AIR-GROUND COLLABORATIVE HETEROGENEOUS ROBOT AUTONOMOUS INSPECTION SYSTEM AND METHOD

Field of the Invention

The present invention relates to the field of robot technology, and in particular to an air-ground collaborative heterogeneous robot autonomous inspection system and method.

Background to the Invention

With the development of industrial automation technology, the collaborative operation mode of ground and aerial robots has been widely applied in inspection tasks of complex environments such as power facilities, large-scale parks, and mines due to its flexibility and high efficiency. Since such tasks usually have the characteristics of long operation cycles and large environmental load changes, the power motors, drive circuits, and battery components inside the robots are prone to performance degradation or fatigue wear under long-term high-load operation. Therefore, how to real-time grasp the health status of the executive mechanism and reasonably allocate operation tasks accordingly has become the key to ensuring the long-term stable operation of the heterogeneous robot system.

However, most existing robot inspection systems adopt fixed-cycle offline maintenance or emergency shutdown strategies based on a single threshold, making the robots still forced to perform tasks according to rated high parameters when early slight degradation occurs, which is likely to cause irreversible safety accidents such as collisions due to lagging power response.

Statement of Invention

To make up for the above deficiencies, the present invention provides an air-ground collaborative heterogeneous robot autonomous inspection system and method, aiming to improve the problem that most existing robot inspection systems adopt fixed-cycle offline maintenance or emergency shutdown strategies based on a single threshold.

In a first aspect, the present invention provides the following technical solution: an air-ground collaborative heterogeneous robot autonomous inspection system includes:

a heterogeneous perception module, configured to fuse laser point clouds of ground robots and navigation images of aerial robots to construct a global three-dimensional environment map and a pose transformation matrix;

a predictive maintenance module, configured to analyze remaining service life and generate a health feature vector according to vibration and current data of power and drive components;

a collaborative planning module, configured to generate a spatiotemporally coupled task sequence including ground movement paths, aerial flight trajectories, and collaborative energy supplement coordinates based on the global three-dimensional environment map, the health feature vector, and a dynamic energy consumption model;

an autonomous take-off and landing module, configured to respond to the spatiotemporally coupled task sequence and control the aerial robot to land on a docking platform of the ground robot in combination with ground robot motion prediction and relative positioning data; and

a defect analysis module, configured to perform spatiotemporal comparison between inspection image features and a reference three-dimensional map to output an inspection report including defect categories, coordinates, and change trends.

In a second aspect, the present invention provides the following technical solution: an air-ground collaborative heterogeneous robot autonomous inspection method includes the following steps:

S100: fusing laser point clouds of ground robots and navigation images of aerial robots to construct a global three-dimensional environment map and a pose transformation matrix;

S200: analyzing remaining service life and generating a health feature vector according to vibration and current data of power and drive components;

S300: generating a spatiotemporally coupled task sequence including ground movement paths, aerial flight trajectories, and collaborative energy supplement coordinates based on the global three-dimensional environment map, the health feature vector, and a dynamic energy consumption model;

S400: responding to the spatiotemporally coupled task sequence and controlling the aerial robot to land on a docking platform of the ground robot in combination with ground robot motion prediction and relative positioning data; and

S500: performing spatiotemporal comparison between inspection image features and a reference three-dimensional map to output an inspection report including defect categories, coordinates, and change trends.

The present invention has the following beneficial effects:

1. In the present invention, the vibration and current data of power components are real-time mapped into the health feature vector including speed and climbing restrictions, and a collaborative planning strategy is dynamically adjusted accordingly to prevent equipment from operating with faults. While ensuring the safe operation of the system, the service life and maintenance cycle of key components are maximized.

2. In the present invention, by fusing high-precision ground laser point clouds with aerial wide-angle visual data and using ground robots as mobile energy supplement platforms, it not only effectively solves the bottlenecks of short endurance and limited computing power of aerial robots, but also realizes comprehensive environmental perception with complementary air-ground perspectives, improving the coverage and continuous operation capability of autonomous inspection in complex scenarios.

