# ROBOT MAP SIMILARITY EVALUATION FOR NON-IDENTICAL MAPS

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**Abstract.** When several robots explore the same environment, it is at some point necessary to merge their local maps into a global map to exploit the full potential of the robot team. Efficient multi-robot task coordination is virtually impossible without a common interpretation of the environment. If there is no information available about the relative positioning of the robots or if this information is uncertain, the evaluation of the map merging result is a vital step in the creation of a global map. The proposed map similarity evaluation offers a way to successfully evaluate the similarity of occupancy grid maps that are not locally identical.

**Keywords:** robot mapping, map merging, map similarity.

## 1. Introduction

The evaluation of the map merging result is an essential step in the creation of a global robot map. In this paper a map similarity evaluation is proposed that evaluates the similarity of occupancy grid maps that are not locally identical. To achieve it the local maps are converted into distance grids, and a threshold of maximum acceptable Manhattan distance deviation is set. In addition, the evaluation distinguishes "occupied" and "free" cell comparison and offers a way to represent the importance of a particular cell type (representing "free" or "occupied" area) similarity by setting weights.

The maps considered in this paper are occupancy grids. Occupancy grids are robot maps that represent the environment as a discrete grid [1]. In this paper it is assumed that the occupancy values of the occupancy grid cells can acquire any value from 0 to 1 (0 – "free" area, 1 – "occupied" area). If the occupancy of the corresponding area is completely unknown, the value of the cell is 0.5. In graphical illustrations (see Figure 1) the occupancy grids are commonly represented as having black "occupied" cells, white "free" cells and various shades of gray for any value between the two extremes.

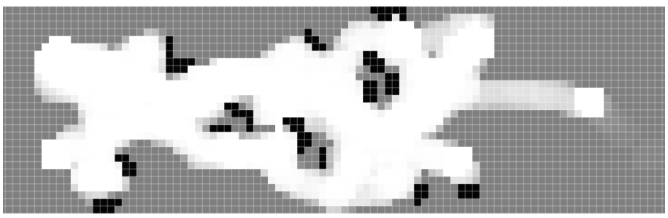


Fig. 1. **Example of occupancy grid map**

Inaccurate local maps make successful creation of the global map significantly more difficult. The inaccuracies of the local maps can be divided in two groups.

- **Local inaccuracies** represent sensor errors and small position estimate deviations from the actual robot location. As a result the constructed local map does not represent the objects completely accurately.
- **Global inaccuracies** represent the map errors that are caused by accumulating the robot position error. As a result of the global mapping errors the map may be very different from the actual configuration of the environment.

If the relative positioning of the robot maps is unknown, even the merging of completely accurate local maps is not a trivial task [2-6]. Local inaccuracies make the merging task harder, and globally inaccurate maps are virtually impossible to merge. Therefore, in the map merging task it is usually assumed that the local maps are accurate or only contain local inaccuracies. In real life applications maps without local inaccuracies are non-existent due to the probabilistic nature of the mapping, and therefore all maps contain local errors. It can be concluded that for successful use in multi-robot systems the map similarity evaluation must be resistant to the local differences of the maps.

This paper is organized as follows. Chapter 2 illustrates the related work in the evaluation of the map merging results. Chapter 3 describes the proposed map similarity evaluation. In chapter 4 the results of the map similarity evaluation application are shown.

## 2. Related work

One approach in multi-robot mapping implementations is to create the map collectively by assuming that the robots are operating in a common reference frame [7-10]. In this case the map similarity evaluation is not necessary, because the robot sensor readings are incorporated in the map directly. However, if the maps are merged at a later point in environment exploration by using robot relative position estimate or by making a guess about the common part of the maps without pose information, it is important to evaluate the map merging hypothesis.

Some works do not consider map merging evaluation at all [11; 12]. However, there may be situations, when the best found merging hypothesis is not correct. Even if the best merging is found in the terms of the employed approach, it does not exclude the possibility that the two maps do not overlap.

There are several works about the estimation of the map merging quality. Konolige and others [2] offer to verify hypothesis of map merging by organising robot meeting. If the robots do not meet at the appointed place, the map merging is deemed incorrect. Other approaches do verify the result of the map merging without the robot meeting but are not applicable to occupancy grid maps [13-16].

