Grid Map for Local Motion Planning with using Sonar Sensors

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Abstract:
In this paper, we address the problem of representing dynamic environment as accurately as possible using inexpensive and error-prone sonar sensors. For a robot which should move to a goal with avoiding dynamic obstacles, the robot should have a capability to build a map which represents dynamic environment as exactly as possible. Under the necessity, we propose an efficient and accurate grid-mapping approach that is based on the sound pressure; we call the map the sound pressure map. The performance of the sound pressure map was confirmed through real experiments. Even with using sonar sensors, the sound pressure map can build the best grid map in terms of representing dynamic environment.

1. INTRODUCTION

As robotics research emphasizes intelligent behavior, mobile robots need a capability to explore known / unknown environments. For the capability, the robot should be endowed with an autonomous navigational ability in unknown, unstructured, dynamic and unpredictable environments. Autonomous navigation is the task of finding and following a trajectory to a goal without human intervention. The trajectory should be safe to avoid static and dynamic obstacles and be efficient to escape local traps and minima. The trajectory generator is called as a motion planner.

The motion planner is generally classified into two types: global and local. The global motion planner1)–4) has been called as a high-level planner5) because it is based on a global world model (map). The global motion planner generates a path or a trajectory to a goal. In general, because the world is not static, this planner is not suitable for dynamic environment. Inversely, the local motion planner, called as a reactive strategy5), is a method to make a robot to avoid dynamic obstacles using recent sensor information. It enables the robot to adapt dynamic surroundings and guarantee collision free movement. Because the local motion planner, however, is prone to fall into local traps and does not guarantee to reach a goal, it should be effectively integrated with a global motion planner.

In this paper, we concentrate on the local motion planner. Much effort already has been made regarding various local motion planners6)–(13). These approaches have been successfully used for the case of using a laser range finder. Because the laser range finder generally provides accurate range information, dynamic environment can be represented accurately. For the case of using sonar sensors, however, those local motion planners are hard to show their own performance due to erroneous sonar measurements14). Even though there have been many researches for representing static environment or building a grid map for the environment, previous mapping approaches15)–(26) are not enough for dynamic environment.

We start this research from the motivation that the major challenge in the local motion planner with using sonar sensors is to represent dynamic environment accurately.

In this paper, we propose a method which represents dynamic environment exactly even with using sonar sensors. The sound pressure from a sonar sensor would be used for determining state of a cell. When the sound pressure which supports emptiness of a cell is bigger than that provides occupancy of the cell, state of the cell is decided as empty. For the opposite case, state of the cell becomes occupied. Through this procedure, the sound pressure map is generated. Advantages of the sound pressure map are as follows:

- The sound pressure map is not necessary for adjusting parameters even though environment is changed.
- The computational time for acquiring the sound pressure map is the fastest among them of previous mapping approaches.
- Through experimental validation, the sound pressure map shows the best performance in terms of accuracy of representing dynamic environment.

The remainder of the paper is organized as follows. We begin by describing related research in Section 2. Section 3 describes the sound pressure map. Section 4 provides the experimental results and Section 5 presents the summary and conclusions.

2. RELATED WORKS

2.1 Local Motion Planners

- Potential Field method6): it, the most commonly used method for the local motion planner, assigns an artificial attractive potential field around the goal position, a repulsive potential field around obstacles which are
detected by range sensors and zero potential field at the robot position. Under composition of all potential field, a local path is obtained toward a gradient descent direction.

- **Vector Field Histogram method** (9) (10): it uses a polar histogram representing obstacle density for 360° coverage and selects a steering direction which minimizes a cost function that measures openings in the polar histogram. This method is easy to implement and produces smooth motions.

- **Dynamic Window approach** (7) (8): it is performed by simulating all achievable velocity commands in a discrete search space which consists of translational and rotational velocity and selecting a configuration which maximizes an objective function.

- **Nearness Diagram method** (11) (13): it employs a “divide and conquer” strategy and proposes a situated-activity paradigm based on identifying situations and applying the corresponding actions. Those are represented with a binary decision tree. Since the tree is exclusive and complete, it does not have any exceptional situations.

  Except the Vector Field Histogram method, the other approaches were developed for a laser range finders. Even though the Vector Field Histogram method was for a sonar sensor, it used a center line model which assumed the existence of an obstacle at the end of a sonar measurement. Therefore, when using erroneous sonar sensors, there should be a proper method to represent dynamic environment.

