds, and optimized smartphones' operating systems, such as the latest versions of Android and IOS. Interestingly, not only smartphones provide the users with adequate computational power for running these types of tracking-based applications, but the availability of powerful and well-known APIs such as Google map API enhances the accuracy and usability of such systems as well. Generally, the architects of such systems rely on three key components, namely Automatic Vehicle Locator (AVL), online server, and smartphone devices [13]. Although the exhibition of real-time vehicle's positions on digital maps, based on their AVL GPS data, is exceptionally informative to the users and works well with the current technologies, the accurate estimation of the vehicle's arrival time would be hard to accomplish. The main obstacles to correctly estimating bus arrival time are the fluctuation of delay times at intersections, dwell time at stops, and travel speed of the operating vehicles. To overcome these barriers, numerous studies started to implement various efficient techniques such as deep learning and neural network into the AVL transit systems [16–20].

Following the trend towards new arrival time predicting approaches, parallel to the manifestation of new transit tracking systems exploiting smartphones, researchers started to present innovative vehicle arrival time algorithms mostly concentrated on bus tracking applications [13,18,19]. In 2010, Thiagarajan et al. presented a cooperative transit tracking system that significantly lowers the commuter wait time. With the help of power-efficient and resourceful algorithms pertaining to activity classification, route matching, and underground vehicle tracking, they were able to reduce the wait time by more than 2 minutes, with only 5 percent of the riders using such a system [19]. Biagioni et al. presented smartphones as cheap AVLs, alternative to more costly GPS devices, that resulted in a cost-efficient arrival estimating application [13]. Besides, as mentioned above, with the rise of new machine learning techniques, some of these prediction algorithms have been accustomed to the machine learning models trained by collecting data from the vehicles operating on the known routes. For example, by collecting data from the bus transit system in Sao Paulo, Brazil, and subsequently utilizing machine learning techniques, Nissimoff was able to predict the bus arrival time with acceptable accuracy [18]. Similar research presented Support Vector Machines (SVM) as a feasible and applicable technique to predict bus arrival time in China. However, Bin et al. stated that the SVM approach for predicting bus arrival time works more accurately if the real-time data from traffic surveillance systems are available [16].

By considering the aforementioned techniques in predicting the bus arrival time, a significant number of studies utilized the routes of the network as a known unchanged polygon by which the location of the vehicle could be mapped correctly on the digital map [21–25]. However, in many cases, the availability of the updated route geometry information is costly and time-consuming, even though the operating vehicles' locations can be retrieved seamlessly and with short interval time. Bearing in mind these crucial caveats in designing AVL tracking-based applications, one might think of an approach that would exploit real-time GPS data of the operating vehicles on a specific route and indirectly draw the corresponding route. If drawn correctly, the information about the geometry of the route, and perhaps the direction of the path, would always be updated with minimum maintenance cost. This is a fundamental pre-processing step for these types of transit tracking systems and many other tracking-based ones. To that end, numerous studies offered map-matching algorithms that would use GPS data of the operating vehicle as input and present the geometry data of the route as an output [26–28]. In terms of accuracy, by introducing innovative approaches, some of these map-matching techniques vastly surpass others [29,30]. Lou et al. proposed a map-matching algorithm, "ST-Matching," for low-sampling-rate GPS data that outperforms other famous techniques such as Average-Frechet-Distance (AFD) [31] and incremental algorithms [27]. In their ST-Matching algorithm, the candidate points are selected based on the spatial analysis of geometric and topological information of the road network, which later will be used to "logically" match the selected points on the digital map [30]. Another critical factor in the cost-effective tracking-based applications is the information about the precise geometry and direction of the roads on which the operating vehicles are being tracked. Fortunately, there are many services that provide such a service to the users; however, they are not free for more than a specific number of quarries per day. For instance, Google presents a robust and accurate map-matching API, free of charge for a certain number of quarries per day [32]. Therefore, designing a tracking algorithm to use a smaller number of quarries would be a wise approach to achieving cost and time-effective route-updating and map-matching algorithms. To that end, the first step is the preparation of the raw cloud of data for exportation to the server. Using famous regression algorithms, it is possible to reduce the number of nominated points for exportation and, consequently, the number of quarries from the online server. By implementing map-matching techniques into a transit tracking system, the current study endeavors to (1) provide accurate routes' geometry and direction to the users' tracking applications, and (2) use a new simple arrival time algorithm that optimizes the time and data consumption for monitoring and subsequently predicting the arrival times of the buses.

