Evaluating Techniques for Resolving Redundant Information and Specularity in Occupancy Grids

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Abstract. Map building is a natural and often underestimated property of biological entities. Such entities posses highly developed senses such as touch, sight and hearing. Such abilities allow the development of cognitive maps from which paths through complex environments can be developed through the use of depth perception and location recognition. In this paper we consider the effect that algorithmic extensions designed to deal with the problems of redundant information and erroneous sensory data have on the results of robotic mapping. We accomplish this by evaluating several configurations of these extensions using identical test data. Through evaluating the results of these experiments using an extensible benchmarking suite that our group has developed we outline which approach to the mapping problem yields the greatest representational ability.

Keywords: Robotic mapping, mobile agents, machine learning, robotics

1 Introduction

The performance of an autonomous mobile robot in acquiring a meaningful spatial model of its operating environment depends greatly on the accuracy of its perceptual capabilities. As it operates in the environment the robot gathers sensory information and subsequently incorporates this into a representation of the environment. The field that is concerned with such issues is known as robotic mapping and is a highly active research field in AI and mobile robotics.
The traditional approach, in the robotic mapping field, to recovering such information is based on the use of a tessellated 2D grid known as an *Occupancy Grid* (OccGrid) [1]. OccGrid's store, fine grained, qualitative information regarding which areas of the robots operating environment are occupied and which are empty. Specifically each individual cell in the grid records a certainty factor relating to the confidence that the particular cell is occupied.
In mobile robotics one of the most popular sensors used is ultrasonic sonar due to its low cost, its speed of operation and ease of use. These sensors report relative distances between the actual unit and obstacles located within their perceptual cone. This means that an obstacle, if detected, may be located somewhere within the sonar cone at the distance specified. However, despite their advantages, sonars are prone to error in measurement due to such factors as wave reflection and absorption etc. This introduces uncertainty into the map building process which can reduce the overall quality of the maps created. Catering for such ambiguity is the reason that robotic mapping is such a difficult problem[2].
We present a comprehensive analysis of the effect that techniques designed to deal with the problems of redundant information and erroneous sensory data have on robotic mapping. Specifically we consider:

- Pose Buckets[3]
- Feature Prediction[4]
- Neural Network based specular reading detection[5]

Pose buckets are a means of dealing with redundant information during the mapping process that were originally developed by Konolige as part of his MURIEL (Multiple Representation, Independent Evidence Log) mapping method [3]. Feature prediction and neural network based specular reading detection are both means of dealing with the problem of erroneous readings which may be received during operation. These techniques are expanded on in the following section.
We use four standard mapping paradigms, [1,3,5,6], augmented with the techniques mentioned above, as the basis for our experimentation. The paradigms are evaluated using identical testbed data and benchmarks from a suite which we have specifically designed for empirical evaluation of robotic mapping. This allows the determination of which technique or combination of technique provides a mobile robot with the greatest environmental representational ability.

The remainder of this paper is structured as follows. Section 2.1 provides an overview of four the mapping paradigms with section 2.2 outlining the techniques for dealing with redundant and specular information. Section 3 outlines the benchmarking techniques used in our evaluation and section 4 outlines the experimental configuration and results obtained. Section 5 presents analysis of the results and section 6 provides the final conclusion

2 Occupancy Grid Mapping and Techniques for Dealing with Uncertainty

2.1 Occupancy Grid Mapping

The problem of robotic mapping is that of acquiring a spatial model of a robots environment. An occupancy grid is a tessellated grid with each individual cell in the grid recording a certainty factor relating to the confidence that the particular cell is occupied. For the purposes of the evaluation outlined herein we utilise four established mapping techniques which we slightly modify so as to incorporate the various algorithmic extensions. The specific mapping techniques are:

- Moravec and Elfes - 1985, probabilistic framework[1]
- Matthies and Elfes - 1988, Bayesian framework [6]
- Thrun - 1993, neural network based approach [5]
- Konolige - 1997, enhanced Bayesian framework [3]

The following provides a brief overview and analysis of these techniques. For further information the reader is referred to the referenced publications.

