

HIGH-ACCURACY AMR POSITIONING SYSTEM WITH HYBRID MULTI-SENSOR FUSION ODOMETRY ESTIMATION AND POSITIONING METHOD THEREOF

FIELD OF THE INVENTION

[0001] The present disclosure relates to a high-accuracy AMR positioning system, and more particularly to a high-accuracy AMR positioning system with hybrid multi-sensor fusion odometry estimation and a positioning method thereof.

BACKGROUND OF THE INVENTION

[0002] Autonomous mobile robots (AMRs) are increasingly used in a variety of industries and applications for handling and moving a variety of goods and materials without human intervention. However, in order for a robot to achieve autonomous and intelligent control, it must rely on autonomous positioning and navigation technology, which includes, for example, positioning, mapping, and path planning. In many autonomous positioning and navigation methods, LiDAR and wheel odometer information is mainly used for auxiliary localization.

[0003] Odometry is the integration of incremental motion of an object over time, and can be measured by motion data obtained from motion sensors disposed on the object. It is commonly used in robotic systems to estimate the distance the robot has travelled with respect to its initial position. In the field of mobile robot control, the odometry is the pose state of the robot in the world coordinate system at all times. The motion sensors that can be used to measure odometry of an AMR may be, for example, wheel encoder or LiDAR.

[0004] Usually AMR is equipped with LiDAR having better accuracy that can be used to correct the error of the odometer within a certain range. But in some special environments (such as when the number of effective points scanned by the LiDAR is small), the readiness of the odometer will still affect the positioning result. In addition, the wheel odometer uses the wheel encoder on the wheels of the mobile robot to record the rotation of the two wheels, and obtains the positions and directions of the mobile robot through integration (generally using the Euler method). However, there are many error factors, such as imperfection of the wheels, wheel slippage or bumps and cracks, that may result in larger and larger odometry errors over time.

[0005] Therefore, there is a need to provide a high-accuracy AMR positioning system with hybrid multi-sensor fusion odometry estimation and a positioning method thereof, so as to produce high-precision localized odometry and position information for AMR positioning and navigation. Advantageously, odometry error over time can be significantly reduced and positioning precision can be greatly improved.

SUMMARY OF THE INVENTION

[0006] An object of the present disclosure is to provide a high-accuracy AMR positioning system with hybrid multi-sensor fusion odometry estimation and a positioning method thereof. By combining different types of sensors for fusion (such as LiDAR, IMU and wheel encoder) and converting different data into database in the same reference system, continuous update of the odometry estimation can be achieved by continuously iterating the observation model values, thus obtain higher positioning accuracy. With the high-accuracy AMR positioning system and

the high-accuracy AMR positioning method of the present disclosure, the AMR is capable to dynamically record localized landmarks during autonomous navigation and provide AMR odometry corrections even in disturbing environment conditions to correct the external sensor-derived odometry errors. At the same time, with the aid of machine vision based detection and identification of docking objects, the AMR may interact with the docking objects more accurately, such as: autonomous charging, docking with shelf conveyor belts, taking elevators, etc. On the other hand, as the moving time and traveled distance gradually increase, the hybrid odometry error may increase. For solving the problem of the odometry error accumulated after the AMR moving for a long time, identified key landmark coordinates stored in a map database during navigation of the AMR on the map can be used to correct the hybrid odometry error. For example, by moving the AMR based on the key landmark with nearest pose relative to the AMR to estimate the hybrid odometry, errors of the hybrid odometry based on the key landmark can be calculated, so that the hybrid odometry can be updated in the subsequent navigation.

