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Mapping Walkable Spaces Using Activity Recognition

N/A

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Introduction

The present disclosure provides systems and methods that utilize activity recognition to determine walkable user paths in areas where other geographic positioning systems such as Global Positioning System (GPS) devices are unavailable. More particularly, sensor data from a mobile computing device (e.g., a smartphone, wearable computing device, laptop, tablet computing device, or other portable user computing device) can be used to detect steps and turns taken by a user of the mobile computing device using one or more machine-learned models. The walkable space mapping system can extrapolate the distance a user has traveled and a direction of travel, which can be used to generate an approximated user path. User paths generated from a plurality of different mobile computing devices can be utilized collectively to build maps of walkable spaces.

Current mapping applications can sometimes lack accurate maps of indoor areas, temporary spaces, or other pedestrian-centric places. The present disclosure allows for mapping such spaces in near-real time using just the sensors on a user's mobile device without the need for special devices or extra hardware. This solution provides advantages because it can be local to a device, it can crowdsource sensor data to train and refine a machine-learned model, and can be very efficient due to its reliance on basic sensor data only and performing analysis once per step. The disclosed solution can be especially useful in areas where GPS is inaccessible (e.g., indoor spaces and/or remote spaces) as well as temporary spaces (e.g., pop-up markets, holiday markets, outdoor markets) and other pedestrian-centric places.

Summary

Systems and methods for mapping walkable spaces in accordance with the disclosed technology can be configured to generate user paths based on sensor data obtained by a user computing device. In some instances, a geographic position sensor such as a GPS component can provide one source of accurate coordinates and course/direction for user paths. However, when a user enters an area where they have unavailable or low accuracy GPS functionality, the disclosed techniques can be used to determine a user path approximation that can be appended to the last accurate GPS coordinates obtained by the user computing device.

More particularly, sensor data can be gathered from a plurality of sensors within a user computing device. For example, sensor data can be gathered from one or more of a GPS component (when available), a proximity sensor, an accelerometer, a gyrometer, a magnetometer, a barometer, a Hall effect sensor, and one or more other motion sensors and/or condition sensors within the user computing device. Sensor data gathered from such sensors can include GPS coordinates (when available), Attitude (Roll, Pitch, and Yaw), Rotation in X, Y, and Z dimensions, Gravity in X, Y, and Z dimensions, User Acceleration in X, Y, and Z dimensions, and Magnetic Field in X, Y, and Z dimensions.

The present disclosure can utilize activity recognition to detect steps and turns from the sensor data gathered from a user computing device to extrapolate the distance that a user has traveled. Sensor data can be pre-processed using a rolling mean algorithm to smooth the data. A peak detection algorithm can then be applied to determine when a step has taken place. A user's average step size can be calculated such that each step can be compared to the average step size to create a granular approximation of how far a person has traveled. A machine-learned course prediction model can be trained to output a course or direction traveled.

The machine-learned course prediction model can be trained using a set of training data collected from user computing device sensors while a user is walking. Labels associated with the training data can correspond to GPS data that is simultaneously gathered from the user computing device to provide accurate ground truth data describing a user trajectory. As such, the training data used to train machine-learned course prediction models described herein can be obtained when GPS data is available, such as when a user is walking outdoors. However, the trained models can then be used to determine a user's path when GPS data is unavailable. The user paths can then be utilized to build maps of walkable spaces in areas where GPS is inaccessible and identify potentially temporary pathways and spaces such as pop-up markets.

Some implementations use only mobile device sensors and associated machine-learned models as described herein. It should be appreciated that the disclosed mapping techniques using sensor-based activity recognition can be used alone or in combination with other mapping techniques such as but not limited to manual mapping, Wi-Fi triangulation, Infrared (IR) proximity sensing, and/or beacon-based solutions.

Detailed Description

Figure 1 depicts an example computing system 100 to estimate user paths using activity recognition and machine learning. The system 100 includes a user computing device 102, a machine learning computing system 130 and/or training computing system 150 that are communicatively coupled over a network 180.