The work of the occupancy grid merging evaluation most often cited in the literature examined by the authors of this paper is proposed by Birk and Carpin in [3], which is also adapted by several later map merging researches [4-6]. They use an acceptance indicator that computes the ratio between the cells with similar values and the cells with both similar and dissimilar values. Unfortunately, this approach is not resistant to the local dissimilarities of the maps.

## 3. Map similarity evaluation for non-identical maps

The proposed map similarity evaluation defines the influence of both cell types and takes into account the possibility of local inaccuracies in the maps. It is computed as seen in equation 1:

$$SM_{m_1,m_2} = w_{occ} \cdot s_{occ} + \left(1 - w_{occ}\right) \cdot s_{free} \quad (1)$$

where $w_{occ}$ – importance (weight) of the "occupied" cell similarity;
$s_{occ}$ – evaluation results of "occupied" cell similarity;
$s_{free}$ – evaluation results of "free" cell similarity.

In computation of both cell similarities one parameter is required – a threshold that describes, how far the mapping error may extend in the particular maps. This threshold defines the Manhattan distance, at which two cells are considered "in range" – close enough that they may represent the same obstacle. The distance threshold should be experimentally set and take into account the resolution of the maps and the sensor error.

### 3.1. Occupied cell similarity evaluation

The "occupied" cell similarity is computed by creating and using the distance grids of the maps. The distance grid of a map represents each cell Manhattan distance to the closest cell with previously defined target value (in this case it is a cell with the value "occupied" or 'free').

An effective way to compute distance grids is an algorithm developed by Andreas Birk [17]. This algorithm originally consists of three steps, but one additional step has been added to create the distance grid version used in the proposed map similarity evaluation. Additionally, the grid initialization is supplemented with "unknown" cell initialization. The original algorithm is as follows [17]:

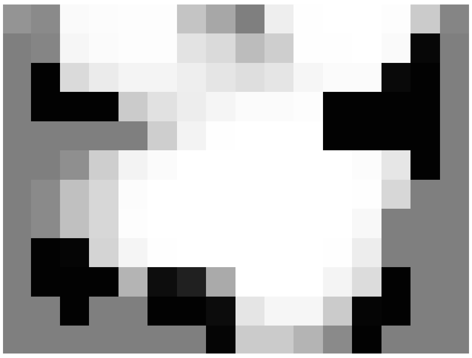
1. Initialization – all "occupied" cells are initialized with "0". All the other cells are initialized with a "∞". In real life applications a number that equals or exceeds the largest possible Manhattan distance between two cells is used instead of infinity.
2. First step of relaxation – the distance grid cell values are updated, beginning with upper left corner of the map. The new cell value is a minimum of a) current cell value, b) upper cell value + 1, c) left cell value + 1.

3. Second step of relaxation – it is similar to the first step of relaxation with the differences that the cells are updated beginning from the lower right corner of the map and the new cell value is a minimum of a) current cell value, b) lower cell value + 1, c) right cell value + 1.

To accommodate the specifics of the robot mapping the following modifications have been made to the distance grid map:

- "Unknown" cells are considered as "occupied" during the distance computations with the difference that their base value is "1". This is necessary because the "unknown" cells may be "occupied", and the differences between the border (bordering "unknown" cells) cells of two maps may actually be local inaccuracies. The base value is set to "1", not "0", as a penalty for the uncertainty of the actual cell value.
- At the end of the distance grid computation the "unknown" cell values in the distance grid are set to "-1". This is to avoid estimating two cells as similar or dissimilar, when one cell value is not known.

The resulting distance grid with these modifications is represented in Figure 2.



| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 2 | 3 | 3 | 4 | 4 | 3 | 2 | - | 2 | 3 | 3 | 3 | 2 | 1 | - |
| - | 1 | 2 | 2 | 3 | 4 | 4 | 3 | 2 | 3 | 3 | 2 | 2 | 1 | 0 | - |
| - | 0 | 1 | 1 | 2 | 3 | 4 | 4 | 3 | 3 | 2 | 1 | 1 | 0 | 0 | - |
| - | 0 | 0 | 0 | 1 | 2 | 3 | 4 | 3 | 2 | 1 | 0 | 0 | 0 | 0 | - |
| - | - | - | - | - | 2 | 3 | 4 | 3 | 2 | 1 | 0 | 0 | 0 | 0 | - |
| - | - | 2 | 2 | 2 | 3 | 4 | 5 | 4 | 3 | 2 | 1 | 1 | 1 | 0 | - |
| - | 2 | 2 | 3 | 3 | 3 | 3 | 4 | 5 | 4 | 3 | 2 | 2 | 2 | - | - |
| - | 1 | 1 | 2 | 3 | 2 | 2 | 3 | 4 | 5 | 4 | 3 | 2 | - | - | - |
| - | 0 | 0 | 1 | 2 | 1 | 1 | 2 | 3 | 4 | 4 | 3 | 2 | - | - | - |
| - | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 2 | 3 | 3 | 2 | 1 | 0 | - | - |
| - | - | 0 | - | - | 0 | 0 | 0 | 1 | 2 | 2 | 1 | 0 | 0 | - | - |
| - | - | - | - | - | - | - | 0 | 1 | 2 | 2 | - | 0 | - | - | - |

