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Corner features extraction: underwater SLAM in structured environments

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Abstract

Purpose – The purpose of this paper is to present a method to extract corner features for map building purposes in man-made structured underwater environments using the sliding-window technique.

Design/methodology/approach – The sliding-window technique is used to extract corner features, and Mechanically Scanned Imaging Sonar (MSIS) is used to scan the environment for map building purposes. The tests were performed with real data collected in a swimming pool.

Findings – The change in application environment and the use of MSIS present some important differences, which must be taken into account when dealing with acoustic data. These include motion-induced distortions, continuous data flow, low scan frequency and high noise levels. Only part of the data stored in each scan sector is important for feature extraction; therefore, a segmentation process is necessary to extract more significant information. To deal with continuous flow of data, data must be separated into 360° scan sectors. Although the vehicle is assumed to be static, there is a drift in both its rotational and translational motions because of currents in the water; these drifts induce distortions in acoustic images. Therefore, the bearing information and the current vehicle pose corresponding to the selected scan-lines must be stored and used to compensate for motion-induced distortions in the acoustic images. As the data received is very noisy, an averaging filter should be applied to achieve an even distribution of data points, although this is partly achieved through the segmentation process. On the selected sliding window, all the point pairs must pass the distance and angle tests before a corner can be initialised. This minimises mapping of outlier data points but can make the algorithm computationally expensive if the selected window is too wide. The results show the viability of this procedure under very noisy data. The technique has been applied to 50 data sets/scans sectors with a success rate of 83 per cent.

Research limitations/implications – MSIS gives very noisy data. There are limited sensorial modes for underwater applications.

Practical implications – The extraction of corner features in structured man-made underwater environments opens the door for SLAM systems to a wide range of applications and environments.

Originality/value – A method to extract corner features for map building purposes in man-made structured underwater environments is presented using the sliding-window technique.

Keywords Control systems, Artificial intelligence

Paper type Research paper

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Introduction

Simultaneous localization and mapping (SLAM) relies on the feature extraction process to extract appropriate and reliable features with which to build stochastic maps. SLAM is a process by which a mobile robot maps the environment and concurrently localizes itself within the map (White and Bailey, 2006a, 2006b). Mobile robots such as autonomous underwater vehicles (AUVs) have found applications in structured man-made underwater environments such as marinas, drilling platforms, harbours, channels and dams for inspection and maintenance missions. These environments motivate the use of feature types such as corners, planes and curves to provide rich environment representations and, hence, open the door for underwater SLAM systems to a wide range of environments and applications (Ribas, 2008). Currently, there are no approaches that address the issue of corner features extraction in man-made structured underwater environments. In line with the above motivation, we present a method to extract corner features for map building purposes in man-made structured underwater environments using the sliding-window technique and Mechanically Scanned Imaging Sonar (MSIS) for environment scanning purposes. Real data collected in a swimming pool is used for the tests.

MSIS presents some differences when compared with laser scanners. MSIS gathers data by rotating a mechanically actuated transducer head at pre-defined angular steps. This results in a continuous data flow and a low scan frequency as compared with laser scanners, which take snap shots of the environment. The transducer head takes a considerable amount of time to complete a scan. Although the first and last beams are placed near each other, there is a considerable time lapse between instances in which they were taken and, at times, the vehicle would have drifted. The drift leads to distortions in the acoustic image because of both translational and rotational motions. The amount of time to complete a scan sector also varies depending on the range settings of the sensor. Higher range settings will normally require more time to complete a scan sector because the signal travels a longer distance. These effects have to be taken into account when dealing with MSIS mounted on a vehicle (Ribas, 2008).

The use of corner features has been traditionally related to the use of two-dimensional (2D) laser scans in indoor environments using sliding-window techniques (Spinello, 2007; Matsebe, 2011). Underwater SLAM systems using MSIS usually model natural environments as point features corresponding to clusters of acoustic data (Ribas, 2005).

In Ribas (2005)), a process of feature extraction from acoustic images obtained by the Miniking imaging sonar in a subsea environment is described. Before any processing, false returns are eliminated from the data. The extraction process starts by applying an averaging filter to diminish the effects of noise, followed by segmenting the high-intensity blobs. Different properties of the blobs such as a centroid are obtained, which are then used as a point features.