### 2.2 Representative environmental representation

- **Posterior approach** (15) (18): it was proposed for managing the inconsistency with the concept of probability and measures the occupancy of the cell.

- **Dempster-Shafer approach** (16) (19) (21): based on the concept of ignorance, it infers a belief function that indicates whether a cell is occupied, empty, or in an unknown state based on the Dempster-Shafer theory.

- **Fuzzy approach** (16) (22) (24): it quantifies the possibility that indicates a cell belongs to an obstacle. It is based on the theory of fuzzy sets designed to deal with vagueness, and determines safe cells that are free of obstacles.

- **Maximum likelihood approach** (25) (26): unlike the above approaches, it does not assume the independence of other cells. It is obtained by maximizing the likelihood of sonar measurements.

While the computational complexity of the posterior approach, the Dempster-Shafer approach and the fuzzy approach is linear with the number of sonar measurements $O(n)$, that of the maximum likelihood approach is $O(2^k n)$ where $n$ is the number of sonar measurements and $k$ is the number of cells (27). Due to huge complexity of the maximum likelihood approach, it would be excluded from the consideration of this article. For the local motion planner, the complexity should be light.

### 3. SOUND PRESSURE MAP

This section describes what the sound pressure is and how the sound pressure is used for building a grid map which is able to represent dynamic obstacles rapidly and exactly.

#### 3.1 Sound Pressure

A sonar sensor emits a wave that returns to the sensor after hitting an obstacle. The distance to the obstacle is calculated from the time of flight of the wave. The pressure of the returning wave on the sensor is called the sound pressure (27), and is expressed as

$$SP(r, \theta) = \frac{1}{r} 10^{\frac{D_T(\theta) + D_R(\theta)}{20}}$$  \hspace{1cm} (1)

where $r$ is the distance from the sensor to the obstacle, $\theta$ is the angle from the heading of the sensor, $D_T(\theta)$ is the transmitting directivity or the directivity pattern (14), and $D_R(\theta)$ is the receiving directivity or the sensitivity pattern (14). The parameters $D_T(\theta)$ and $D_R(\theta)$ depend on the specific characteristics of the sonar sensor being used. The derivation of (1) is provided in (27).

The log function is introduced for computational reasons.
and (1) can be simplified to
\[ LSP(r, \theta) = \frac{D_T(\theta) + D_R(\theta)}{20} - \log r. \] (2)

Because one sound pressure would be compared with another sound pressure, the use of the log function does not affect the result of the comparison.

We used one well-known sonar sensor: the MA40B8 from Murata Co., Ltd (MA40B8). After applying the specific \( D_T(\theta) \) and \( D_R(\theta) \) from the MA40B8, the final sound pressure levels were:
- MA40B8 \((|\theta| \leq 22.5^\circ)\)

\[ LSP(r, \theta) = -0.001025\theta^2 + 0.00147|\theta| - \log r. \] (3)

The sound pressure can be illustrated as Fig. 1. Fig. 1 provides that the sound pressure is bigger as an obstacle is closer to the sensor or nearer to the heading of the sensor.

### 3.2 Sound Pressure Map

The sound pressure map is built by the sound pressure comparison. The result of the comparison is represented by a map \( \tilde{M} \), called the sound pressure (SP) map. The SP map is obtained using

\[ \tilde{M} \equiv \left\{ M \mid O_c(M) \equiv \bigcup c_{xy}^P \right\} \] (4)

where \( O_c(M) \) indicates all occupied cells. (4) indicates that the SP map flags only specific cells \( c_{xy}^P \) as occupied where \( c_{xy}^P \) is defined as

\[ c_{xy}^P \equiv \left\{ c_{xy} \mid \max(LSP_R(c_{xy})) > \max(LSP_N(c_{xy})) \right\} \] (5)

where \( c_{xy} \) is a cell, \( LSP_R(c_{xy}) \) is the sound pressure of the measurement that indicates there may be an obstacle in cell \( c_{xy} \), and \( LSP_N(c_{xy}) \) is the sound pressure of the measurement that indicates there are no obstacles in the cell \( c_{xy} \). Eventually, each cell of the SP map is determined by the information supported by the higher sound pressure. There might be a case when \( LSP_R(c_{xy}) = LSP_N(c_{xy}) \). This case would be considered as a result of dynamic obstacles. Therefore, the latest information decides the cell state for the case.

