An Autonomous Mobile Inspection Robot for an Electric Power Sub-station

Simon Thompson[1], Satoshi Kagami[1] and Masafumi Okajima[2]
[1]Digital Human Research Center, National Institute of Advanced Industrial Science and Technology, Tokyo, Japan
[2]Research and Development Department, Kansai Electric Power Company, Inc., Osaka, Japan

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Abstract: In this work, we describe the development of an outdoor, autonomous mobile robot that performs inspections of various facilities within an electric power sub-station. A segway-based robot was developed that can perform autonomous navigation along a given set of waypoints and perform inspection tasks (taking photographs at set locations). A retractable leg system was developed to allow the robot to enter/exit self-balancing mode and achieve a stable rest position from which to perform inspection tasks. The robot platform, localisation and control systems, and the inspection process are described, and a real world experiment consisting of navigation over a 1km path with 5 inspection points is reported. All inspection tasks were completed to the satisfaction of plant operators.

1 INTRODUCTION

This paper describes the development of an outdoor autonomous mobile robot platform that performs inspections of various facilities within an electric power substation. Specifically the robot must navigate along a given path, defined as a series of waypoints, stopping at certain waypoints to take photographs of plant facilities using a zoom-able pan/tilt camera. The environment of the electric power substation is large, 400x400 meters, complex, containing irregular shaped machinery, and having areas of rough and/or uneven terrain.

The main requirement for such a system, is an autonomous platform capable of physically moving through the sub-station environment while being able to perform localisation with sufficient accuracy to navigate through the plant and to perform the inspection task. Accurate localisation at inspection points reduces the need for image processing to identify target locations which could prove difficult in outdoor environments. A further requirement was the localisation system should not use GPS, as experiments with hand-held GPS units within the sub-station proved unreliable, perhaps due to the presence of powerful electro-magnetic fields. To allow flexibility in assigning the inspection route, it is also desirable to eliminate the need for artificial landmarks.

Typical approaches to mobile robot localisation use bayesian techniques to estimated a robot's location within a geometric map. Such systems usually use laser range finder range measurements and wheel based odometry information to localise the robot within 2D occupancy grids (Thrun et al., 2001). The localisation process then becoming an iterative process of predicting motion from the robot's odometry measurements and evaluating the predicted estimates by matching the current sensor data with the expected sensor data calculated from the map.

Moving from indoor robots to outdoor robots, because of the relatively unstructured nature of the environment, the localisation problem typically changes from 3DOF (2D position and azimuth orientation) in 2D maps, to 6DOF (3D position and roll, pitch, yaw) in 3D maps. This increase in the dimensions of the state space to be estimated (and in the environment map) results in extra computational requirements compared to indoor robots. With outdoor robots typically moving faster and being larger, this presents some problem in terms of safe and accurate motion control based on feedback from the localisation process.

This increase in computation for outdoor localisation has led to introduction of additional localisation cues such as GPS signals and artificial landmarks in order to reduce the need for matching between sensor data and large, complex environment maps (Thrun et al., 2006) (Ohno et al., 2004) (Moralez and Tsub-

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ouchi, 2007). This can be a problem, however in environments where GPS signals are unavailable or unreliable, or when the installation of artificial landmarks within the environment is unacceptable or impractical. In such cases, systems typically revert back to 3DOF localisation as in (Madhavan and Durrant-Whyte, 2004), who report a laser range finder based 3DOF localisation system for ground vehicles using full laser scans (with 1*m* error) and landmarks (0.5*m* error). Likewise, (Levinson et al., 2003) use the reflectivity of road surfaces to build image like maps of urban environments and localise in 3DOF by correcting GPS readings with map based matching of LIDAR range and reflectivity data, and report an impressive 10*cm* localisation accuracy. Without GPS they report a maximum error (measured at 50m intervals - presumably while stopped) of 35*cm*. This approach, however requires regular lane markings. A similar system based on visual sensing of lane markings is reported by (Xia et al., 2006) but can suffer from occlusions due to a limited field of view.

As for mobile inspection robots, the majority of reported systems are for inspections of hard to access environments such as pipe inspection (Suzumori et al., 1999) or for rescue activities (Osuka, 2003), with research focused on specific mobility or sensing environments required by such environments. (Davison and Kita, 2003) report a pair of cooperating indoor inspection robots with the application of inspecting the outside of pipes in a nuclear power plant. Stereo vision and sparse feature maps are used to accurately localise the robots in small scale environments.