Moravec and Elfes - 1985: this technique generates two intermediate models, an empty map *Emp* and an occupied map *Occ*, which are subsequently integrated to form a final domain representation. The sensory beam uses a binary classification with cells being in either the free-space or the surface (occupied) area. A two dimensional Gaussian sensor model is used to calculate the probability of the cell being empty if it is in the free-space area and likewise for occupied cells in the occupied area. The map update used by this technique is heuristic in nature with the probability of a cell being empty integrated into *Emp* and likewise the probability of a cell being occupied being integrated into the *Occ* map. Finally the *Emp* and *Occ* maps are combined into a single representation with a thresholding step where the larger value for each cell is chosen for inclusion in the map.

The first limitation with this technique comes from the fact that specular reflection is not considered. Specular reflection occurs when the sensory (in this context sonar) beam reflects of multiple surfaces and then either returns or does not return to the emitter, causing an erroneous reading in either case. This causes areas to be incorrectly labelled as unoccupied, or an unoccupied area to be incorrectly labelled as occupied. The second issue comes from the fact that when dealing with cells in the *Occ* and *Emp* maps once the probability value associated with a cell converges to a certainty of 1, the probability value associated with that cell cannot be altered by any future evidence.

Matthies and Elfes - 1988: this approach used the same sensory model as Moravec and Elfes for the purposes of sensor interpretation in their approach. However they did develop a more rigorous Bayesian based map updating formula which replaces the heuristic method from Moravec and Elf's - 1985 approach.
There are two main disadvantages to using the Bayesian update formula introduced in this approach. Firstly a single update can change the occupancy value of a cell drastically which means that cell values can fluctuate. The second disadvantage is that once a cell has converged to certainty i.e. either 0 or 1 the occupancy value cannot be changed.

Thrun - 1993: this method outlines an occupancy grid mapping approach which utilises neural networks (NN). The sensory interpretation aspect of this algorithm is implicitly defined in the *sensor interpretation network* which reports values in the range `<0...1>` for the sensory readings that it is presented with. Certainty values relating to these readings are determined through the second network, the *confidence network*. The map update procedure in this technique is similar to that in Matthies and Elf's - 1988 approach.
The limitation of this approach arises form the nature of NN's. When dealing with NN's it is desirable to train the network until convergence. However it is not practical to train the *sensor interpretation network* to convergence in this context. This is because to do so would encode environmental characteristics in addition to sensory characteristics in the network which makes evaluating the quality of the sensory model developed an issue.

Konolige - 1997: this method also uses a sensory model which separates the sensory model into occupied and empty sections. However in this case an identical formula is used for both with a probabilistic profile determining whether a cell is in the free-space or occupied part of the sensory beam. He also introduced 'Pose Buckets' as a means of dealing with redundant information and tackled the problem of specular sensory information through probabilistic inference. For purposes of updating the map the Konolige's method combines the probability of the cell being occupied and empty using a logarithmic technique.
One issue with this approach is the way in which specularity estimation is applied to individual cells. Specifically if a cell is very confident of the specularity of a sonar reading then this should be propagated to all cells in the sonar beam not just the cell itself as there is a great deal of inter-dependence between cells in a sonar beam. Also when a sonar reading is given a high probability of specularity the effect of that reading on the map should be reduced. However the technique deals with the free-space segment of the sonar beam. It would be desirable if both the free and occupied segments of the beam were considered. Finally the assumption is made that environmental surfaces are distributed randomly and that the probability density of a reflection from such a surface is constant. However while this may be true in the simplified case no justification of this assumption is presented for the general case.

2.2 Techniques for Dealing with Uncertainty During Mapping

The previous section outlined standard approaches to the robotic mapping problem. However for all mapping approaches unreliability of information obtained from sensors is a major issue when dealing with robotic map building. This issue is characterised by two problems, redundant information and specular reflection.

- *Redundant Information* The assumption is made that each new sensor reading gives new information, whereas the actual case may be that the information is simply repetition of what has been previously sensed which would be reflected in the associated cell probabilities resulting in a biased view of the world.
- *Specular Reflection* The energy emitted from a sensory device is scattered off a surface before returning to the sensor or is reflected at a wide angle and subsequently never returns to the device which results in the sensor reporting incorrect readings.

Currently in the domain there exists very little quantative information regarding the tackling of such issues. Therefore in this paper we empirically evaluate techniques developed to address these problems. Specifically we consider two techniques designed to deal with the specular reflection problem, Feature Prediction (FP) and a Neural Network based technique (NN). We also consider the problem of redundant information through Konolige's Pose Buckets (PB).