3. METHODOLOGY

3.1. Cyber-physical transportation system

The first step towards generating the automated cyber-physical transportation system is to extract the route information from raw GPS data. In order to do that, a computer needs to retrieve the GPS locations of the desired vehicles (i.e., public buses) operating in a specific area from an online server. Upon successful server responses, useful information, such as vehicles' latitude and longitude, speed, angle, identification number, and representing color, can be acquired and used for data analysis. For data analysis, the proposed algorithm must be able to perform the following tasks:

1. Create vehicle objects based on the number of active vehicles operating on the route exploits the server's JSON response.
2. Logically update the location of the vehicle objects from the server based on their distance to the target destination on the route.
3. Detect the operating hours by storing the time of the first and last vehicles operating in a day.

Once the cloud of GPS locations for each route is obtained, an appropriate analytical method must be selected to provide an approximate polygon representation of the route. To that end, the regularized least-square (with norm-2 penalty) regression algorithm is employed to determine the geometry of the route. It is worth mentioning that this step is essential in removing the GPS data collected while the bus was leaving the route (e.g., gas filling or end of operating hours). Subsequently, the filtered data points, which are passed from the regression (points within the penalty range) algorithm, would be uploaded to the Google server using Google's map matching API. The response from the Google server should contain the accurate location points with which the precise polygon representation of the route can be constructed. Notably, the proposed technique requires the least number of queries from Google's map matching API because only the "approved" location points would be sent for the map matching process.

The next step is to identify the direction of the route based on the time tags of the data points retrieved earlier from the vehicles. As each GPS data point has a time tag from the retrieval time of the vehicle location, the sequences of the "approved" points for route construction can be identified. In this vein, the final points of a specific route in the system have time tags that determine that route's direction. The last step towards an intelligent cyber-physical transportation system is to map the location of the operating vehicles on their corresponding maps by which the arrival time of the vehicle can be estimated. This mapping procedure can be accomplished by finding the points on the route within the proximity of the near-real-time location of the vehicle and selecting the closest point that complies with the direction of the vehicle. Such compliance can be examined by considering the previous locations of the vehicle that can delineate the direction of the vehicle. Figure 1 provides the overall procedures of the proposed cyber-physical system for automated bus-arrival estimation.