(Thompson et al., 2010) (Thompson et al., 2011b) report the development of a 6DOF localisation system that can perform accurate localisation within dense 3D polygon maps of large outdoor environments without the use of GPS. In this work we use this localisation system to develop a mobile robot platform capable of performing an autonomous inspection task as described above.

Below, the components of the autonomous inspection robot are described, including the robot platform, the retractable legs, the 6DOF localisation system, the method used for motion control, and the implementation of the inspection task. Also a real world inspection task in a power sub-station consisting of 5 inspection points along a 1km path is reported. The main contribution of the paper is the successful demonstration of an autonomous outdoor inspection task over a wide area within an operational electric power substation.

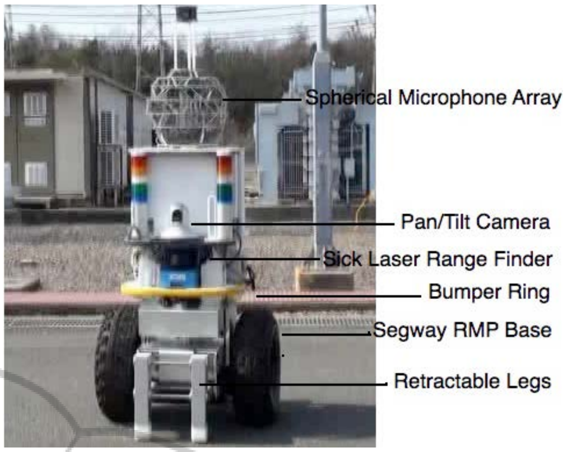

Figure 1: The inspection robot, based on a Segway RMP base.

2 AUTONOMOUS ROBOT SYSTEM

2.1 Robot Platform

The robot platform used is the Segway RMP 200/ATV (Nguyen et al., 2004) which is an inverted-pendulum type, self-balancing two-wheeled mobile robot. The RMP was chosen as it provides a reliable base that can operate outdoors, and has the power to traverse rough terrain and the maneuverability to turn on the spot. This base has been modified to mount front and back facing Sick LMS laser range finders, and a bumper ring. A box computer running ART Linux performs motion control and communicates with the RMP base, while a laptop computer (Linux, Core 2 Duo 2.26Ghz CPU, nVidia Quadro FX 770M graphics card) runs the localisation software. (Figure 1 shows the robot platform. The robot also has retractable legs which it uses for stability when not moving, and which allows it to start/stop self-balancing mode without human intervention. For inspection purposes the robot is equipped with a zoom-able pan/tilt camera. A 3D spherical microphone array for detecting irregular sounds within the sub-station is also shown, but is outside the scope of this paper (for details see (Sasaki et al., 2012)). Stacks of different colour lights are used to communicate the robot state to nearby humans for safety purposes.

2.2 Retractable Leg System

The Segway RMP base is a self balancing wheeled inverted pendulum type of robot and typically must maintain some degree of motion to stand upright.

a)

b)

Figure 2: Active trapezoidal linked legs in a) retracted position, and b) extended position.

This complicates any inspection task requiring a stable base, such as taking a picture from a camera mounted on the robot platform. To overcome this, a pair of retractable legs was developed (Kabasawa et al., 2012), to enable the robot to exit self balancing mode and assume a stable position. Figure 2 shows the legs mounted on the robot base in a) the retracted (or ”up”) position, and b) the extended (or ”down”) position. The legs are two pairs of active trapezoidal linked legs which also allows the robot to stop on inclined surfaces, or with an inclined body. From a starting position, legs down, the system initiates leg retraction an immediately switches the Segway control into self balancing mode. To stop, legs are extended and when they touch the ground the self-balancing control mode is switched off.

2.3 Dense 3D Polygon Maps

In order to localise accurately within a large, complex environment such as a power sub-station, we use dense 3D polygon maps constructed from 3D laser scans as reported in (Kagami et al., 2010). Range data from each scan location are associated with adjacent scans, and the transformation matrices were solved. Aligned points were then converted into dense 3D polygon maps. Such realistic 3D maps allow for knowledge of traversable terrain, as well as providing flexibility in choice of navigation route, as most of the structure of the environment is captured. In this study, a map covering approximately $400 \times 400m$ was constructed which contained $2,018,418$ polygons. Part of the map is shown in Figure 3, ground surface is shown in blue, while the grey shows various structures within the sub-station. Such complex structures, interspersed with wide open spaces are typical of the plant environment. This image shows approximately $120 \times 80m$ of ground area.