Fig. 2. **Example of modified distance grid**

Any other method can be used for computation as long as it returns the desired form of the distance grids. Once the distance grids are computed, the algorithm to compute the "occupied" cell similarity is simple and uses two counters – "sim" for similar cells and "dis" for dissimilar cells:

- If a cell value is "occupied" in both maps, then the cells are considered similar and the "sim" counter is increased by one.
- If a cell value is "occupied" in one map and "free" in the other map, then the distance grid is used to determine the Manhattan distance to the closest "occupied" or "unknown" cell. If the distance falls within the distance threshold, then the cells are considered similar and the "sim" counter is increased by one. Otherwise, "dis" counter is increased by one.
- If a cell value is not "occupied" in both maps or if a cell value is "unknown" in either map, then no counters are increased.

When all cells are compared, the "occupied" cell similarity is computed as seen in equation 2:

$$s_{occ} = \frac{sim}{sim + dis} \tag{2}$$

where $s_{occ}$ – "occupied" cell similarity;
$sim$ – count of similar cells in the common part of maps;
$dis$ – count of dissimilar cells in the common part of maps.

### 3.2. Free cell similarity evaluation

The "free" cell similarity is evaluated a little differently than the "occupied" cell similarity. Both the original robot local maps and the computed distance grids are used for comparison. The algorithm for determining whether two cells should be deemed similar is as follows:

- If the corresponding cells in both maps are "free", then the cells are similar.

- If the cell is "free" in one map and "occupied" in another, then the cells are dissimilar if the "free" cell distance to the closest "occupied" cell is greater than the set distance threshold. Otherwise, the cells are considered similar.
- If the cell is "unknown" in at least one of the maps, or the cell value is "occupied" in both maps, then the cells are neither similar nor dissimilar.

The "free" cell similarity is then computed in the same way as for "occupied" cells (Equation 2).

### 3.3. Summary

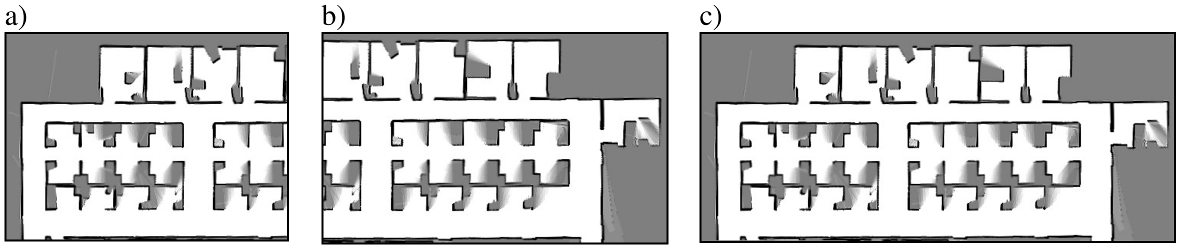
The proposed map similarity evaluation can be used for the evaluation of the map merging hypothesis of locally inaccurate maps, when some meta knowledge about the map characteristics is available. The knowledge about maps is necessary to set an appropriate distance threshold that is required for map comparison. If the threshold is too small, then the evaluation may show poor results even if the transformation hypothesis is correct. On the other hand, if the threshold is too large, then the evaluation will show high similarity even for highly different maps. In general, the recommendation is to keep the distance threshold based on the sensor error and the cell size.

## 4. The results of the proposed map similarity evaluation

To show the indicative performance of the proposed map similarity evaluation it was compared with the evaluation often found in literature – direct cell comparison [3]. There are several cases that might affect the result of the map similarity evaluation and they are assessed further in this chapter. The distance threshold of the proposed approach was set to "3" in all experiments, and the importance weight of "occupied" cells is 0.7. Within the evaluation procedure the maps are considered similar (consistently merged) if their similarity value is 0.97 or more.