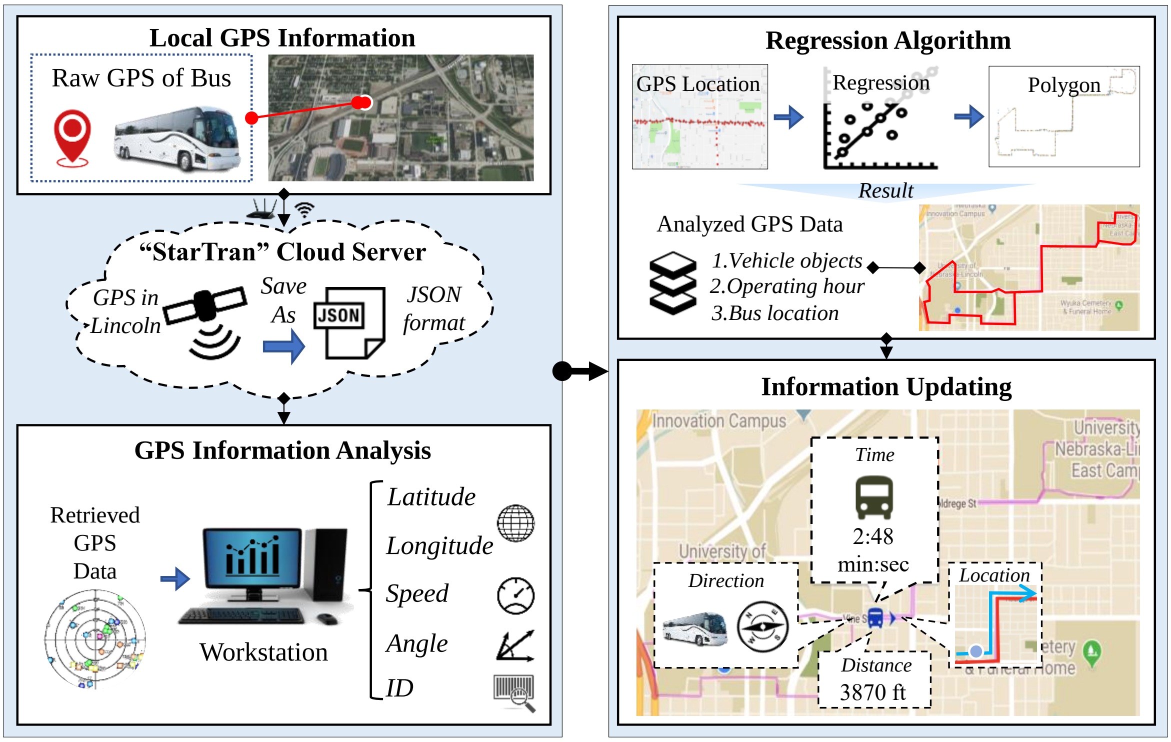

Figure 1. The overall procedure of the proposed cyber-physical route-finding system

3.2. Case Study

To evaluate the feasibility and efficiency of the proposed approach, a case study was designed based on Lincoln's public transportation system. To construct the cloud of geotagged data points, the real-time locations of the vehicles operating on route #24 of the Lincoln transit network, StarTran, have been used. The StarTran server [33] is a public server on which the near-real-time locations of the operating vehicles are available. This server is used for the presented case study. The GPS information of the buses operating in Lincoln is available through JSON queries. Accordingly, thirty-six loops of these operating vehicles have been retrieved from the server to construct a specific route. Afterward, by considering the "average" feature for these points, the "outliers" have been identified and removed from the data set. In this case, more data collection from the operating vehicles would result in more accurate route construction and outlier detection. In the next step, all the points have been connected to form a polygon that represents the route. Finally, by following the real-time mapped location of an operating vehicle on route #24, the direction of the route has been determined. The following steps specify the procedures necessary to construct a directed route from a cloud of geotagged time series data:

1. Create a polygon from the filtered points by using the least square regression algorithm.
2. Establish an accurate polygon by using the Google map matching API on the current polygon.
3. Equally, divide the accurate polygon into small lines to construct new polygon representation points.
4. Set time T to zero. Then, at each Δt_i , find the closest point p to the real-time location of the operating vehicle and add the pair $(p_i, \Delta t_i * i)$ to the polygon array list P_n in which n represents the route number.

The resultant P_n represents the route with the correct direction. After constructing the directed route, the estimation of the arrival time of the operating vehicles on route #24 would be possible. To that end, the location of the buses should be correctly mapped on the route. In this case, the direction of the route plays an essential role in choosing the final mapped location. The reason lies behind the fact that the precision of the GPS devices mounted on the operating vehicles is not accurate enough to distinguish between real locations of the buses on closed lines of the polygon representing the route. To overcome this barrier, the direction of the vehicle should be accounted for the correct mapping process (Figure 2). Accordingly, the necessary steps to correctly map the bus location on the route are as follows:

1. Find the five closest points on the route to the vehicle location, sorting them based on their distance, and finally storing them in the $old\_closest$ array
2. Wait for the new location of the vehicle from the server. Once retrieved, proceeding similar to step one but storing the points in the $new\_closest$ array instead
3. For each of the points $old\_closest[i]$ in the $old\_closest$ array, loop over the point $new\_closest[j]$ in the $new\_closest$ array.
4. If the time label of the point from the old array is less than the one in the new array, and the difference between the indices of points of the route is less than a threshold, accept the current point as the mapped point and break from the for loops.