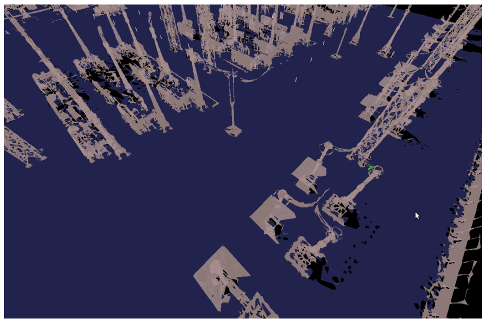

Figure 3: Part of the 3D polygon map of the power sub-station.

2.4 6DOF Localisation

In this study a particle filter framework is adopted to perform 6DOF localisation within the dense 3D polygon maps, using odometry information from the Segway RMP base, and two robot mounted laser range finders (front and back facing). In such an approach, a set of state estimates, or particles, are evaluated for the likelihood that the states they represent would produce the current laser range sensor data, by comparing it with expected range data generated using the map. For 3DOF localisation this is relatively easy, as a 2D map can be used. For 6DOF localisation the extra dimensionality of the state space, and the extension of the map to 3D mean the computational requirements for localisation can become unmanageable for the real time constraints of autonomous navigation.

To perform accurate, efficient localisation in dense polygon maps, several techniques were developed to reduce the computational requirements involved in matching sensor data with expected map views in the particle filter based localisation process.:

- Constrained Motion Model: use of vehicle dynamics and dense 3D polygon map to limit dispersion of localisation belief distribution during motion (Thompson et al., 2010). Knowing the surface of the current location, height pitch and roll dispersion can be bounded.

- Indexed Polygon Map: simple grid index and polygon classification scheme to limit number of polygons used for to generate expected sensor views within a given map area (Thompson et al., 2011a)
- Selection of Polygon Sets: precompute the best sub-set of polygons to use at each index grid based on likely frequency of observation, angle of incidence and angle of elevation of the observation ray (Thompson et al., 2011b). This further reduces the number of polygons to be used for localisation within a given map area.
- GPU Based Expected View Generation: use specialised graphics hardware to reduce cost of generated expected sensor views from polygon maps.

Using these techniques, fast, accurate localisation can be performed in large scale, dense 3D polygon maps. Typical localisation results are an average of $10cm$ localisation error with a cycle rate of approximately $10Hz$. Experiments within the substation environment have produced average localisation error of $3cm$ over simple paths that travel close (within $10m$) to plant machinery and thus have strong localisation cues. For details of experimental results on localisation accuracy see (Thompson et al., 2011a)(Thompson et al., 2011b). Localisation performance was not significantly affected by observed environmental changes such as sparse pedestrians, occasional passing vehicles, addition/removal of stored equipment, and even the addition of demountable buildings.

One problem with the localisation system that was observed in development, was failure due to temporary loss of odometry information. In certain areas of the sub-station, the robot pass through areas with strong electro-magnetic fields which caused the USB connection from the RMP base to the navigation control system to disconnect, resulting in loss of odometry information while the robot comes to a stop. A simple system to monitor the connection, and in the case of disconnection to "fake" approximate odometry (with appropriate uncertainty) of the stopping motion while attempting reconnection, was developed.

2.5 Path Following Control System

To perform autonomous navigation the robot system employs a path following method known as the pure pursuit algorithm (Heredia and Ollero, 2007). The path is defined by a series of way points, and line segments connecting the way points form the reference path. The pure pursuit algorithm attempts to follow the path by computing a circular arc from the estimated robot position to a point some distance along the reference path. This "look ahead" distance varies depending on current velocity and whether a waypoint or goal location is near. In this work, no obstacle avoidance is implemented as it is a controlled environment and the robot should not deviate unexpectedly from its path. If an object is detected in its paths, the robot simply stops and waits until the path is clear.

3 INSPECTION TASK

The inspection task involves taking a photograph of various facilities for later viewing by plant personel. Each inspection consists of the following sub-behaviours:

1. navigating to a predefined point within the substation
2. turning to a desired orientation if required
3. lowering legs for stability
4. camera performing pan/tilt and zoom as required
5. taking the photograph
6. raise legs
7. proceed to next way-point.