2.3 Removing Redundant Information

When dealing with OccGrid mapping, a simplifying assumption of conditional independence is made. This states that each cell in a map has no effect on any other cell, and that each sensory reading received is independent of all other readings. Using the concept of conditional independence, a map is constructed by taking sensor readings from many different positions and angles. However there often arises the case where the robot is stationary. The issue with this scenario is that no new information is being added to the map after the first reading was obtained from the position. Each successive reading is clearly not independent of the one that came before, it is, in fact, conceptually the same.
PB's were designed to deal with this issue. They utilise an OccGrid map which has a dual representation. Each constituent cell of the map represents both the occupancy of the area and the 'pose' of readings that have effected that cell. Therefore PB's essentially store a binary variable stating whether a reading from a given distance and angle has affected a particular cell or not. This variable is set to true when the first reading from a particular pose is received, and all following readings from that pose for the particular cell are subsequently discarded. This is because they are merely duplicating information already incorporated into the model.
The original specification of PB's effectively addressed the problem of redundant information affecting the construction of the map. However, there are some issues with the technique. The main issue with PB's is that it is conceivable that due

to their manner of dealing with received sensory readings, i.e. accept the first reading received as being illustrative of the true state of the environment, some useful information could be discarded. However work recently completed within the group, [7], addressed this problem and it is this enhanced version of PB's that we utilise.

2.4 Dealing With Erroneous Sensor Readings

Feature Prediction: it is commonly assumed that during the mapping process each sensory reading received is a completely independent entity. The readings in a set are not independent, however, and as such the readings from one sensor can be used to determine the validity of other readings in the overall set, particularly neighbouring readings. Feature prediction is a method for detecting specular sonar readings based on exploiting these facts.

Feature prediction works by identifying reliable readings in each reading-set and from these determines the position and orientation of the features in the environment that causes the wave reflection. Subsequently from this a confidence value can be determined for each individual reading in the reading set.

This means that it is necessary to make predictions about the state of a cell before receiving any correct information relating to the cell. Such predictions can be made based on sonar readings received which don't directly affect the particular cell in question and also on the behaviour of a sonar beam in a noisy environment. This is possible as the environment contains structural regularities such as walls that can be approximated using straight line segments. Therefore during operation feature prediction uses three models of the environment, a sonar map, a local map and a global map. The sonar map is a stateless model which contains features, which are essentially straight line segments, that have been extrapolated from the current sonar readings set. Therefore this map is a localised one representing the state of the environment in the vicinity of the robot as extrapolated from the readings reported by the sonars. The local map maintains a set of features that have been estimated from previous readings, but only from the area withing the immediate vicinity of the robot. That is, the local map is also a localised representation of the environment in the vicinity of the robot, however it has been extrapolated from historical readings and not the readings reported at the current time-step. The creation of a feature set from these two maps in conjunction with a check for consistency between sensory readings in the current reading set is used as a basis for determining a confidence value for each sensor reading. These confidence estimates are subsequently used as a basis for influencing the effect that the reading has on the global map.

More information of FP can be found in [4,7] .

Using Neural Networks: in [5], Thrun outlines an OccGrid mapping approach which utilises neural networks (NN). In this approach a network known as the *sensor interpretation network (R)* is used to compute the occupancy values for each individual cell in the overall map and a separate network, known as

the *confidence network (C)*, is used to calculate a confidence estimation for each sensory reading received.
As can be appreciated there are similarities between this approach to the detection of erroneous readings and FP. However FP works on the macro level, considering a world centric view of the current situation whereas the neural network based approach considers a more robot centric view. That is, the network based approach bases it's determination of specularity on consistency between readings in the current reading set. FP on the other hand bases its determination on extrapolation from a historical perspective. Therefore, in theory, both techniques are complimentary.
The NN approach operates as follows. In relation to a cell of interest the network is presented with the following inputs:

- The four sensor readings closest to the cell of interest $< x, y >$
- The relative angle, θ, to the cell of interest
- The relative distance, d, to the cell of interest

The use of relative measurements removes the need for the network to model the global co-ordinate system. The network is trained using the classic Back-Propagation algorithm to output a scalar in the range `<0,1>` which is an error estimate relating to the particular reading r. The training examples used during training consist of the inputs outlined earlier and the desired, error value for the particular reading that is being dealt with in that particular instance. To facilitate data acquisition the robot obtains the training inputs and subsequent desired output through operation in a known, or idealised, environment. The actual idealised environment is constructed manually prior to the data acquisition thereby allowing the desired network outputs to be accurately determined.
As the confidence network estimates the expected error relating to a particular reading the confidence in the reading is low if the output from the network is high and vice versa. It is straight forward to use this error estimate as a means of registering specular readings.