A three-stage point feature extraction procedure using a SeaKing sonar data obtained from both a swimming pool and natural environment is presented in (Williams *et al.*, 2013a, 2013b). In both experiments, artificial landmarks are introduced into the environment. The feature extraction process starts by identifying principal returns in individual pings. These represent ranges to objects in the environment. The principal returns are then grouped into clusters. Small, distinct clusters are then identified as point features (Williams *et al.*, 2013a, 2013b). A point feature extraction procedure from data collected using a Tritech Dual Frequency Sonar in a water tank and a SeaBat carried by a diver towards pier legs is described in (Tena *et al.*, 2001). Each sector image is low-pass filtered using a median filter to remove the backscatter noise. A double threshold is applied to obtain a binary image. The algorithm extracts the centre of mass, the size in pixels of the target and the target's first invariant moment.

An algorithm to extract line features using Tritech MiniKing sonar is presented in (Ribas, 2008). A threshold is applied to discard low echo returns, which contain no significant information. A search for local maximums is carried out for each beam. This reduces the number of considered measurements without loss in the accuracy of the features. For line extraction, a Hough transform with a particular voting scheme is used. Line feature extraction using MSIS is also reported by Ribas *et al.* (2009). The extraction of corner features corresponding to intersecting arcs from a ring of Polaroid sonar sensors using Hough transform in an indoor environment is also reported in Tardos *et al.*, (2002). Other feature types in underwater environments have also been reported: Harris corners from cameras images (Horgan *et al.*, 2008; Roberson *et al.*, 2010), Speeded Up Robust Features (SURF) using stereo vision (Mahon *et al.*, 2008) and generalized features (blobs) by fusing camera and sonar data (Majumder, 2001).

From the literature, it is clear that no work addresses the extraction of corner features in man-made underwater environments using MSIS. In man-made underwater environments, line features extraction using MSIS is reported. Most authors focus on extracting point features in natural environments. The extraction of corner features is reported in indoor environments using laser scanners and cameras.

Experimental setup

The experiment involves an AUV navigating in a swimming pool and, at the same time, logging data using on-board sensors.

Test environment

The tests were performed in a 15 m by 15 m, and 5 m deep public swimming pool (Plate 1) located in the Pretoria, South Africa.

Experimental platform

The AUV used for the work reported in this paper is shown in Plate 2. It is a simple, small and low-cost vehicle comprising a water-tight compartment made of aluminium. The compartment houses the computer system, batteries, ballast tanks, sensors and the electronic components. A metal frame is mounted around the vehicle to protect the compartment and external sensors from damage. The vehicle is designed to be neutrally buoyant. The vehicle is also equipped with a water pressure sensor, an electronic compass and an acoustic beaconing system.

MSIS

The Micron DST Sonar used to scan the environment is shown in Plate 3. The sonar is mounted underneath the AUV in an inverted mode. The sonar's operating range is set at 13.5 m, and it is sampled at 0.0225 m. A mechanical step angle of 0.9° is used to generate 360° scan sectors. With these range settings, 600 data bins are returned by the sonar head, and each bin is sampled at 0.00003 seconds. Individual sonar beams have a return signal travel time of about 0.018 seconds. The sample time between individual beams is about 0.1 seconds, which is about five times the signal travel time. As a result, there is enough waiting time before the sonar could be pinged again, and, hence, this avoids interference from consecutive echo returns. An 8-bit mode is used to represent numbers in the range of 0 to 255.

Plate 1.
Swimming pool in
Pretoria, South
Africa

Plate 2.
The experimental
platform (AUV)

Plate 3.
Tritech Micron DST Sonar

Acoustic beaconing system

An acoustic beaconing system is used to determine the absolute positions of the AUV. This provides ground truth about the positions of the vehicle. The system uses four sonar transducers; three are placed at known positions and used as beacons. One receiving transducer is mounted on top of the vehicle. The system has a maximum 2D position error of 0.21 m (Holtzhausen, 2010).

Electronic compass

An electronic compass is used to estimate the heading of the AUV. The device used is a HMC6343 by Honeywell. This device is calibrated before every dive to reduce the effects of disturbances due to other magnetic objects (Holtzhausen, 2010).