In order to give a set of inspection tasks to the robot, a high level command language was defined:

- *START x y*: defines a start location by *x* and *y* coordinates within the given map.
- *GOTO x y*: define a navigation way-point within the given map
- *TURN theta*: turn the robot to a given global orientation.
- *INSPECT id x y z zoom*: defines an inspection task in terms of an identification number, a three dimensional location, and a camera zoom parameter.

For any specific inspection task, the robot performs the following sequence of commands (with appropriate parameters): *GOTO, TURN, INSPECT*. First the robot navigates to the given way-point in the GOTO command parameters using the localisation and control systems described above. Then the robot turns to the given orientation *theta*, again using the localisation estimate for feedback. The legs are then lowered, and the robot-self-balancing mode disabled.

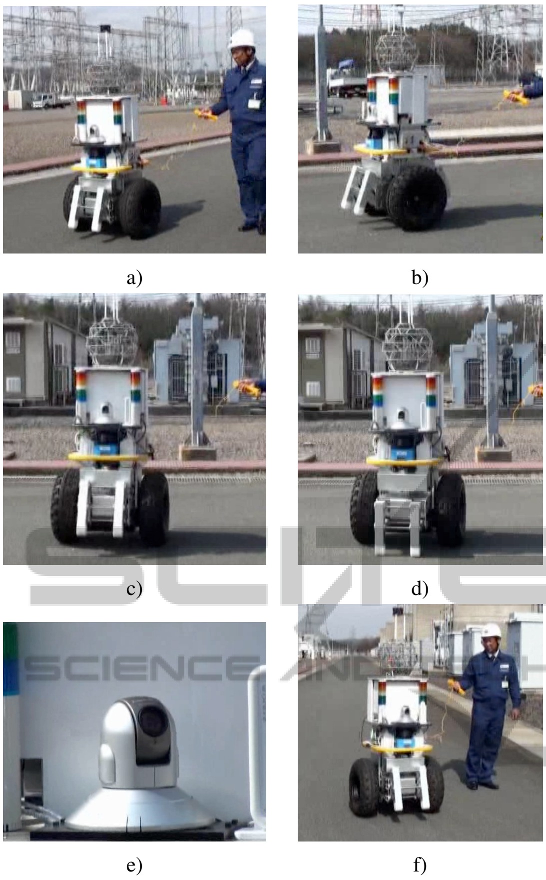

Figure 4: An example of the inspection procedure: a) robot moves towards the inspection point, b) stops at point, c) turns to required orientation, d) put s legs down to stabilize platform, e) activates pan-tilt camera to take inspection photograph, f) retracts legs and continues to next way-point.

Once the robot is motionless and stable, the current 6DOF localisation estimate and the 3D location given in the x, y, z parameters to the *INSPECT* command (defined in relation to global map coordinates), are used to calculate a pan/tilt configuration which orientates the camera towards the inspection point. Once correctly orientated, the camera's zoom control is adjusted according to the *zoom* parameter, and the picture is taken.

4 EXPERIMENTAL RESULTS

Real world experiments demonstrating autonomous inspection were performed at an operational electric power sub-staion operated by Kansai Electric Power Company (Japan).

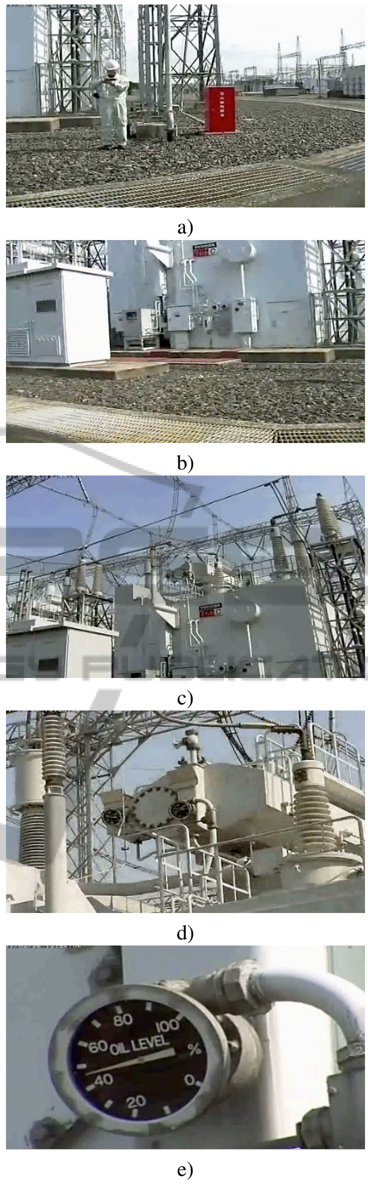

Figure 5: An example of an inspection photograph taken by robot, images show view from pan-tilt camera: a) view when legs are lowered, b) pan to required orientation, c) tilt to required elevation, d) zooming to target, e) photograph taken for inspection task.