More particularly, the client computing device 102 can be any type of computing device, such as, for example, a personal computing device (e.g., laptop or desktop), a mobile computing device (e.g., smartphone or tablet), a server computing device, or any other type of computing device. The client computing device 102 includes one or more processors 104 and a memory

106. The memory 106 can store data 108 and instructions 110 which are executed by the processor(s) 104 to cause the client computing device 102 to perform operations. For example, the instructions 110 can include instructions associated with a walkable space mapping system 120 or applications configured to implement such a system.

In some instances, the client computing device 102 can also include a sensor hub 112 configured to gather sensor data from a plurality of sensors. Sensor hub 112 can be configured to integrate data from different sensors, offload sensor processing from main processor 104, and generally improve battery consumption and device performance of user computing device 102.

Sensor data gathered by sensor hub 112 can be indicative of one or more conditions associated with the user computing device or its immediate environment. For example, sensors associated with sensor hub 112 can include without limitation a geographic position component such as a Global Position System (GPS) component 113, a proximity sensor 114, an accelerometer/gyrometer 115, a magnetometer 116, a barometer 117, a Hall effect sensor 118, and/or one or more optional additional sensors 119. Sensor data gathered by sensor hub 112 can include GPS coordinates (when available), Attitude (Roll, Pitch, and Yaw) as depicted in the example of FIG. 3, Rotation in X, Y, and Z dimensions, Gravity in X, Y, and Z dimensions, User Acceleration in X, Y, and Z dimensions, and Magnetic Field in X, Y, and Z dimensions. Referring to FIG. 2, a sensor data vector 204 can include sensor data 206/208/210 sampled from N different sensors within the user computing device 204. Sensor data 206/208/210 can be sampled at a same rate or different rates across the different sensors 113-119.

Walkable space mapping system 120 can include one or more of an activity recognition detector 122, a machine-learned course prediction model 124, and a path generator 126. The walkable space mapping system 120 and various components thereof can include computer logic utilized to provide desired functionality. Walkable space mapping system 120 can be implemented in hardware, firmware, and/or software controlling a general purpose processor. For example, in some implementations, the mapping application can include program files stored on a storage device, loaded into a memory and executed by one or more processors. In other implementations, the walkable space mapping system 120 includes one or more sets of computer program products and/or computer-executable instructions that are stored in a tangible computer-readable storage medium such as RAM hard disk or optical or magnetic media.

Activity recognition detector 122 implements one or more data transformations to sensor data from the plurality of sensors 113-119 so that such data is formatted in a suitable manner for activity recognition analysis and/or being provided as input to the machine-learned course prediction model 124.

More particularly, activity recognition detector 122 can be configured to smooth out one or more portions of sensor data using a data smoothing filter such as but not limited to a Simple Moving Average (SMA) algorithm. Implementation of a data smoothing filter can be beneficial to filter out inconsistencies and or outliers that may be present within the sensor data. Given a series of numbers and a fixed subset size, an SMA algorithm can obtain a first element of a moving average by taking the average of the initial fixed subset of the number series. Then the subset is modified by "shifting forward," that is, excluding the first number of the series and including the next value in the subset. This can be repeated for some or all elements in the series.

Activity recognition detector 122 can also be configured to implement peak detection within the smoothed sensor data to extract one set of datapoints for each step taken by a user. In particular, peak detection can be implemented relative to rotational data obtained by sensors within the user computing device. More particularly, user steps can be detected as corresponding spikes in the rotational data. Activity recognition detector 122 can implement a peak detection algorithm to pull out the corresponding peak data. The peak detection algorithm can employ a predetermined threshold cutoff so that other random spikes (e.g., spikes not corresponding to a user step) are not also identified in the smoothed sensor data. From detected peak values, a step size can be normalized. In some implementations, normalization of step sizes can include creating a lookup table of step percentages that could be applied to sensor data. For example, a smaller step may be associated in the lookup table as 0.9 times the size of an average step, while a larger step could be 1.2 times the average step size. Activity recognition detector 122 can determine an estimated distance that a user travels based on detected steps and an associated step size.