[0007] In accordance with an aspect of the present disclosure, a high-accuracy AMR positioning system with hybrid multi-sensor fusion odometry estimation is provided. The high-accuracy AMR positioning system includes a hybrid odometry generation module, an object recognition module, a coordinate update module and an odometry correction module. The hybrid odometry generation module receives raw information obtained through multiple sensors on an AMR so as to generate hybrid odometry of the AMR during navigation of the AMR according to a map. The object recognition module performs machine vision-based object recognition to identify an obtain from one or more image frames and obtain a corresponding object

pose relative to the AMR during the navigation. The coordinate update module is connected with the hybrid odometry generation module and the object recognition module, and configured to receive the object pose from the object recognition module and the hybrid odometry from the hybrid odometry generation module to obtain and update an object coordinate on map. The odometry correction module is connected to the hybrid odometry generation module, the coordinate updated module and the object recognition module, and configured to generate a corrected odometry based on the object pose of the object identified as a nearest landmark by the object recognition module.

[0008] In an embodiment, the hybrid odometry generation module is configured to perform a phase 1 sensor fusion for determining position information and a phase 2 sensor fusion for determining orientation information.

[0009] In an embodiment, an Iterative Closest Point (ICP) algorithm is used in the phase 1 sensor fusion to generate a primary odometry; and an extended Kalman filter (EKF) algorithm is used in the phase 2 sensor fusion to generate a secondary odometry.

[0010] In an embodiment, the multiple sensors are chosen from: LiDAR, inertial measurement unit (IMU), and wheel odometer.

[0011] In an embodiment, the object recognition module includes a pre-trained learning model for performing the machine vision-based object recognition and a mathematical model for distance and orientation estimation.

[0012] In an embodiment, the pre-trained learning model is configured to detect the object and extract relevant features across image frames, and the mathematical model is configured to estimate distance and orientation of

the object and transform from an image coordinate system to a robot coordinate system.

[0013] In an embodiment, the object coordinate is labeled as a key landmark on the map according to total traveled paths of the AMR ,and label information of the key landmark is stored in a map database.

[0014] In an embodiment, the key landmark with nearest pose relative to the AMR is utilized to generate the corrected odometry.

[0015] In accordance with another aspect of the present disclosure, an odometry estimation method is provided and includes steps of: a) receiving raw information obtained through multiple sensors on an AMR so as to generate hybrid odometry of the AMR during navigation of the AMR according to a map; b) performing machine vision-based object recognition to identify an object from one or more images and obtain corresponding object pose relative to the AMR and during the navigation of the AMR; c) receiving the object pose and the hybrid odometry to obtain and update an object coordinate on the map, wherein the object coordinate is updated according to the object pose and the hybrid odometry; and d) generating a corrected odometry based on the object pose of the object recognized as a nearest landmark by the object recognition module.

[0016] In an embodiment, a phase 1 sensor fusion is performed for determining position information, and a phase sensor fusion is performed for determining orientation information, to generate the hybrid odometry.

[0017] In an embodiment, an Iterative Closest Point (ICP) algorithm is used in the phase 1 sensor fusion to generate a primary odometer; and an extended Kalman filter (EKF) algorithm is used in the phase 2 sensor fusion to generate a secondary odometry.

[0018] In an embodiment, the multiple sensors are chosen from: LiDAR, inertial measurement unit (IMU), and wheel odometer.

[0019] In an embodiment, a pre-trained leaning model is used for machine vision-based recognition and a mathematical model is used for distance and orientation estimation.

[0020] In an embodiment, the step (b) includes steps of: (b1) detect the object and extract relevant features across image frames; and (b2) estimating distance and orientation of the object and transform from an image coordinate system to a robot coordinate system.

[0021] In an embodiment, the step (c) further includes a step of: (c1) labeling the object coordinate as a key landmark on the map according to a traveled path of the AMR and recording the label information of the key landmark in a map database.

[0022] In an embodiment, the step (d) further includes steps of: (d1) identifying the key landmark along the traveled path with nearest pose relative; and (d2) calculating errors of the hybrid odometry based on the object coordinate of the key landmark to generate the corrected odometry.