Water pressure sensor

An LM series low-pressure media-isolated pressure sensor is used to estimate the vehicle depth. (Holtzhausen, 2010).

Methodology

Corner features to take advantage of structures with intersecting planar surfaces found in man-made underwater environments such as marinas, dams, drilling platforms, channels, harbours are sought. In this paper, corners are defined by intersecting planar surfaces making angles between 70 and 120° inclusive. MSIS has been chosen for this work because of its low-cost, its capability to perform user selectable scan sectors up to 360° and its capacity to produce rich representations of the environment. Generally, there are limited sensorial modes for underwater applications and the data is normally corrupted by noise. Challenges associated with MSIS include continuous data flow, low scan frequency and high noise levels. The low scan rates of the sensor results in motion-induced distortions in the acoustic images. Therefore, the vehicle must move very slowly or remain stationary during scanning. Since the data is very noisy, a smoothing filter must be applied to avoid mapping outlier data points as corner features. On the selected sliding window, all the point pairs must pass the distance and angle tests before a corner can be initialised. This minimises mapping of outlier data points but can make the algorithm computationally expensive if the selected window is too wide. To deal with continuous flow of data and the low scanning frequency of MSIS, data is separated into 360° scan sectors (Ribas, 2008). The vehicle is assumed to be static during scanning periods.

Data segmentation

Objects in the environment appear as high echo-amplitude returns in acoustic images. This means that only part of the data stored in each beam is useful for feature extraction (Ribas *et al.*, 2006, 2009). As a result, a segmentation process is carried out to extract more significant information. This process reduces the computational cost of processing the data since fewer data points are considered. The segmentation process consists of three steps which are carried out beam to beam. In the first step, only those bins with an intensity value above a low level noise threshold are considered; a typical operating noise threshold value is 13 decibels (Limited, 2012). This filters out low-level background noise, transducer reverberation noise and noise because of aerations which might be present in the water. In the second step, a higher-level threshold value of 22 decibels is applied; this step filters out some of the multiple reflections off the water surface, walls and objects, leaving behind significant information corresponding to objects. The third step involves selecting bins with the highest intensity return values above the threshold value of 22 decibels. A highest intensity return is defined as a bin with a maximum amplitude return value along a scan-line. This further segments the data without loss in significant information. Computationally segmentation step is done only once by applying a threshold value of 22 decibels, the other steps are included here to explain the level of noise inherent in acoustic images. An averaging filter is further applied to achieve an even distribution of data points (Ribas *et al.*, 2009).

Following the segmentation process and highest intensity return selection, ranges corresponding to the highest intensity return bins are also determined and accumulated into a buffer until a required number has been stored. These ranges correspond to ranges to objects in the environment. The bearing information and the current vehicle pose corresponding to the selected scan-lines are also stored. The current vehicle pose is used to compensate for motion-induced distortions in the acoustic images.

Sliding window technique

The polar measurements are first transformed to Cartesian coordinates. Then a fixed size window made up of three data points is defined. The assumption made is that the three data points define the sides of a triangular window (Figure 1). The mid-point sample k, is taken as one of the vertices of the window, and this is the sample point where the angle is checked. The other two sample points i and j are taken as the other vertices of the window; these are at the same number of points away from the mid-point sample. For instance, a sample window of size 13 will have a mid-point at sample point 7, and the other two vertices at sample points 1 and 13, respectively.

After a window has been defined, the distance $dis(i,j)$ between the vertices at i and j is determined according to the following equation:

$$dis(i,j) = \sqrt{(\Delta x_{ij})^2 + (\Delta y_{ij})^2} \tag{1}$$

Where, Δx_{ij} and Δy_{ij} are the changes in x-coordinates and y-coordinates, respectively. If the distance $dis(i\,,j)$ is greater than a pre-defined threshold value, then the mid-point of the window is shifted to the next data point and the process is repeated. If the distance $dis(i,j)$ is lower than a pre-defined threshold value, then an angle check is performed. But first, the distance $dis(k,j)$ between vertices at k and j, and the distance $dis(k,i)$ between vertices at k and i have to be determined, these are given as follows:

$$dis(k,j) = \sqrt{(\Delta x_{kj})^2 + (\Delta y_{kj})^2} \tag{2}$$

$$dis(k,i) = \sqrt{(\Delta x_{ki})^2 + (\Delta y_{ki})^2} \tag{3}$$

Where, Δx and Δy are the changes in x-coordinates and y-coordinates, respectively. This information is then used to determine the angle θ at the mid-point sample using the re-arranged dot product rule according to the following equation:

$$\theta = \arccos\left(\frac{v_i\,.\,v_j}{|v_i|\,|v_j|}\right) \tag{4}$$

where the vectors v_i and v_j are given as:

$$v_i = (\Delta x_{ki} \quad \Delta y_{ki}) \tag{5}$$

$$v_j = (\Delta x_{kj} \quad \Delta y_{kj}) \tag{6}$$

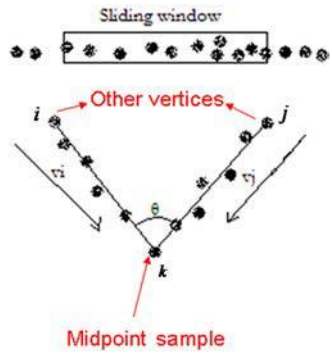

Figure 1.
Sliding Window for the corner detection

If the angle θ is outside the pre-defined minimum and maximum threshold values, then the mid-point of the window is shifted to the next data point and the process is repeated. If the angle θ is within the pre-defined minimum and maximum threshold values, then an inward validation is performed by picking corresponding sample points from each side of the window centred at the current mid-point and repeating the corner validation all the way to the last two points closest to the mid-point. All these point pairs must pass the distance and angle tests for a corner to be initialised at the current mid-point. This ensures that corners are not initialised at outlier sample points but on the other hand, it makes the algorithm computationally expensive if the window selected is too wide. Figure 2 shows the flow diagram of the corner feature extraction algorithm.

Experimental results

Figure 3 shows a 360° sector acoustic scan in polar form taken in a swimming pool. Figure 4 shows the first step of the segmentation process; the scan obtained after applying a low-level noise threshold value of 13 decibels. Figure 5 shows the second step of the segmentation process; the scan obtained after applying a threshold value of 22 decibels. Figure 6 shows the third step of segmentation process; the scan after selecting bins with the highest intensity return values above a threshold value of 22 decibels and the extracted corner feature.

Discussion

Figure 6 shows a 360° raw acoustic scan in the polar form. The image is colour coded to distinguish between strong intensity returns from objects and weak intensity returns as a result of noise and multiple reflections. Regions with intensity return values > 0 but $<$ 13 decibels are sampled in blue, regions with intensity return values > 13 but < 22 decibels are sampled in green, regions with intensity return values > 22 decibels are sampled in red. The expected swimming pool walls are shown with a thick black line. Some of the reflections are quite clear, whereas others are a bit ambiguous and are difficult to make out. Multiple reflections off the walls are annotated in green; these reflections continue out to the maximum range and decrease in intensity as the range increases. Multiple reflections off targets are annotated in brown; these reflections continue out to the maximum range and increase in intensity as the range increases. Reflections from the water surface (surface reflections) appear as low-intensity circular returns equidistant from the sonar head. Swimming pool bottom reflections also make up the noise but they are generally of a higher intensity than the water surface reflections because of the hardness of the reflecting material. There is a further high amplitude reflection annotated in purple that appears to be a bottom reflection. There are also a lot of low-level returns sampled in blue on the image, which are likely to be receiver self-noise and aerations in the water. Very little or no signal from the walls further away is reflected back in the direction of the transducer, and this appears to be a result of oblique grazing angle that the beam strikes the wall surface; therefore, most of the sound energy reflects outward with very little signals reflected back in the direction of the transducer.

Figure 7 shows the image after applying a low-level noise threshold value of 13 decibels; this is the first step of the segmentation process. Most of the low-level background noise and noise because of any aeration in the water is eliminated from the