Data from a selected set of the plurality of sensors 113-119 can also be provided as input to machine-learned course prediction model 124. In response to receiving a set of sensor data as input, machine-learned course prediction model 124 can output a prediction of the user's bearing/course for each step taken. Machine-learned course prediction model 124 can include one or more neural networks (e.g., deep neural networks), support vector machines, decision trees, ensemble models (e.g., random forest models), k-nearest neighbors models, Bayesian networks, or other types of models including linear models and/or non-linear models. Example neural networks can include feed-forward neural networks, convolutional neural networks, recurrent neural networks (e.g., long short-term memory recurrent neural networks), gated recurrent unit (GRU) neural networks, or other forms of neural networks.

Path generator 126 can receive distance values determined by activity recognition detector 122 and bearing/course prediction values determined by machine-learned course prediction model 124 to generate a user path approximation (e.g., user path approximation 220 of FIG. 2). In some implementations, user path approximation 220 can be in the form of GPS coordinates so that the user path approximation determined by walkable space mapping system 120 can be appended to a last set of accurate GPS coordinates obtained by the user computing device before transitioning to the disclosed techniques for obtaining user paths. In some implementations, the following equation can be used to convert the distance and bearing values to GPS coordinates:

Formula: $\varphi_2 = \mathrm{asin}(\sin\varphi_1 \cdot \cos\delta + \cos\varphi_1 \cdot \sin\delta \cdot \cos\theta)$

$\lambda_2 = \lambda_1 + \mathrm{atan2}(\sin\theta \cdot \sin\delta \cdot \cos\varphi_1, \cos\delta - \sin\varphi_1 \cdot \sin\varphi_2)$

where φ is latitude, λ is longitude, θ is the bearing (clockwise from north), δ is the angular distance d/R; d being the distance travelled, R the earth's radius

Path generator 126 can translate determined GPS coordinates to other representations of geographic position (e.g., latitude and longitude values). In some implementations, path generator 126 can translate the determined GPS coordinates into a browser-readable file configured to render a graphical depiction of a user path approximation 220 as shown in FIG. 4.

According to another aspect of the present disclosure, user path approximations 220 as generated by walkable space mapping system 120 can be used in a variety of applications including but not limited to generation of floorplans or maps of other walkable spaces. For example, user path approximations received from a plurality of user computing devices can be overlayed to determine where people are walking (e.g., most likely hallways, walkways, walkable paths, etc.) and to infer where people are not walking. Areas where people are not walking can be used to predict structural entities such as walls, doors, vendor displays, etc. User path approximations from multiple user computing devices can also be overlaid to generate context data. In one example, if multiple people are walking along the same path multiple times a day, context data can indicate a high probability that this place is a hallway or walkway. In another example, if a user checks into a place once or twice a week and their calendar item says

"Magic Garden Conference Room," context data can provide an indication that the area corresponds to a particular conference room. In still further applications, an awareness API can be employed to help obtain user feedback and other data to help with determinations of context data. In addition, activity recognition detector can be configured to determine still further states such as but not limited to stair detection, elevator detection, door detection, etc.

Referring still to FIG. 1, the machine learning computing system 130 can include or be otherwise implemented by one or more server computing devices, and includes one or more processors 132 and a memory 134. The memory 134 can store data 136 and instructions 138 which are executed by the processor 132 to cause the machine learning computing system 130 to perform operations. The machine learning computing system 130 stores or otherwise includes one or more machine-learned models 140, which can include a machine-learned course prediction model 124. In some implementations, machine-learned model 140 is trained then relayed to user computing device 102 for use within walkable space mapping system 120.

In some instances, the system 100 further includes a training computing system 150 communicatively coupled over the network 180. The training computing system 150 can be separate from the machine learning computing system 130 or can be a portion of the machine learning computing system 130. The training computing system 150 includes one or more processors 152 and a memory 154. The memory 154 can store data 156 and instructions 158 which are executed by the processor 152 to cause the training computing system 150 to perform operations. In some instances, the training computing system 150 includes or is otherwise implemented by one or more server computing devices.