Brief Description of the Drawings

FIG. 1 is an architecture diagram of an air-ground collaborative heterogeneous robot autonomous inspection system provided by the present invention; and

FIG. 2 is a flowchart of an air-ground collaborative heterogeneous robot autonomous inspection method provided by the present invention.

Detailed Description

Technical solutions in examples of the present invention will be described clearly and completely in the following with reference to the attached drawings. Obviously, all the described examples are only some, rather than all examples of the present invention. Based on the examples in the present invention, all other examples obtained by those of ordinary skill in the art without creative efforts belong to the scope of protection of the present invention.

The present invention provides an air-ground collaborative heterogeneous robot autonomous inspection system, as shown in FIG. 1, including the following modules:

A heterogeneous perception module is configured to fuse laser point clouds of ground robots and navigation images of aerial robots to construct a global three-dimensional environment map and a pose transformation matrix.

Further, in the heterogeneous perception module, the construction of a global three-dimensional environment map and a pose transformation matrix specifically includes:

constructing a ground laser sub-map and an aerial visual sparse point cloud;

calculating initial relative pose parameters of aerial and ground coordinate systems for rough alignment;

projecting the aerial visual sparse point cloud to the ground coordinate system using the initial parameters, and solving an optimized pose transformation matrix through point cloud registration; and

fusing air-ground perception data based on the pose transformation matrix to generate the global three-dimensional environment map.

Specifically, the heterogeneous perception module first processes sensor data in parallel. The ground robot uses a laser radar and constructs a dense ground laser point cloud set $\mathrm{P_G}$ with scale information through a simultaneous localization and mapping algorithm. The aerial robot uses a visual sensor to solve the three-dimensional coordinates of environmental feature points and constructs an aerial visual sparse point cloud set $\mathrm{P_A}$. The absolute positioning data at the same time is obtained using the global positioning modules equipped on both, and the relative position difference vector $\mathrm{t_{init}}$ and the heading angle deviation are calculated to construct an initial rotation matrix $\mathrm{R_{init}}$, which are combined to generate an initial relative pose parameter matrix T_{init} of the aerial coordinate system relative to the ground coordinate system.

The aerial visual sparse point cloud P_A is projected to the ground coordinate system using the initial parameter T_{init}, and fine registration is performed through an iterative closest point algorithm. The algorithm aims to minimize the Euclidean distance between the transformed aerial point cloud and the ground reference point cloud, and iteratively solves the optimized rotation matrix R and translation vector t. The objective function formula is as follows:

$$E(R,t) = \frac{1}{N}\sum_{i=1}^{N} \| \ q_i - (R \cdot p_i + t) \ \|^2$$

where $E(R,t)$ represents a mean square error of registration calculation;

N represents the number of effective matching point pairs participating in the calculation;

p_i represents a three-dimensional coordinate vector of an i-th feature point in the aerial visual sparse point cloud P_A, serving as the source data to be transformed; and

q_i represents a three-dimensional coordinate vector of the corresponding point in the ground laser point cloud set P_G that is closest to the transformed p_i in spatial distance, serving as target reference data. When the error E converges to a preset threshold, the iteration is stopped and the final pose transformation matrix T_{opt} is output.

The system applies the pose transformation matrix T_{opt} to real-time convert the visual point cloud data subsequently collected by the aerial robot to the ground coordinate system, uses an octree data structure to superimpose, store, and update the probability of the ground laser point cloud and the transformed aerial visual point cloud, and outputs a global three-dimensional environment map containing global obstacle information of ground and air, thereby realizing the spatial unification of heterogeneous sensor data and effectively expanding the environmental perception range of the system.

A predictive maintenance module is configured to analyze remaining service life and generate a health feature vector according to vibration and current data of power and drive components.