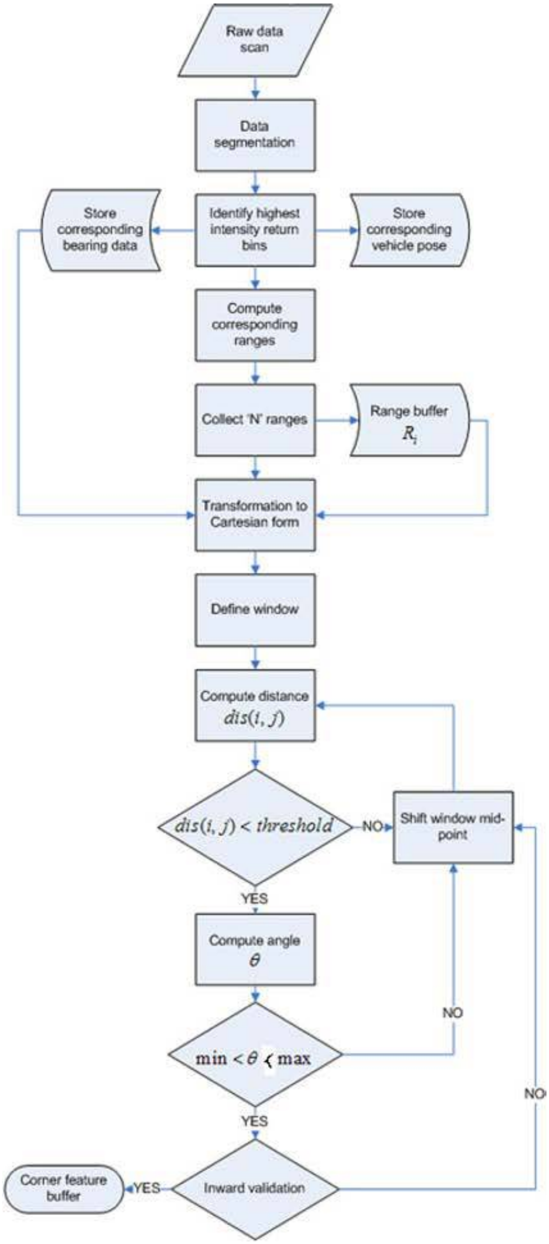

Figure 2.
Corner features extraction flow chart

acoustic image. Some of the low-intensity multiple reflections off walls and targets and some low-intensity water surface and swimming pool bottom reflections are also eliminated. A range of 2 m from the sonar is ignored to eliminate the transducer reverberation noise.

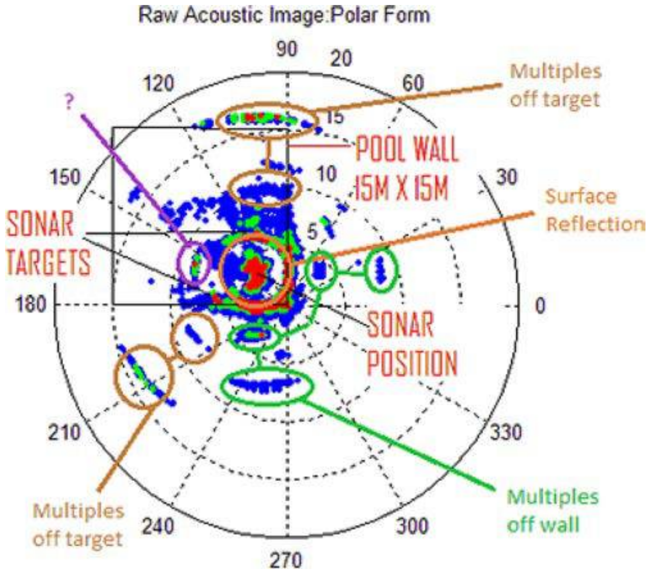

Figure 3. Raw acoustic image in polar form

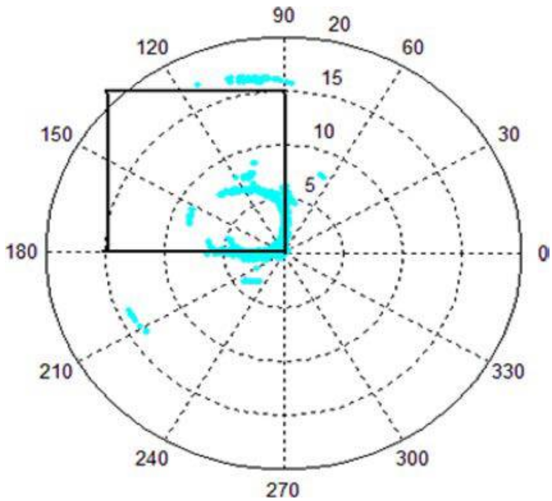

Figure 4. The first step of the segmentation process

Figure 8 shows the image obtained after applying a threshold value of 22 decibels; this is the second step of the segmentation process. This process leaves behind significant information that corresponds to the swimming pool walls. Some of the high-intensity multiple reflections off walls and targets and some high-intensity surface and bottom reflections are further eliminated.