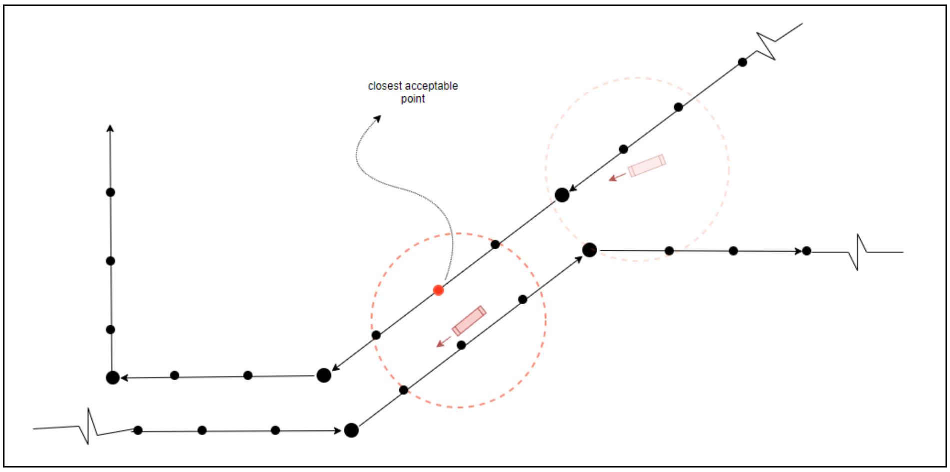

Figure 2. Schematic representation of the general idea to map the location of the bus on the constructed route

The resultant route-finding and location-mapping algorithms serve as the backbone of the automated cloud-based transportation system. This system can then be visualized, managed, and evaluated through a constant comparison between the real-world buses and routes and their digital replica. Figure 3 demonstrates the overall digital twin functionality of the proposed cyber-physical transportation system that suggests the feasibility of using such an approach to compare the results of the simulations in an attempt to manage and improve the system.

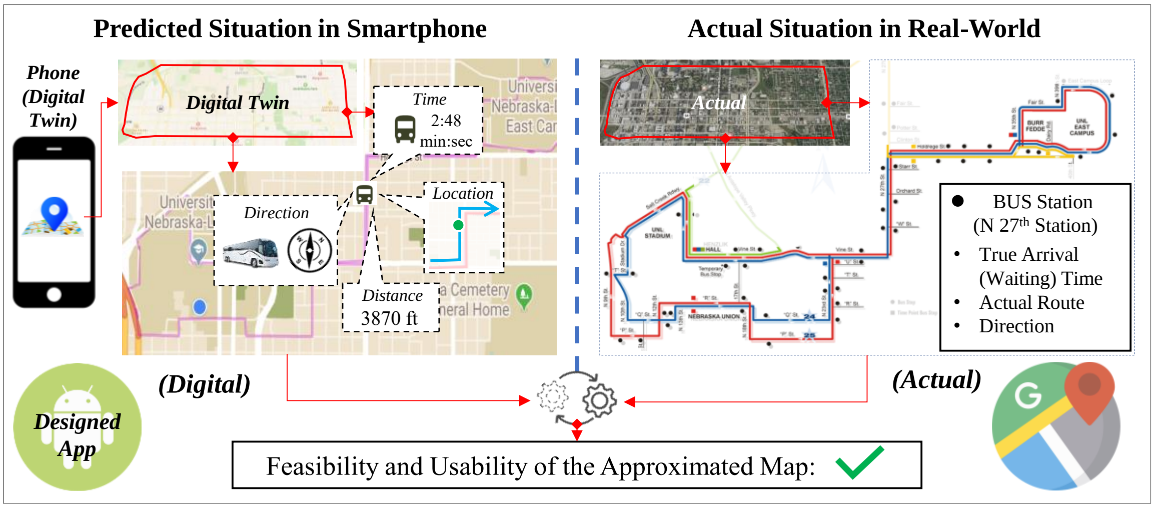

Figure 3. The comparison between the proposed cyber-physical system and the actual situation by using the digital twin concept

4. RESULTS

Figure 4 shows the approximate route constructed by using the cloud of data. The data points visualized in this figure are the raw GPS data extracted from the cloud server. As can be seen, there are some outliers (red and blue points) in this figure. Figure 5 demonstrates the resultant polygon (pink line) superimposed on the 2D map. Such a shape was derived by employing the regularized least-squares regression algorithm (with norm-2 penalty). According to the settings of this algorithm, the ill-posed GPS points were rejected, and the route was constructed in an accurate shape.