### 4. Experimental Results

To confirm the capability of the sound pressure map, we conducted two experiments. To eliminate effect of localizing error, the robot did not move and only the environmental condition was changed while conducting experiments. The configurations of the sonar sensors are shown in Fig. 2. The details of the experimental specifications are as follows:
- **Map**
  - Cell size: 5 cm × 5 cm
- **Measurement**
  - Maximum admissible range: 2.5m
  - Sampling frequency: 4 Hz

We compared the performance the sound pressure map with a number of representative grid mapping approaches: the posterior approach, the Dempster-Shafer approach, the fuzzy approach. The experiments consists of two parts: the first experiment was a situation which a person was passing from left to right of the robot, and the second one was a situation which a person was moving forward and backward to the robot.

#### 4.1 The first experiment

Fig. 3(a) shows initial maps when the experiment starts. At the bottom of the Fig. 3(a), the environmental condition is illustrated with the time. The top of the figure consists of four maps which are posterior map, fuzzy map, Dempster-shafer map and sound pressure map. Due the box which located at the left of the robot, initial maps represent the box (Fig. 3(a)). After about 2 seconds, a person was starting to move from the left to the right of the robot. As provided in Fig. 3(b)-3(e), the sound pressure map successfully represents the moving person. The other maps, however, block whole area where the person is moving. As illustrated in Fig. 3(f), after the person was gone, only the sound pressure map exactly represents current environmental condition. From this experiment, we can conclude that the sound pressure map has the the best ability to represent the dynamic environment even with erroneous sonar measurements. The capability would indicate the possibility that the sound pressure map is used for a local motion planner.

Revising the parameters of the other approaches (the posterior approach, the Dempster-shafer approach and the fuzzy approach) to emphasize occupied regions causes longer time to change the occupied cells generated by the disappeared obstacles to empty cells. Revising the parameters in the opposite direction makes to take shorter time for the change while also causing longer time to change the empty cells to the occupied cells generated by the being obstacles. Therefore, these approaches have trade-offs that make it difficult to represent the dynamic environment.

#### 4.2 The second experiment

In the second experiment, a person started to move from the near front of the robot to the far front and then he moved back to the staring position. This experiment was conducted of verifying the effect of the previous measurement information. As provided in Fig. 4(a)-4(b), the sound pressure map was succeeded for representing dynamic situation while the person was moving to the far front of the robot. In the situation, the other approaches failed to represent; the posterior approach and the fuzzy approach provided whole traces of the person, and the Dempster-Shafer approach did not express the trace of the person. When the person was back to the near front of the robot, the sound pressure map shows the trace of the person (Fig. 4(c)). This phenomenon comes from the reason why the sound pressure map does not care outside of the range which is limited by a sonar measurement. Eventually, after the person was disappeared, only the sound pressure map shows the current environmental condition exactly.
Fig. 3  (a) Initial maps. (b) - (e) Maps that represent a situation which a person is moving from left to right of the robot. (f) Maps after approximately 20 seconds after disappearing the person.

5. CONCLUSION

We began this research by asking how sonar sensors could be used effectively for a local motion planner. We started with focusing the environmental representation because there have been many already researches about local motion planner. When the dynamic environment is represented effectively, various local motion planners can be used with the representation. When using sonar sensors, previous mapping approaches have a critical problem: the parameter adjustment.

To overcome the problem, it is essential to determine the state of a cell efficiently and exactly. For the determination, the sound pressure is adapted. By comparing the information which the sound pressure supports, current state of a cell is decided. This procedure generates the sound pressure map.

The sound pressure map has computational complexity of $O(n)$, which is comparable to the posterior approach, the Dempster-Shafer approach, and the fuzzy approach ($O(n)$). Empirically, the computational time for acquiring the sound pressure map is the shortest, and is enough to
be used as real time. Furthermore, different with the other approaches, the sound pressure map does not need to adjust parameters if a fixed type of sonar sensor is used even though the environment is changed. From the real experiments, it was confirmed that the sound pressure map is a good compromise between the quality of the map it produces and the computational complexity it entails.

In future research, we will apply the sound pressure map for local motion planners (8)-(11) which have been designed for a laser range finder.

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