BRIEF DESCRIPTION OF THE DRAWINGS

[0023] The above contents of the present disclosure will become more readily apparent to those ordinarily skilled in the art after reviewing the following detailed description and accompanying drawings, in which:

[0024] FIG. 1 shows an AMR with hybrid multi-sensor fusion odometry estimation for positioning and navigation according to an embodiment of the present disclosure;

[0025] FIG. 2 is a block diagram illustrating the high-accuracy AMR positioning system according to an embodiment of the present disclosure;

[0026] FIG. 3 shows a process flow of the hybrid odometry generation module according to the embodiment of the present disclosure;

[0027] FIG. 4 shows a process flow of the object recognition module according to the embodiment of the present disclosure;

[0028] FIG. 5 shows a process flow of the coordinate update module according to the embodiment of the present disclosure;

[0029] FIG. 6A and FIG. 6B are schematic diagrams illustrating the landmark/object coordinate update algorithm performed to scan the landmark candidates during navigation of AMR;

[0030] FIG. 7 shows a process flow of the odometry correction module according to the embodiment of the present disclosure; and

[0031] FIG. 8A and FIG. 8B are schematic diagrams illustrating the application of the present disclosure.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENT

[0032] The present disclosure will now be described more specifically with reference to the following embodiments. It is to be noted that the following descriptions of preferred embodiments of this disclosure are presented herein for purpose of illustration and description only. It is not intended to be exhaustive or to be limited to the precise form disclosed.

[0033] FIG. 1 is a block diagram illustrating a position system 1 of an AMR with hybrid multi-sensor fusion odometry estimation for positioning and navigation according to an embodiment of the present disclosure. In the embodiment, the positioning system 1 including a hybrid odometry generation module 10, an object recognition module 20, a coordinate update module 30 and an odometry correction module 40. The hybrid odometry generation module 10 receives raw information obtained through multiple

sensors on an AMR during navigation of the AMR to generate a hybrid odometry. The hybrid odometry generation module 10 includes a phase 1 sensor fusion unit 11 for estimating a primary odometry and a phase 2 sensor fusion unit 12 for estimating a secondary odometry. The primary odometry is estimated by tight coupling of multiple sensors to calculate position information. The secondary odometry is estimated by loose coupling integrating additional sensors to calculate state or pose information. The hybrid odometry is thus generated through odometry estimation 13 with better accuracy. The object recognition module 20 is configured performs image based or machine vision based recognition to obtain a landmark or/and an object presented in the view of the AMR during navigation and estimate its pose (distance, orientation) relative to the AMR. The object to be recognized may be a landmark in the physical space or a docking object capable to interact with the AMR. The object recognition module 20 may perform object recognition using a pre-trained model and estimate the pose using mathematical methods or another pre-trained model. The coordinate update module 30 is configured to perform coordinate update of the recognized object. The coordinate update module 30 receives the landmarks pose or/and the object pose from the object recognition module 20 and the hybrid odometry from the hybrid odometry generation module 10 to perform landmark/object coordinate update. By analyzing the pose information obtained from the object recognition module 20 and the AMR pose information obtained from the hybrid odometry generation module 10, the object coordinate may be updated and stored in the map database 50. The odometry correction module 40 is connected to the hybrid odometry generation module 10, the coordinate updated module 30 and the object recognition module 20, and is configured to generate a corrected odometry

of the AMR based on the object pose of the object recognized as a nearest landmark by the object recognition module 20.

[0034] FIG. 2 shows a block diagram illustrating the high-accuracy AMR positioning system according to an embodiment of the present disclosure. Please refer to FIG. 1 and FIG. 2. The main algorithm flow of the odometry estimation as performed by the positioning system 1 includes phase 1 sensors fusion, phase 2 sensors fusion, landmarks/object recognition and odometry correction. In order to achieve hybrid odometry with multi-sensors fusion and use landmarks for positioning corrections for AMR autonomous mobility, the positioning system 1 needs to have the capabilities of 1) hybrid odometry generation, 2) object recognition and pose estimation, 3) object recordation, and 4) odometry correction.

[0035] The localization of autonomous robot odometry is an important value in autonomous navigation and docking control. The overall algorithm framework of the odometry estimation method is shown in FIG. 1. It includes four parts: a) multi-level odometer fusion b) object recognition c) landmark and object coordinate update d) odometry correction.