Following the application of a threshold value of 22 decibels, bins with the highest intensity return values along individual beams are selected; this is the third step of the segmentation process. Figure 9 shows the image obtained after selecting the highest

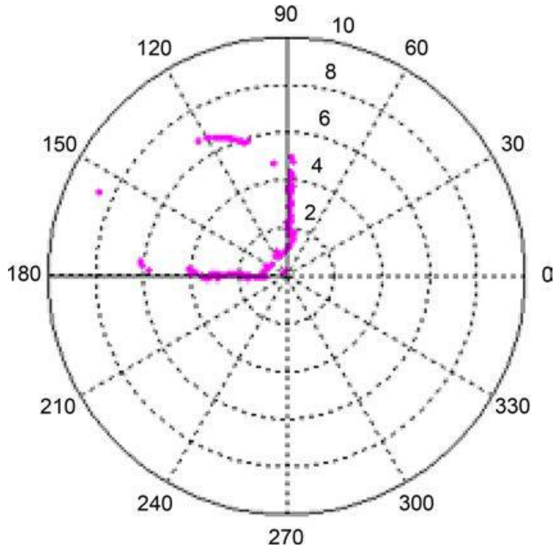

Figure 5.
The second step of segmentation process

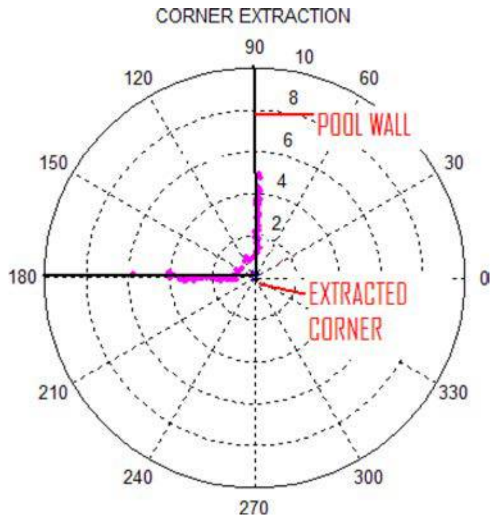

Figure 6.
The third step of segmentation process and the extracted corner feature (blue star)

intensity returns. This process further segments the data and leaves behind significant information corresponding to swimming pool walls. The image also depicts the extracted corner feature. As it can be observed in the figure, the extracted corner is a good representation of the region where a corner is expected. On the selected sliding window, all the point pairs must pass the distance and angle tests before a corner can be initialised. This minimises mapping of outlier data points but can make the algorithm computationally expensive if the selected window is too wide. The results presented show the viability of this method under very uncertain measurements. The technique has been tested on 50 data sets/scans sectors with a success rate of 93 per cent.

Conclusion

This paper presents a method to extract corner features for map building purposes in man-made structured underwater environments using the sliding window technique and MSIS to scan the environment. The real data used for the tests were collected in a swimming pool. Corners here are defined by intersecting planar surfaces making angles between 70 and 120° inclusive. The sliding window technique has been traditionally applied to laser data obtained in indoor environments. The change in application environment and the use of MSIS present important differences. To deal with continuous flow of data, data is separated into 360° scan sectors. The bearing information and the current vehicle pose corresponding to the selected scan-lines are stored and used to compensate for motion-induced distortions in the acoustic images.

Only part of the data stored in each scan sector is important for feature extraction; therefore, a segmentation process is carried out to extract more significant information. An averaging filter is applied to achieve an even distribution of data points. On the selected sliding window, all the point pairs must pass the distance and angle tests before a corner can be initialised. This minimises mapping of outlier data points but can make the algorithm computationally expensive if the selected window is too wide.

The results presented show the viability of this method under very uncertain measurements. The technique has been tested on 50 data sets/scans sectors with a success rate of 93 per cent. Further work will involve the implementation of the algorithm in real time with a SLAM system.

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