As mentioned previously the aim of this paper is to consider the effect that techniques designed to deal with the problems of redundant information and erroneous sensory data have on the results of robotic mapping. Toward this end the extensions outlined previously were incorporated into the four mapping approaches outlined in section 2.1 to arrived at augmented versions of these approaches. The specific changes made were:

- Feature prediction was added to each of the approaches to help deal with the problem of specular readings.
- An enhanced version of Konoligie's Dynamic Mixture Model was added to each of the techniques. This is a mechanism that complements pose buckets and allows for improved detection of specular reading.
- Pose buckets were added as an additional feature to the mapping methods.

These augmented mapping versions were subsequently used as the experimental basis.

3 Benchmarking Techniques

The purpose of this paper is to determine which algorithmic extension, or combination of extensions are the most effective in the context of robotic mapping. To actually determine this maps generated using the extensions must be evaluated. Toward this end we use an extensible suite of benchmarks which allow for the empirical evaluation of map building paradigms [8]. This suite includes utilising techniques from image analysis, techniques designed specifically developed for the evaluation of OccGrid maps in addition to techniques designed to evaluate the usability of a generated map by a robot.

1. *Correlation*: As a generated map is similar to an image it is possible to use a technique from image analysis known as *Baron's cross correlation coefficient* [9] as a basis for evaluating the map. With this metric a higher percentage indicates that the map being tested has a high degree of similarity to an ideal map of the environment.
2. *Map Score*: This is a technique originally proposed by Martin and Moravec in [10] which calculates the difference between a generated map and an ideal map of the environment. The lower the percentage difference the greater the similarity between the two maps.
3. *Map Score of Occupied Cells* This metric is similar to the previous one but only tests those cells in the map that are occupied. This metric address the weakness in the first map score metric that mapping techniques which over-specify free space could achieve a better score than maps which identify obstacles more accurately. The reason for this is that in many environments there are large amounts of bounded unoccupied spaces with perhaps a few small obstacles distributed within that space. Therefore there are often more unoccupied than occupied cells. When determining the map score there are few occupied cells with which to correctly determine the correct state of affairs and hence an erroneous results is achieved. To tackle this problem the second map score metric is used.
4. *Path Based Analysis*: To fully evaluate a generated map its usefulness to a mobile robot must be considered, as the main context in which such maps are used is for the completion of tasks such as navigation. Therefore simply evaluating a map against a perfect snapshot of the operating environment is unrealistic as a map might still be usable to a robot without being a completely faithful representation. Specifically if the map provides an abstraction of the environment with which a path planning algorithm can specify navigable real world paths then the map can be used. Therefore it is the quality of these paths that indicates the value of the map and the subsequent map evaluation is based on testing two elements:
   - The degree to which the paths created in the generated map would cause the robot to collide with an obstacle in the real world, and are therefore invalid. These are known as *false positives.*
   - The degree to which the robot should be able to plan a path from one position to the another using the generated map, but cannot. These are known as *false negatives.*

Obtaining an overall score Each of the previous benchmarks evaluate a map within a specific context. However arriving at an overall classification using the benchmarks requires specific domain knowledge, which is an inhibitor to their generalised use. Therefore, to allow an overall score to be determined and also preserve the metric inter relationships, we developed an amalgamation technique. The result provided by this classification scheme can be used as a basis for comparison of the individual mapping techniques.

$$CLS_{\mathtt{map} \in M} = \frac{D_{\mathtt{map}} P_{\mathtt{map}}}{\Sigma(D_{\mathtt{map}} P_{\mathtt{map}})} \tag{1}$$

where

$$D_{\mathtt{map}} = \frac{CT - \text{MapScore}_{all} * CT - \text{MapScore}_{occ} * B_n}{\Sigma(CT - \text{MapScore}_{all} * CT - \text{MapScore}_{occ} * B_n)}$$

and

$$P_m = \frac{(\text{FP}) * (CT - \text{FN})}{\Sigma((\text{FP}) * (CT - \text{FN}))}$$