[0036] In the embodiment, the multi-level odometer fusion is performed by the hybrid odometry generation module 10 and utilized to merge sensor data representing the same scenes or objects. In the first stage of phase 1 sensor fusion, tight coupling is used to process the intermediate data obtained from multiple sensors through an optimization filter. Preferably but not exclusively, the multiple sensors include LiDAR and wheel odometry. Tight coupling needs to add features to the feature vector. In the second stage of phase 2 sensor fusion, another fusion method is used to fuse these sensor data through loose coupling. Loose coupling is to use different sensors as two separate modules for calculating respective pose

information, and then perform fusion of the two poses. In the embodiment, the algorithm framework can choose different fusion modes for fusion in two-level fusion mode (for example: use tight coupling in the first stage, loose coupling in the second stage, etc.) to produce a high-precision hybrid odometer. In the embodiment, the multiple sensors used to obtain raw information can be classified into proprioceptors or exteroceptors. Preferably but not exclusively, the proprioceptors measure the state of the AMR regardless of its interaction with the environment. For example, wheel odometry measures the rotation of the drive shaft, and the IMU reports the change in orientation relative to the initial state. Preferably but not exclusively, the exteroceptors measure the motion of the AMR relative to the surrounding environment. For example, GPS receives attitude updates relative to a fixed world coordinate system, and visual odometry calculates displacement relative to visual indicators of the environment. The present disclosure is not limited thereto.

[0037] In the embodiment, the object recognition is performed by the object recognition module 20. An efficient algorithm for machine vision object detection with reference to a landmark database stored in the map database 50 is used to detect landmarks and objects. After the image data is acquired, the data needs to be preprocessed in order to make the data conform to the input requirements of the model of the machine vision recognition. Images of landmarks and docking objects are captured first, and machine learning or deep learning is used to train the neural model to achieve machine vision-based recognition. During the training process, the model of the machine vision-based recognition will learn the features of landmarks and objects, and establish the correspondence between landmarks, objects and images. After the training is completed, it may build the image knowledge

database of the landmarks and/or objects by capturing the image information of the surrounding environment.

[0038] In the embodiment, updating of the coordinates of landmarks and objects is performed by the coordinate update module 30. The landmark database is recorded and updated through the mixture of the odometry information obtained in the multi-level sensor fusion and the landmark pose obtained in the object recognition. Afterwards, the coordinate data is stored in the map database 50 and can be used to correct the odometer error.

[0039] In the embodiment, the odometry correction algorithm is performed by the odometry correction module 40. Preferably but not exclusively, the odometry correction algorithm use the landmark pose information to correct the hybrid odometry, so that the hybrid odometry error accumulated after the AMR moving for a long time can be corrected to obtain a high-accuracy corrected odometry. The detailed process flows of the four modules will be described respectively in the following.

[0040] FIG. 3 shows a process flow of the hybrid odometry generation module 10 according to the embodiment of the present disclosure. In the embodiment, AMR's LiDAR sensor, IMU and wheel odometer are used to obtain the raw information as hybrid odometry sensing value sources. In the embodiment, the errors in wheel odometry tend to increase with time and displacement. Therefore, the external sensors (such as LiDAR) are required to assist in improving accuracy. In the embodiment, the hybrid odometry generation module 10 performs a phase 1 sensor fusion and a phase 2 sensor fusion to generate the hybrid odometry. In the phase 1 sensor fusion, a laser scan matcher algorithm is used to generate the primary odometer fused in the first stage. Several LiDAR point cloud data are merged into a large point cloud data, which is served as the input of the laser scan matcher algorithm