4.1 Single Inspection Task

Figure 4 shows the robot during an inspection task, sub-figure a) robot moves towards the inspection point, b) stops at point, c) turns to required orientation, d) put s legs down to stabilize platform, e) activates pan-tilt camera to take inspection photograph, f) retracts legs and continues to next way-point. Figure 5 shows images from the pan-tilt camera during the inspection task. Sub-figure a) shows the view after the

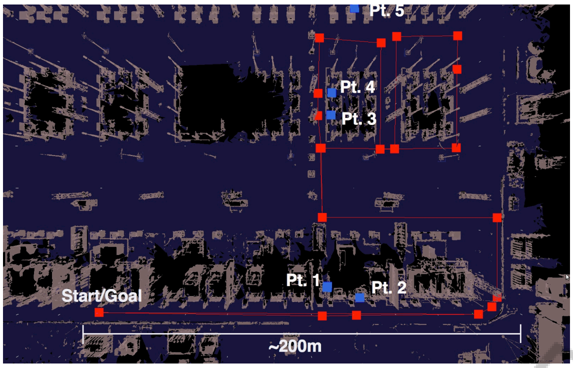

Figure 6: Inspection task within polygon map. Navigation path (red squares (waypoints) and red lines (connecting paths), and inspection points (blue squares) labelled one to five.

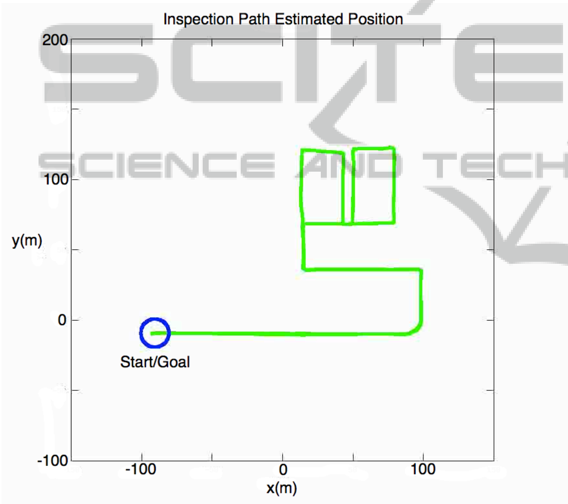

Figure 7: The estimated path traveled by the robot during the inspection task.

robot has, stopped turned to the required orientation and lowered it's legs; b) after the camera has performed a pan motion; c) after tilt motion; d) in the process of zooming; e) the photo taken for the inspection task. In this example the inspection point was over $15m$ from the robot stopping position, and a gauge of approximately $15cm$ was photographed using just the robot's estimated position for guidance.

4.2 Inspection of an Electric Power Sub-station

The inspection task required the robot to navigate over a 1km path throughout a power sub-station within one hour, performing inspection tasks at five separate places within the environment (Fig. 6). Inspection points are things like transformers, gauges and latches. The inspection points were manually defined by operators, with the 3D coordinates of the points being recovered from the polygon map. The robot traveled over the path with a maximum speed of $0.6m/s$ The inspection task was completed within 23 minutes, with all five inspection points captured to the satisfaction of plant operators. The estimated path the robot traveled is shown in Figure 7. Average localisation error was approximately $10cm$.

5 CONCLUSIONS

In this paper we have presented an autonomous mobile robot capable of performing an inspection task within the grounds of an electric power sub-station. Fast, accurate 6DOF localisation, using onboard-sensors only, in conjunction with a retractable leg system which stabilizes the robot base, allowed the mobile robot to take precise photographs of inspection targets. A high level command language was described, and a successful, real-world inspection task was reported.

Although in this study, the inspection task was completed satisfactorily with just the use of the estimated robot position, ideally the localisation result would provide an initial estimate for an image processing system to perform a local search for the inspection target, and subsequently to give autonomous confirmation that the task was achieved. Also in this case, the robot did not perform any obstacle avoidance. Subsequent work aims at 3D sensing and avoidance of potential obstacles, although this should occur in a predictable, safe and operator approved manner. Further study is also needed to evaluate long term autonomous operation in terms of inspection success rate and localisation performance in various weather conditions.

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