The training computing system 150 can include a model trainer 160 that trains the machine-learned models 140 stored at the machine learning computing system 130 using various training or learning techniques, such as, for example, backwards propagation. In particular, the model trainer 160 can train a model 140 based on a set of training examples. In some instances, the training examples can be provided or otherwise selected by the client computing device 102 (e.g., from the sensor hub 112).

Figures

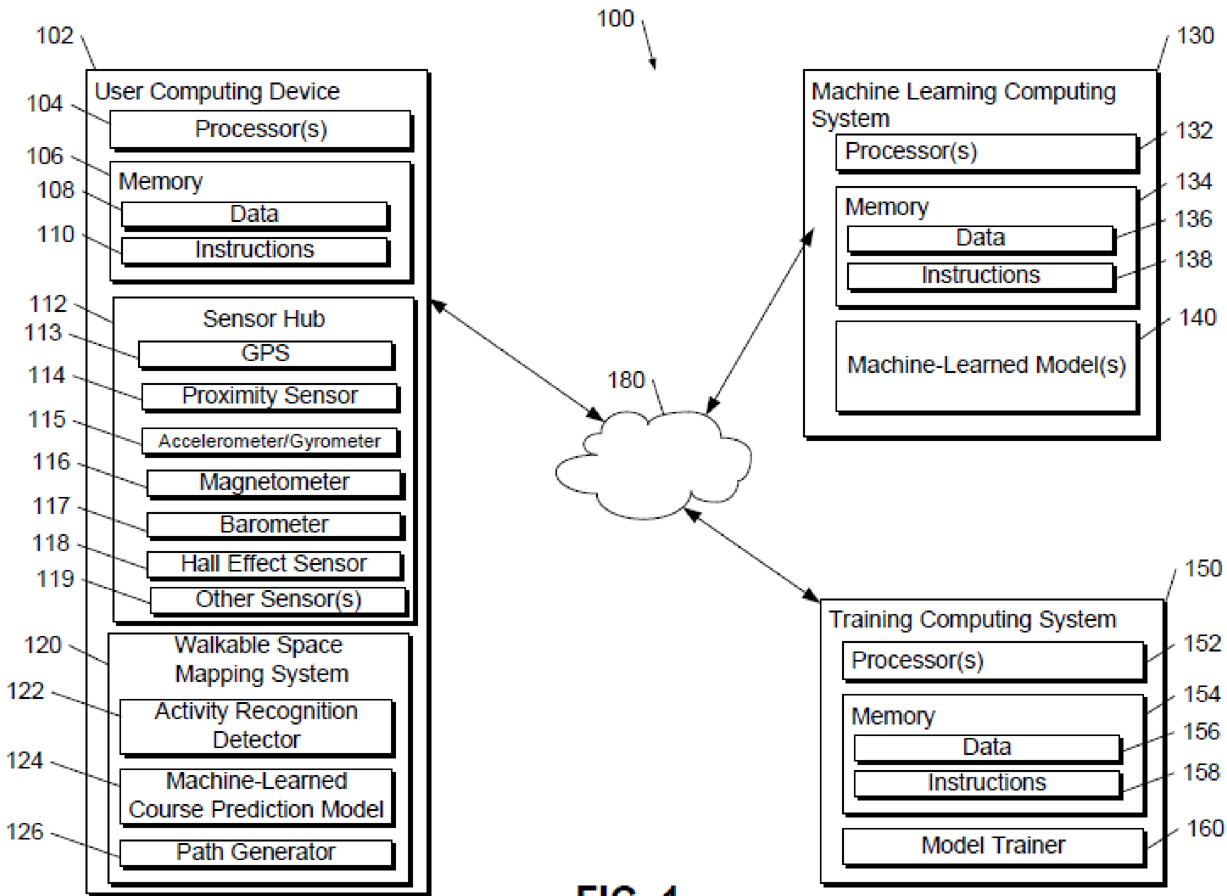

FIG. 1

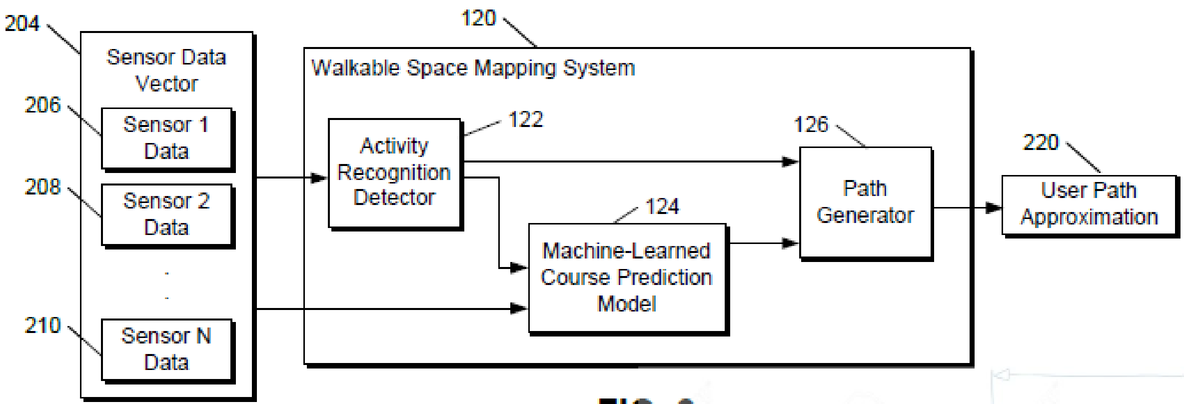

FIG. 2

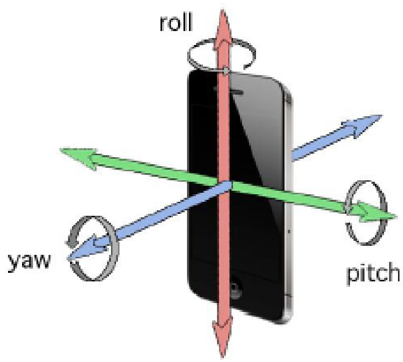

FIG. 3

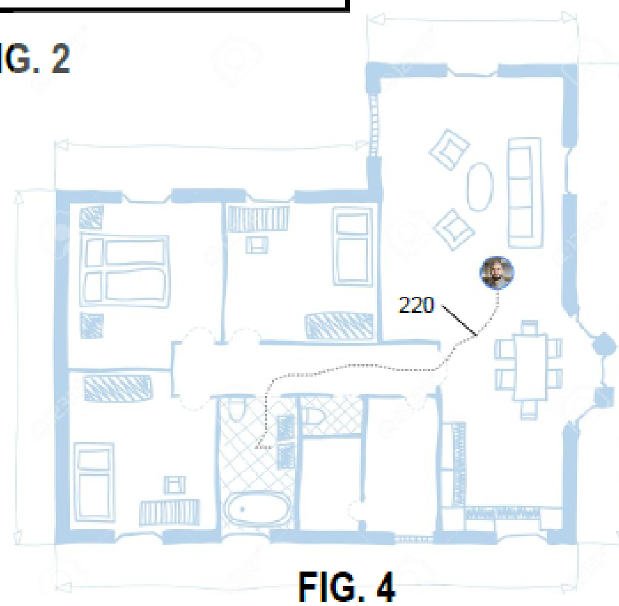

FIG. 4

Abstract

The present disclosure describes systems and methods that use activity recognition detection (e.g., step detection) and machine-learned course prediction models to generate user path approximations from sensor data obtained by a user computing device, which is particularly beneficial when GPS devices are unavailable. User paths generated from a plurality of different mobile computing devices can be utilized collectively to build maps of walkable spaces. Keywords associated with the present disclosure include: mapping; locations; walkable spaces; machine learning; model; training; GPS; sensors; activity recognition; sensor fusion; crowdsourcing; collaborative learning; user path; path generation; course prediction.