together with wheel odometry. Preferably but not exclusively, an iterative closest point (ICP) algorithm is mainly used to calculate the optimal position transformation between two 3D point clouds through continuous iterative solution. The ICP algorithm is widely used in both computer vision and LiDAR measurements, especially in autonomous vehicles and robotic navigation systems, to calculate odometry information. The advantage of the iterative closest point ICP algorithm is that it can solve the position transformation between two 3D point clouds very quickly, and the results are usually very accurate. In the phase 2 sensor fusion, an extended Kalman Filter (EKF) algorithm is used as the second stage of fusion to produce hybrid odometry. The EKF algorithm is a filter used to calculate the state of a random system. It estimates the optimal state value by predicting and updating the state of the system. At this phase 2 fusion, another proprioceptor IMU data can be introduced for providing orientation and acceleration as 3D vectors. The outliers can be removed by Mahalanobis distance detection. The fused data is then incorporated into the state estimation. Then the prediction and update steps of the EKF algorithm can be used to correct the position transformation calculated by the fusion result in the previous phase. In this way, the effects of noise and mismatch points on accuracy degradation are removed, and thus more accurate and reliable odometry information is calculated through the odometry estimation 13 of the hybrid odometry generation module 10. In the embodiment, the hybrid odometry can be directly used to present a total traveled paths of the AMR, or be further corrected to present the total traveled paths of the AMR. Certainly, the present disclosure is not limited thereto.

[0041] In an embodiment, the hybrid odometry algorithm is tested on an actual AMR equipped with two LiDARs (for example disposed at front

and side), an IMU and a wheel odometry. Several waypoints are defined in the experimental field. AMR moves toward 5 waypoints in order for 11 times. During the AMR movement, the real position of the AMR is recorded in real time. The AMR moves toward these waypoints in sequence. Table 1 lists the odometry error comparison with the real position. After 11 laps, the average position error of hybrid odometry relative to the real position of the AMR is only (X: $\pm 15.62\text{cm}$, Y: $\pm 17.35\text{cm}$). It can be seen that the two-phase sensor fusion of the present disclosure can greatly reduce the error of the original wheel odometry or the primary odometry relative to the real position of AMR.

Table 1: Odometry error comparison

Odometry Methodology	Wheel Odometry	Primary Odometry	Hybrid Odometry
Average Position Error	X: $\pm 25\text{cm}$, Y: $\pm 65\text{cm}$	X: $\pm 23\text{cm}$, Y: $\pm 26\text{cm}$	X: $\pm 15.62\text{cm}$, Y: $\pm 17.35\text{cm}$

[0042] FIG. 4 shows a process flow of the object recognition module 20 according to an embodiment of the present disclosure. In the embodiment, an object recognition to identify landmarks and/or docking objects is performed by the object recognition module 20, and is further used to develop the robot-landmark relative position. The robot-landmark relative position is developed for the purpose of detecting and localizing landmarks or docking objects to estimate their distances and orientations relative to the robot camera. In the embodiment, an integrated learning and mathematical framework from RGBD information is used. RGBD camera is used to obtain the raw sensing data, and the image and depth alignment is performed for pre-processing. The learning method is used to detect and localize

landmarks by pre-training the corresponding landmarks and extracting relevant features across frames. These pre-trainings are performed with the aid of the map database 50, and the model is trained with a large number of images to obtain identification labels that can be labeled as key landmarks on the map according to a traveled path of the AMR and recording the label information of the key landmarks in the map database 50. For example, when the AMR is navigated to ride the elevator, the elevator display panel, the elevator call button, the elevator door, and the elevator floor button can be identified sequentially and each of them can be served as key landmarks during the elevator riding. Preferably but not exclusively, the map with the identification labels that can be labeled as key landmarks are stored in the map database 50, so that AMR can perform the object recognition with reference to objects, particularly that can be labeled as key landmarks, localized in map. The mathematical method is utilized to estimate the distance and orientation of each localized landmark relative to the robot camera. Preferably but not exclusively, each of the landmark poses or/and the object poses obtained through the object recognition module 20 includes a distance estimation and an orientation estimation (relative pose). The distance estimation and the orientation estimation (relative pose) will be converted from camera coordinates to robot coordinates through a camera-to-robot coordinate transformation. With the object recognition module 20 performing the object recognition, a landmark pose or/and an object pose relative to the AMR during the navigation of the AMR can be obtained. For example, in a mock-up elevator area (environment), two different types of landmarks such as the elevator display panel and the elevator call button can be successfully detected and identified. From these successfully recognized

landmarks, it is possible to get the relative pose (position and orientation). Certainly, the present disclosure is not limited thereto.