In the above, CLS is the overall classification score obtained M is the overall set of maps in an experiment subset, `map` is a particular map within the set of maps M, CT is a normalising constant that accounts for the inverse benchmark relationships, MapScore_{all} is the result from the *Map Score* metric applied to all cells in the applicable map, MapScore_{occ} is the result from the *Map Score* metric applied to the occupied cells in the maps, B_n is the result obtained from *Correlation*, FP is the result obtained from the *False Positive* path analysis metric and FN is the result obtained from the *False Negative* path analysis metric. This rule combines the normalised certainty factors from the five benchmarks in a manner that is consistent with the differing orientations of the benchmarking techniques.

4 Results

The experimentation carried out for this evaluation consisted of testing the augmented mapping approaches with identical data obtained from a number of runs in two test environments. To ensure statistical validity, in total there were three runs completed in each environment. To fully determine the contribution that the extensions outlined previously have on the mapping process we ran a number of experiments which used combinations of the extensions. In total eight configurations were utilised, table 1 (where, again, FP represents Feature Prediction, PB represents Pose Buckets, NN represents Neural Network based reading confidence estimation). In the following table N, represents the fact that a particular technique was not used in a particular configuration state and likewise Y represents the case that the technique was used.

Reference	**FP**	**PB**	**NN**
Config 1	N	N	N
Config 2	Y	N	N
Config 3	Y	N	Y
Config 4	Y	Y	N
Config 5	N	Y	N
Config 6	N	N	Y
Config 7	N	Y	Y
Config 8	Y	Y	Y

Table 1: Combinations of techniques

We used the eight configurations outlined in table 1 as the basis for specific experiments. Each of the four mapping systems was configured according to this discretisation and used to generate a number of OccGrid maps. We used two differing test environments and as mentioned three separate runs were completed in each environment. This means that the results presented in this paper are obtained from analysing a total of 192 OccGrid maps.
Table 2 presents the overall results from the experimentation. Therein ME85 represents the augmented version of Moravec and Elfes 1985 mapping technique which was used in the experimentation and ME88, K97, T93 represent the augmented versions of Matthies and Elfe's, Konoligie's and Thrun's techniques from 1988, 1997 and 1993 respectively. Figure 1 present some illustrative maps generated by Konolige's method using configurations one, two, five and six from table 1 in addition to an ideal map of the environment which is provided for reference.

Key	Reference	ME85	ME88	K97	T93
A	Config 1	0.42	0.47	0.52	0.42
B	Config 2	0.54	0.55	0.61	0.48
C	Config 3	0.54	0.55	0.60	0.48
D	Config 4	0.64	0.51	0.62	0.52
E	Config 5	0.47	0.47	0.63	0.44
F	Config 6	0.46	0.63	0.54	0.44
G	Config 7	0.44	0.55	0.56	0.43
H	Config 8	0.64	0.51	0.60	0.48

Table 2: Experiment Results

5 Analysis

The results outlined in the previous section originated from experiments aimed at evaluating the overall contribution made by the various extensions to the robotic