### 4.1. Accurate and correctly merged maps

In reality the maps acquired by real robot systems are never completely accurate. However, the maps used in this experiment [18] (see Figure 3.a and 3.b) are actually two parts of one map and are therefore identical, and it can be assumed that they are accurate.




Direct cell comparison – 1 The proposed approach – 1

Fig. 3. **Accurate and correctly merged maps [18]**

Two maps were merged (see Figure 3.c), and both, the direct occupancy grid cell comparison and the proposed map similarity evaluation for non-identical maps show that the common part of the maps is identical – their similarity evaluation value is 1.

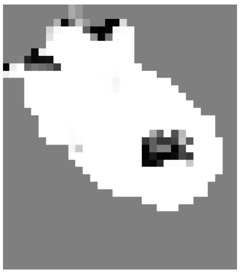
### 4.2. Locally inaccurate and correctly merged maps

In most cases both evaluations show good results and evaluate map merging as consistent, if the maps are correctly merged and locally inaccurate. There are cases, however, when direct cell comparison performs worse, if the common explored area is not very large. Each dissimilar cell has larger impact on the direct cell comparison, and for this reason the similarity evaluation drops below the similarity value of 0.97 and the merging is not accepted as correct. One such case can be seen in Figure 4 – evaluation of the proposed approach is still 1 while the direct cell comparison evaluation is 0.959.

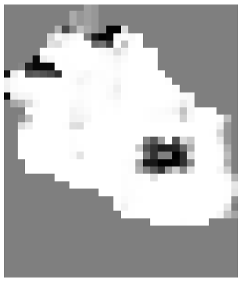
The maps in Figure 4 are acquired from the multi-robot system developed by the authors of this paper. The maps 4.a and 4.b are the maps used for merging, and 4.c is the resulting merged map. The maps 4.a and 4.b are also the source maps for all further examples (Figures 5 and 6).

a)

b)



c)



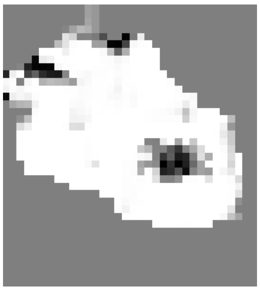
Direct cell comparison – 0.959 The proposed approach – 1.000

Fig. 4. **Locally inaccurate and correctly merged maps:** maps a) and b) are the source maps used for merging and map c) is the resulting merging

### 4.3. Locally inaccurate and slightly incorrectly merged maps

Figure 5 shows two map mergings with slightly incorrect transformations. The left side global map (Figure 5.a) has small translational errors (1 and 2 cell deviations), and the right side global map (Figure 5.b) has a rotational error of 3 degrees. The proposed evaluation evaluates both results as correct (0.989 and 1) while the direct cell comparison rejects the merging hypotheses (0.904. and 0.926). However, it can be seen that both results are actually very similar to the correct merging (see Figure 4.c) and could be successfully used by the robots.

a)



Direct cell comparison – 0.904
The proposed approach – 0.989

b)

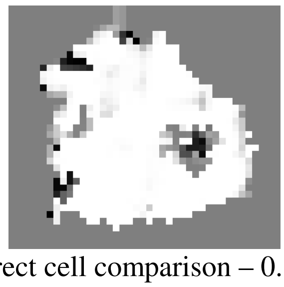
Direct cell comparison – 0.926
The proposed approach – 1.000

Fig. 5. **Locally inaccurate and slightly incorrectly merged maps**

### 4.4. Locally inaccurate and visibly incorrectly merged maps

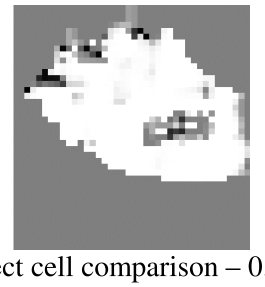
The results, when the maps are locally inaccurate and incorrectly merged, differ in each case. Figure 6 shows two incorrect mergings, and it can be seen that the performance of similarity evaluations varies – the proposed approach correctly shows lower similarity for the map in Figure 5.a - 0.808 (direct cell similarity 0.876) but higher similarity for the map in Figure 5.b – 0.929 (direct cell similarity 0.854). However, in both cases evaluations show that the maps are merged incorrectly (the failed merging similarity is below 0.97). It is possible that in some cases evaluations may show positive results when the merging is actually wrong but this is inevitable if there are several acceptable ways of fusing maps.