[0043] FIG. 5 shows a process flow of the coordinate update module according to the embodiment of the present disclosure. FIG. 6A and FIG. 6B are schematic diagrams illustrating the landmark/object coordinate update algorithm performed to scan the landmark candidates during navigation of AMR. In the embodiment, for solving the problem of the odometry error accumulated after the AMR moving for a long time, the landmarks on the map can be used to correct the odometry error in a set of algorithm processes. The odometry error can be for example but not limited to wheel odometry, a mixed odometry or the hybrid odometry of the present disclosure. In order to achieve the purpose, it needs to record identified key landmark coordinates during navigation of the AMR. For example, the landmark/object coordinate update algorithm is performed to scan the landmarks on the map while the AMR 9 is taking the elevator 8 as shown in FIG. 6A and FIG. 6B. At the beginning, the autonomous navigation for elevator riding starts from the starting position as shown in FIG. 6A. Candidate landmarks LC1, LC2, LC3, LC4 such as the elevator display panel, the elevator call button, the elevator door, and the elevator floor button are identified sequentially during the elevator riding. In the embodiment, these candidate landmarks LC1, LC2, LC3, LC4 are dynamically determined as key landmarks through the following three steps of: 1) estimating the total traveled paths of the AMR on the map by the mixed odometer movement; 2) analyzing whether these traveled paths have been reached during the hybrid odometry movement; and 3) determining the key landmarks from the candidate landmarks according to the moving path. During navigation for elevator riding, the numbers of key landmarks can be added or deleted.

[0044] Once the key landmarks are generated and the relative poses are obtained from the object recognition module 20, the odometry coordinates of the key landmarks from the hybrid odometry generation module 10 are also provided when the error of the first pass of the hybrid odometry is small. The poses of the key landmarks estimated by the object recognition module 20 are transformed from the image coordinate system into the hybrid odometry coordinate system, and the transformed pose coordinates of the key landmarks are recorded and updated in the map database 50. The key landmarks recorded and updated in the map database 50 can be used to correct the odometry error after the AMR moving for a long time. In an exemplary elevator scene, the distance threshold of landmark recognition and recordation during travel is set to 1 meter. In the example of FIG. 6A and FIG. 6B, two landmarks such as the call button outside the elevator and the floor button inside are identified and recorded as the key landmarks. In addition, object labels are defined to record the pose of the object (such as the elevator button) during the travel of the AMR to the elevator. These object pose records are used later for docking control. The AMR can control its actuator to approach the docking object according to the hybrid odometry and the pose information of the docking object. For example, in the process of elevator riding, the AMR needs to get close to the elevator button and enables the actuator to press the button. Then the AMR needs to align with the center of the elevator door if it wants to enter the elevator. These object pose records help AMR perform docking control. Certainly, the present disclosure is not limited thereto.

[0045] FIG. 7 shows a process flow of the odometry correction module according to an embodiment of the present disclosure. FIG. 8A and FIG. 8B are schematic diagrams illustrating the application of the present disclosure.

Although the hybrid odometry error is greatly reduced compared with the original wheel odometry error. However, as the moving time and traveled distance gradually increase, the hybrid odometry error will also increase. Without some way to correct for this "drift" of the sensor relative to a fixed or world frame, the error in the position estimate can eventually become so large that the AMR cannot perform its task. Therefore, a set of algorithm flow of the present disclosure is performed to use the key landmarks to correct the hybrid odometry error. In the embodiment, some key landmark poses are recorded in the map database 50 during the initial exploration in the target field or the environment. Hybrid odometry correction of the present disclosure can be performed with utilizing the key landmark poses identified and stored in the map database 50 according to the following steps: 1) obtaining a candidate landmark with nearest pose relative to the AMR by the object recognition algorithm; 2) comparing the pose information of the candidate landmark with the key landmarks recorded in the map database 50; and 3) calculating errors to generate a corrected odometry of the candidate landmark. Based on the corrected odometry of the candidate landmark, the hybrid odometry is updated in the subsequent navigation. Preferably but not exclusively, the key landmark along the traveled path with nearest pose relative to the AMR can be identified, and then errors of the hybrid odometry based on the object coordinate of the key landmark to generate the corrected odometry. As shown in FIG. 8A and FIG. 8B, when the AMR 9 takes the elevator 8 autonomously, odometry data with higher precision is needed. In the embodiment of FIG. 8A and FIG. 8B, after the landmarks LM1, LM2 have been recorded in the map database 50, the hybrid odometry may be corrected by detecting landmarks LM1, LM2 such as the elevator call buttons (outside) or the floor buttons (inside) to generate a corrected odometry for