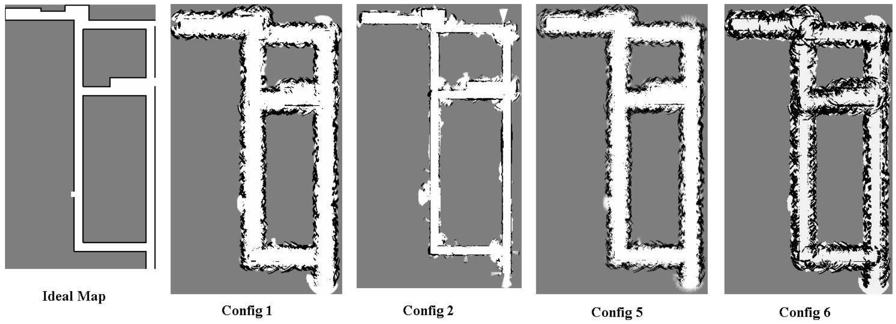

Fig. 1. Ideal map and some illustrative maps generated during experimentation

mapping paradigm. The tests have shown that these extensions do have a positive effect on the overall accuracy of the maps constructed by the various systems. The tests have also shown that various extensions or combinations of extensions have a tendency to promote improved performance in various systems while simultaneously not generating the same enhancement in other mapping systems which is a direct result of the characteristics of the actual systems themselves. In the following, as per table 2 ME85 refers to the augmented version of Moravec and Elfe's 1985 approach [1], ME88 refers to the augmented version of Matthie and Elfe's 1988 approach [6], K97 to the augmented version of Konoligie's 1997 approach [3] and T93 to the augmented version of Thruns 1993 approach [5] mapping systems which were used as the basis for the experimentation outlined herein. The following analysis considers the results from the context of the overall classification that we are evaluating i.e. sensory reading critique through FP and NN and redundant information filtering through PB.

Reading Confidence Estimation The experimental configurations from table 1 that involved determining a confidence estimate were configurations two, three, six which relate to the results in table 2 B,C and F. As the results show the use of feature prediction on its own, the use of feature prediction in conjunction with neural network based confidence estimation and the use of neural network based confidence estimation on its own all promoted more of a general improvement in the K97 and ME85 mapping systems than in the ME88 or the T93 systems. This can be attributed to the fact that there is a conceptual similarity in the mechanisms used by ME88 and T93NN which cause them to have similar performance characteristics when presented with filtered operational data. These trends show that these two drastically differing approaches to the problem of specularity are compatible and ultimately achieve the same aims.

Redundant Information Filtering On this occasion we are considering configuration five from table 1 and table 2 E. When pose buckets were used on their own in conjunction with the mapping systems there was an improvement in the overall performance of the systems. Again K97 profited more from the removal of redundant information by the pose buckets. However as the results have shown K97's performance in relation to false negative paths was poor. This is because, while pose buckets believe both free-space and occupied readings equally they ensure that there is at most a difference of one reading between the number of free and occupied readings from any given position. This is because K97's slight favouring of occupied space over empty space will effect the ability of the the free space readings from altering the incorrect occupied readings registered with the pose buckets.

Reading Confidence Estimation in conjunction with Redundant Information Filtering In this case we are considering configurations four and seven i.e. table 2 D and G. When feature prediction and pose buckets were used together there was a slightly better performance than the case where pose buckets were used in conjunction with the neural network based confidence estimation. This shows that pose buckets are more compatible with algorithmic rather than a learned means of critiquing sensory readings. This is because of the overlap in their performance i.e. if one of the filtering mechanisms fails to identify an erroneous reading the pose buckets will generally deal with it and vice versa. However feature prediction maintains an explicit historical record which serves as the basis for determining the erroneous readings which the neural network based approach does not. This means that feature prediction is slightly more subtle in its removal of readings due to its historical perspective whereas the network based approach is more harsh i.e. there exists the possibility that the network based approach will regard more readings as erroneous that the algorithmic method due to its temporally localised nature. As an aside the extension of the network based approach so as to utilise historical data was considered but as this change would render a significant amount of the operational context of the network redundant the extension was not considered for inclusion in the experimentation outlined herein.

Using all extensions Here we are considering configuration eight from table 1 and table 2 H. When all three extensions were used together the overall result was that the performance was similar to the case where only feature prediction and pose buckets were used. This can be attributed to the fact that, as mentioned above, feature prediction and neural network based confidence estimation do perform essentially the same job feature prediction can be slightly more subtle than the network based approach to reading critique. Essentially this means that when both techniques are used in conjunction with pose buckets the feature prediction will catch any readings that the network based approach missed which means that feature prediction is the dominant reading critique mechanism. Therefore the results are similar in this case to the scenario where the network based approach was not used. However as can be seen the performance for all mapping systems has improved when compared to the configuration where we do not use any of the extensions, table 2 A.

6 Conclusion

In this paper we have presented an analysis of algorithmic extensions, which are designed to deal with the problems of redundant information and erroneous sensory data in robotic mapping. We have outlined a benchmarking suite developed to allow empirical evaluation of such maps and used it to evaluate the impact of the extensions. Our results have shown that Feature Prediction, Pose Buckets and Neural Network Based reading critique all serve to enhance the performance of the mapping process resulting in the creation of accurate and usable maps of a robots operating environment. However, as the results have shown, the neural network based enhancement has a negligible impact on the overall performance of the systems.

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