Further, in the predictive maintenance module, the analysis of remaining service life and the generation of a health feature vector specifically include:

converting the vibration and current data into frequency-domain features and statistical features;

calculating residual values between a theoretical state and actual feedback data using a reference dynamic model;

inputting the frequency-domain features, statistical features, and residual values into a degradation model to deduce the remaining service life of power and drive components; and

mapping and generating the health feature vector including flight speed, climbing angle, and endurance coefficient according to the remaining service life.

Specifically, the predictive maintenance module first collects the time-domain vibration signals and three-phase working current data of the drive motor of the ground robot and the rotor motor of the aerial robot in real-time through a sensor interface. The module performs fast Fourier transform on the vibration signals to extract the amplitude energy at the fundamental frequency and harmonic frequencies as frequency-domain features; at the same time, calculates the root mean square value, peak factor, and kurtosis index of the current data within a sliding time window as statistical features. Using a pre-calibrated motor reference dynamic model, the current control input command is used as model excitation to calculate the theoretical speed and theoretical torque, which are subjected to difference operation with the actual speed and actual torque fed back by the sensor to obtain a residual value sequence reflecting the degree of deviation of system performance.

The module adopts a random degradation process based on linear drift to model the component state, weighted fuses the extracted frequency-domain features, statistical features, and residual values into a comprehensive health index, and real-time updates the degradation rate parameter using historical monitoring data to further deduce the remaining service life of the power and drive components from the failure threshold. A calculation formula of the remaining service life is as follows:

$$L_{rem} = \frac{H_{th} - H_{curr}}{\lambda_{deg}}$$

where L_{rem} represents a deduced remaining service life duration;

H_{th} represents a preset functional failure health threshold of power and drive components, which is determined according to physical limit parameters of the components;

H_{curr} represents a comprehensive health index at a current moment integrating frequency-domain features, statistical features, and residual values; and

λ_{deg} represents a current average degradation rate fitted by the least square method using historical monitoring data.

After obtaining the remaining service life, the module converts it into a health feature vector guiding task planning through a nonlinear mapping function. The vector specifically defines the maximum allowable flight speed, maximum climbing angle, and battery endurance correction coefficient of the robot. The mapping calculation formula is as follows:

$$v_{limit} = v_{max} \cdot \left(\frac{1}{1 + e^{-\alpha(L_{rem} - T_{warn})}}\right)$$

where v_{limit} represents a maximum allowable flight speed limit value in the health feature vector;

v_{max} represents the nominal maximum speed designed by the robot factory;

L_{rem} is the remaining service life calculated above;

T_{warn} is a set life warning time constant; and

α is a speed attenuation slope adjustment factor, used to control the decline rate of the speed limit when the life is close to the warning value. The module generates the maximum climbing angle and endurance coefficient using a similar mapping relationship, which together form the health feature vector and output it to the collaborative planning module.

A collaborative planning module is configured to generate a spatiotemporally coupled task sequence including ground movement paths, aerial flight trajectories, and collaborative energy supplement coordinates based on the global three-dimensional environment map, the health feature vector, and a dynamic energy consumption model.

Further, in the collaborative planning module, the generation of a spatiotemporally coupled task sequence including ground movement paths, aerial flight trajectories, and collaborative energy supplement coordinates specifically includes:

converting the health feature vector into dynamic flight constraints and constructing a weighted topological graph based on the energy consumption model;

identifying breakpoints exceeding a flight radius and determining target collaborative energy supplement coordinates on a ground robot path using an optimization algorithm;

taking the energy supplement coordinates as connection points to separately plan ground obstacle avoidance paths and aerial smooth trajectories; and

verifying time synchronization of ground and aerial arrival at the energy supplement coordinates and generating the spatiotemporally coupled task sequence.