the subsequent navigation. In addition, some object labels may be defined to record the poses of the objects DO1, DO2, such as the elevator door for docking control. The present disclosure is not limited thereto. In an exemplary embodiment, AMR 9 is tested by moving toward four waypoints in designated order. The test is done by moving to/from the 4 waypoints 11 times for verifying the accuracy and error of the algorithm. Table 2 lists the odometry error comparison. After 11 laps, the average position error of corrected odometry based on the landmark at the position A is only (X: $\pm 3.55\text{cm}$ Y: $\pm 3.97\text{cm}$). It can be seen that the accuracy of the hybrid odometry can be further improved according to the corrected odometry of the landmarks, and the hybrid odometry can be corrected during the movement of the AMR.

Table 2: Comparison of odometry errors after correction using the corrected odometry of the landmark

Odometry Methodology	Hybrid Odometry	Corrected Odometry based on Landmark at Position A
Average Position Error	X: $\pm 7.12\text{cm}$, Y: $\pm 8.56\text{cm}$	X: $\pm 3.55\text{cm}$, Y: $\pm 3.97\text{cm}$

[0046] In summary, the present disclosure provides a high-accuracy AMR positioning system with hybrid multi-sensor fusion odometry estimation and positioning method thereof. By combining different types of sensors for fusion (such as LiDAR, IMU and wheel encoder) and converting different data into database in the same reference system, continuous update of the odometry estimation can be achieved by continuously iterating observation model values, and thus higher positioning accuracy. With the

high-accuracy AMR positioning system and the high-accuracy AMR positioning method of the present disclosure, the AMR is capable to dynamically record localized landmarks during autonomous navigation and provide AMR odometry corrections even in disturbing environment conditions to correct the external sensor-derived odometry errors. At the same time, with the aid of machine vision based detection and identification of vision objects, the AMR allows may interact with the objects more accurately, such as: autonomous charging, docking with shelf conveyor belts, taking elevators, etc. On the other hand, as the moving time and traveled distance gradually increase, the hybrid odometry error may increase. For solving the problem of the odometry error accumulated after the AMR moving for a long time, identified key landmark coordinates during navigation of the AMR on the map can be used to correct the hybrid odometry error. For example, by moving the AMR based on the key landmark with nearest pose relative to the AMR to estimate the hybrid odometry, errors of the hybrid odometry based on the key landmark can be calculated, so that the hybrid odometry can be updated in the subsequent navigation.

[0047] While the disclosure has been described in terms of what is presently considered to be the most practical and preferred embodiments, it is to be understood that the disclosure needs not be limited to the disclosed embodiment. On the contrary, it is intended to cover various modifications and similar arrangements included within the spirit and scope of the appended claims which are to be accorded with the broadest interpretation so as to encompass all such modifications and similar structures.

WHAT IS CLAIMED IS:

1. A high-accuracy AMR positioning system, comprising:

a hybrid odometry generation module configured to receive raw information obtained through multiple sensors on an AMR so as to generate hybrid odometry of the AMR during navigation of the AMR according to a map;

an object recognition module configured to perform machine vision-based object recognition to identify an object from one or more image frames and obtain a corresponding object pose relative to the AMR during the navigation;

a coordinate update module connected with the hybrid odometry generation module and the object recognition module, and configured to receive the object pose from the object recognition module and the hybrid odometry from the hybrid odometry generation module to obtain and update an object coordinate on the map, wherein the object coordinate is updated according to the object pose and the hybrid odometry; and

an odometry correction module connected to the hybrid odometry generation module, the coordinate updated module and the object recognition module, and configured to generate a corrected odometry based on the object pose of the object identified as a nearest landmark by the object recognition module.