a)



Direct cell comparison – 0.876
The proposed approach – 0.808

b)



Direct cell comparison – 0.854
The proposed approach – 0.929

Fig. 6. **Locally inaccurate and visibly incorrectly merged maps**

## 5. Conclusions

This paper proposes a robot map similarity evaluation that is capable of evaluating the occupancy grid map merging hypothesis, when the maps are locally inaccurate. It is achieved by comparing the grid cells taking into account the possible errors of the robot sensor measurements.

The proposed evaluation was compared with the evaluation widely used in occupancy grid map merging. The comparison shows that the proposed evaluation achieves at least as good results, when the maps are accurate and correctly merged, and better results, when the maps are locally inaccurate or the merging hypothesis is close to the correct merging. The incorrect map mergings show different results depending on the particular case. If the distance threshold is set according to the recommendations, then the proposed evaluation correctly shows, which map merging is acceptable and which is not.

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## References

1. Siegwart R., Nourbakhsh I.R. Introduction to Autonomous Mobile Robots. MIT Press, 2004,335p.
2. Konolige K, Fox D., Limketkai B., Ko J., Stewart B. Map merging for distributed robot navigation. International Conference on Intelligent Robots and Systems, 2003, pp. 212-217.
3. Birk A., Carpin S. Merging Occupancy Grid Maps From Multiple Robots. Proceedings of the IEEE, vol. 94, 2006, pp. 1384-1397.
4. Guo R., Li Y., and Chen W. Adaptive genetic algorithm for occupancy grid maps merging. 7th World Congress on Intelligent Control and Automation, 2008, pp. 5716–5720.
5. Alnounou Y., Paulik M., Hudas G., Overholt J. Occupancy Grid Map Merging Using Feature Maps, 15th International Conference on Robotics and Applications, Cambridge, 2010.
6. Carpin S. Fast and accurate map merging for multi-robot systems. Autonomous Robots, vol. 25, Issue 3, 2008, pp. 305-316.
7. Howard A., Kitchen L. Cooperative localisation and mapping. International Conference on Field and Service, 1999, pp. 92–97.
8. Burgard W., Moors M., Fox D. Collaborative multi-robot exploration. Proceedings of IEEE International Conference on Robotics and Automation, vol. 1, 2000, pp. 476-481.
9. Thrun S. A probabilistic on-line mapping algorithm for teams of mobile robots. The International Journal of Robotics Research, vol. 20, no. 5, 2001, pp. 335-363.
10. Roumeliotis S., Bekey G. Distributed multirobot localization. IEEE Transactions on Robotics and Automation, vol. 18, no. 5, 2002, pp. 781–795.
11. Ballesta M., Gil A., Reinoso O., Julia M., Jimenez L.M. Multi-robot Map Alignment in Visual SLAM. WSEAS Transactions on Systems, vol. 9, Issue 2, 2010, pp. 213-222.
12. Topal S., Erkmen E., Erkmen A. Novel Map Merging Methodology for Multi-Robot Systems. World Congress on Engineering and Computer Science, vol. I, 2010, pp.383-387.
13. Huang W., Beevers K. Topological Map Merging. The International Journal on Robotics Research, Sage science press, vol. 24, No. 8, 2005, pp. 601-613.
14. Amigoni F., Gasparini S., Gini M. Merging Partial Maps Without Using Odometry. Multi-Robot Systems. From Swarms to Intelligent Automata, Springer, vol. III, 2005, pp. 133-144.
15. Ho K., Newman P. Multiple Map Intersection Detection using Visual Appearance. 3rd International Conference on Computational Intelligence, December, 2005, Singapore, pp.740-749.
16. Lakaemper R., Latecki L. J., Wolter D. Incremental multi-robot mapping. IEEE/RSJ International Conference on Intelligent Robots and Systems, Edmonton, August, 2005, pp. 3846-3851.
17. Birk A. Learning Geometric Concepts with and Evolutionary Algorithm. Evolutionary programming V, The MIT Press, 1996
18. Robotics Data Set Repository, Andrew Howard,Nicholas Roy, 2003, http://radish.sourceforge.net/