Specifically, the collaborative planning module first performs connectivity pruning on the global three-dimensional map according to the maximum climbing angle in the health feature vector, constructs a weighted topological graph using the energy consumption model, and identifies breakpoints exceeding the flight radius. The module uses a particle swarm optimization algorithm to search for the optimal collaborative energy supplement coordinate P_{charge} on the feasible path of the ground robot. Taking the energy supplement coordinate as the convergence point, the A* algorithm is used to plan the ground obstacle avoidance path, and the Snap minimization algorithm is used to plan the aerial smooth trajectory.

To ensure the smooth flight process and the speed conforming to the limit in the health feature vector, the trajectory generation process aims to minimize the jerk. The objective function formula of trajectory optimization is as follows:

$$J(p) = \int_0^T \| p^{(4)}(t) \|^2 dt + \sum_{i=1}^{M} \lambda_i \cdot g_c(p(t_i))$$

where $J(p)$ represents a cost function value of trajectory optimization;

T represents a total flight time;

$p^{(4)}(t)$ represents a fourth-order derivative of a position vector with respect to time, i.e., the Snap value, used to measure the trajectory smoothness;

$g_c(p(t_i))$ represents a hard constraint term including obstacle avoidance and maximum flight speed v_{limit} imit, where a value of v_{limit} is derived from the aforementioned health feature vector; and

λ_i is a constraint penalty coefficient.

After generating the path, the module verifies the synchronization between the estimated arrival time t_G of the ground robot and the estimated arrival time t_A of the aerial robot. If there is a time difference, the time allocation parameter of the aerial trajectory is iteratively adjusted until the time deviation between the two is less than a preset threshold, and finally the spatiotemporally coupled task sequence containing accurate timing and position information is generated.

An autonomous take-off and landing module is configured to respond to the spatiotemporally coupled task sequence and control the aerial robot to land on a docking platform of the ground robot in combination with ground robot motion prediction and relative positioning data.

Further, in the autonomous take-off and landing module, the controlling of the aerial robot to land on a docking platform of the ground robot in combination with ground robot motion prediction and relative positioning data specifically includes:

driving the aerial robot to fly following an estimated position of the ground robot;

guiding the aerial robot to enter a visual range using relative positioning data and solving a relative pose and speed;

adjusting an attitude of the aerial robot based on position-velocity closed-loop control to reduce a relative speed difference and maintain a relative position locked state; and

executing vertical landing and latching actions when distance and locking conditions are met.

Specifically, the autonomous take-off and landing module first parses the energy supplement command in the task sequence, subscribes to the real-time position and speed data of the ground robot, predicts the motion state of the ground robot at the next moment using an extended Kalman filter algorithm, and drives the aerial robot to fly to the predicted coordinate. When entering the visual communication range, the aerial robot identifies the visual cooperation mark located on the docking platform using a downward-looking camera, and solves the relative position deviation vector $e_p(t)$ and relative speed between the two through the PnP algorithm.

The module adopts a position-velocity cascade PID control strategy, and real-time adjusts the flight attitude and speed of the aerial robot based on the solved deviation to offset the relative motion with the ground robot. The calculation formula of the control command is as follows:

$$u(t) = K_P \cdot e_p(t) + K_I \cdot \int_0^t e_p(\tau)d\tau + K_D \cdot \frac{de_p(t)}{dt}$$

where $u(t)$ represents an attitude and speed control command output to a flight control system;

$e_p(t)$ represents a relative position deviation between the aerial robot and the center of the ground docking platform at the current moment;

$\frac{de_p(t)}{dt}$ represents a differential term of the deviation, which actually reflects the relative speed difference between the two; and

K_P, K_I, and K_D are the proportional, integral, and differential gain coefficients respectively.

The system continuously monitors the deviation data during the control process. When it detects that both the horizontal position deviation and the relative speed difference are less than the preset locking threshold, and this state is maintained for more than a stable window (e.g., 2 seconds), it is determined to enter the locked state. The module then executes the vertical landing action until the landing gear touches the platform to trigger the sensor, and controls the mechanical structure to complete the latching and fixing. Through dynamic prediction and high-frequency visual servo control, precise landing and recovery with zero relative speed on the ground mobile platform are realized.