Moreover, in Figure 6, the result of the proposed algorithm (section 3) has been used to find the distance of the bus to the user's pinpointed location, and consequently, estimate the arrival time by considering an average speed for urban operating buses. As can be seen, the vehicle's location on the route can be mapped on either the left to right or right to the left route; however, the above algorithm ensures that the correct location mapping is executed in this case. The estimated arrival time can then be calculated based on a predetermined average time and the calculated distance between the mapped location of the vehicle and the destination. Not only the estimation time can help the user become aware of the arrival time of the bus, but the continuous monitoring capability ensures that the bus will not path a certain point on the map. This critical point can be better contemplated if such a system is compared with the time-of-arrival estimations that rely on time tables that are static and do not account for delays along the route on which the vehicle is operating. More importantly, because the location of the vehicle is mapped on the directed route, the inquiry about the location of the vehicle will follow a distance-based rational pattern. More specifically, the GPS information of the vehicle will not be retrieved from the server with a high refresh rate if the distance of the vehicle to the target location is larger than a threshold. This intelligent refresh rate algorithm offers an efficient, adaptive time-of-arrival that can immensely save battery and processing within smartphones.

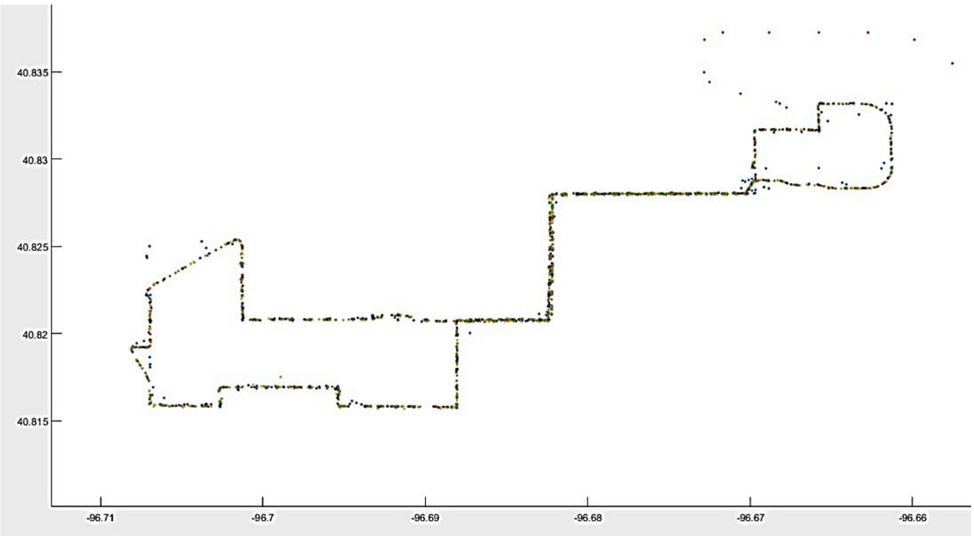

Figure 4. Results of the filtered points from the cloud of data (route #24)

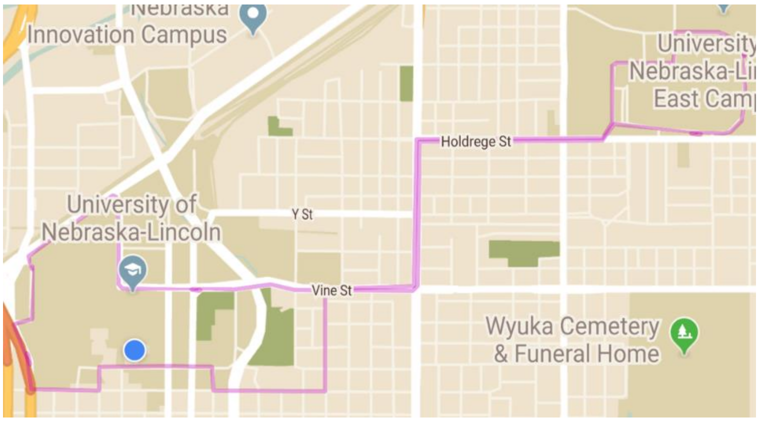

Figure 5. The final constructed directed route from the filtered cloud data.