2. The high-accuracy AMR positioning system according to claim 1, wherein the hybrid odometry generation module is configured to perform a phase 1 sensor fusion for determining position information and a phase 2 sensor fusion for determining orientation information.

3. The high-accuracy AMR positioning system according to claim 2, wherein an Iterative Closest Point (ICP) algorithm is used in the phase 1 sensor fusion to generate a primary odometry; and an extended Kalman filter

(EKF) algorithm is used in the phase 2 sensor fusion to generate a secondary odometry.

4. The high-accuracy AMR positioning system according to claim 1, wherein the multiple sensors are chosen from: LiDAR, inertial measurement unit (IMU), and wheel odometer.

5. The high-accuracy AMR positioning system according to claim 1, wherein the object recognition module comprises a pre-trained learning model for performing the machine vision-based object recognition and a mathematical model for distance and orientation estimation.

6. The high-accuracy AMR positioning system according to claim 5, wherein the pre-trained learning model is configured to detect the object and extract relevant features across image frames, and the mathematical model is configured to estimate distance and orientation of the object and transform from an image coordinate system to a robot coordinate system.

7. The high-accuracy AMR positioning system according to claim 6, wherein the object coordinate is labeled as a key landmark on the map according to total traveled paths of the AMR ,and label information of the key landmark is stored in a map database.

8. The high-accuracy AMR positioning system according to claim 7, wherein the key landmark with nearest pose relative to the AMR is utilized to generate the corrected odometry.

9. A high-accuracy AMR positioning method, comprising steps of :

a) receiving raw information obtained through multiple sensors on an AMR so as to generate hybrid odometry of the AMR during navigation of the AMR according to a map;

b) performing machine vision-based object recognition to identify an object from one or more image frames and obtain corresponding object pose

relative to the AMR and during the navigation of the AMR;

c) receiving the object pose of the object and the hybrid odometry of the AMR to obtain and update an object coordinate on the map, wherein the object coordinate is updated according to the object pose and the hybrid odometry; and

d) generating a corrected odometry based on the object pose of the object recognized as a nearest landmark by the object recognition module.

10. The high-accuracy AMR positioning method according to claim 9, wherein a phase 1 sensor fusion is performed for determining position information, and a phase sensor fusion is performed for determining orientation information, to generate the hybrid odometry.

11. The high-accuracy AMR positioning method according to claim 9, wherein an Iterative Closest Point (ICP) algorithm is used in the phase 1 sensor fusion to generate a primary odometer; and an extended Kalman filter (EKF) algorithm is used in the phase 2 sensor fusion to generate a secondary odometry.

12. The high-accuracy AMR positioning method according to claim 9, wherein the multiple sensors are chosen from: LiDAR, inertial measurement unit (IMU), and wheel odometer.

13. The high-accuracy AMR positioning method according to claim 9, wherein a pre-trained leaning model is used for machine vision-based recognition and a mathematical model is used for distance and orientation estimation.

14. The high-accuracy AMR positioning method according to claim 13, wherein the step (b) comprises steps of:

(b1) detect the object and extract relevant features across image frames; and

(b2) estimating distance and orientation of the object and transform from an image coordinate system to a robot coordinate system.

15. The high-accuracy AMR positioning method according to claim 14, wherein the step (c) further comprises a step of:

(c1) labeling the object coordinate as a key landmark on the map according to a traveled path of the AMR and recording the label information of the key landmark in a map database.

16. The high-accuracy AMR positioning method according to claim 15, wherein the step (d) further comprises steps of:

(d1) identifying the key landmark along the traveled path with nearest pose relative to the AMR; and

(d2) calculating errors of the hybrid odometry based on the object coordinate of the key landmark to generate the corrected odometry.