A defect analysis module is configured to perform spatiotemporal comparison between inspection image features and a reference three-dimensional map to output an inspection report including defect categories, coordinates, and change trends.

Further, in the defect analysis module, the spatiotemporal comparison between inspection image features and a reference three-dimensional map specifically includes:

generating a reference image in the reference three-dimensional map according to a current collection pose;

performing difference operation between the inspection image and the reference image, suppressing environmental interference, and extracting a difference region;

identifying defect features of the difference region and mapping the same back to a three-dimensional map coordinate system; and

retrieving historical data of the coordinate to calculate a temporal change trend of the defect.

Specifically, the defect analysis module first reads the current six-degree-of-freedom pose and internal parameters of the camera returned by the autonomous take-off and landing module, performs virtual viewpoint projection on the pre-stored reference three-dimensional environment map using a graphics rendering pipeline, and generates a reference image consistent with the perspective and scale of the current inspection image. The module converts the real-time collected inspection image and the reference image to the HSV color space, performs histogram equalization only on the brightness channel to suppress the interference caused by environmental illumination differences, and then executes pixel-level difference operation and morphological opening operation to extract the difference region mask representing potential abnormalities.

The module inputs the extracted difference region into a pre-trained convolutional neural network classification model to output the specific category of the defect. At the same time, it obtains the depth value Z_c of the corresponding pixel point of the reference image, maps the two-dimensional pixel coordinate of the defect center in the image plane back to the world coordinate system using the pinhole camera inverse projection model. After determining the three-dimensional coordinate, the module retrieves the past inspection records of the position in the historical database, and calculates the change trend rate of the defect feature through temporal comparison. The calculation formula of the change trend rate is as follows:

$$R_{trend} = \frac{S_{curr} - S_{hist}}{t_{curr} - t_{hist}}$$

where R_{trend} represents a change trend rate of a defect feature over time, used to determine a deterioration speed of the defect;

S_{curr} represents a quantitative value of a defect feature identified in a current inspection, including crack length or rust area;

S_{hist} represents a quantitative value of a feature at the same coordinate in the most recent historical inspection record;

t_{curr} and t_{hist} are timestamps of the current inspection and the historical inspection respectively.

Finally, the module packages and generates an inspection report including the defect category, the calculated three-dimensional coordinate, and the change trend rate. Through digital twin comparison and temporal analysis, it can accurately identify minor defects in complex backgrounds and quantify their evolution risks, providing an intuitive basis for operation and maintenance decisions.

The present invention also provides an air-ground collaborative heterogeneous robot autonomous inspection method, as shown in FIG. 2, including the following steps:

S100: fusing laser point clouds of ground robots and navigation images of aerial robots to construct a global three-dimensional environment map and a pose transformation matrix;

S200: analyzing remaining service life and generating a health feature vector according to vibration and current data of power and drive components;

S300: generating a spatiotemporally coupled task sequence including ground movement paths, aerial flight trajectories, and collaborative energy supplement coordinates based on the global three-dimensional environment map, the health feature vector, and a dynamic energy consumption model;

S400: responding to the spatiotemporally coupled task sequence and controlling the aerial robot to land on a docking platform of the ground robot in combination with ground robot motion prediction and relative positioning data; and

S500: performing spatiotemporal comparison between inspection image features and a reference three-dimensional map to output an inspection report including defect categories, coordinates, and change trends.

Finally, it is to be explained that the above is only the preferred embodiment of the present invention, and it is not used to limit the present invention. Although the present invention is described in detail with reference to the foregoing embodiments, a person skilled in the art may still make modifications to the technical solutions described in the foregoing embodiments or make equivalent replacements to some technical features thereof. Any modification, equivalent replacement, or improvement made without departing from the spirit and principle of the present invention fall within the protection scope of the present invention.