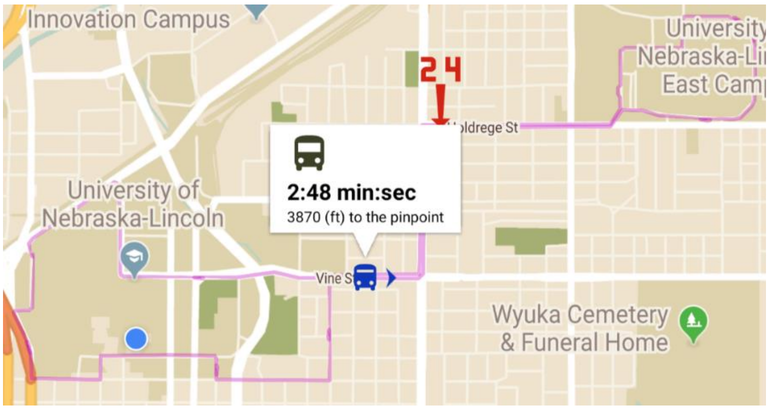

Figure 6. Estimated arrival time based on the distance of the vehicle's mapped location on route #24

5. CONCLUSION

The incorporation of Cyber-physical Systems (CPS) in a transportation network has opened new doors in the routing and scheduling of the network. In this regard, an intelligent digital twin of the network can substantially elevate different operations across the CPS, such as data collection, data integration, and data analysis. To investigate the usability of this synthesis, this study proposes a conceptual architecture to integrate intelligent digital twin and cyber-physical route-finding system to improve the route generation and arrival time estimation of the transportation system. Using an innovative route construction methodology and algorithm, the result of this study suggests that the representation of the route geometry and direction is possible purely based on the real-time location of the operating vehicles on that route. In addition, it is indicated that the proposed bus arrival estimation algorithm can help the users to rely on the estimated time more confidently as the information will be updated regularly and intelligently. While the direction of the route is essential for the correct near-real-time location mapping of the operating vehicle, the calculated distance between the current mapped location of the bus and the user's marked location is the desired value to be found. Upon successful calculation of the latter, an informative and smart vehicle monitoring application can be developed by which the user can be continuously notified about the distance of the vehicles to his/her marked location of the corresponding route. This study demonstrated the capability of intelligent cyber-physical systems to calculate such a value by merely relying on the information retrieved from the AVLs. By using an adaptive update rate that varies based on the distance of the vehicle to the user, the present study demonstrated the suitability of the proposed cyber-physical system for smartphones as the continuous monitoring of the vehicles' locations can be computationally expensive and might consume a large amount of data. This work contributes to the existing body of knowledge by proposing an innovative framework for intelligent cyber-physical route-finding systems that can be managed, simulated, and updated under well-developed digital twins of the real-world transportation asset.

This study demonstrated the capability of the digital twin as a comparison and management tool by which the performance of cyber-physical transportation systems can be evaluated and improved. This comparison can be performed at various levels of system operation, such as the accuracy of the system feedback, the characteristics of the auto-generated routes, and the estimated arrival times. While this study proposed the idea and presented an intelligent cyber-physical system to backup that idea, the future study should exploit such potentials by more accurately simulating the physical transportation entities such as the location of the user and the travel time for each user. Also, more precise estimations of arrival time can be achieved by considering the number of turns and bus stops between the user and the vehicle's mapped location. Moreover, by utilizing the time tag for the collected data points with which the route is constructed, the program can assign different speeds to different parts of the route. This can enhance the prediction of the arrival time to a great extent. Other possible enhancements would be considering the time of day, especially the rush hours, and Google's online information of the traffic on the way.

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