The Influence of the Map Merging Order on the Resulting Global Map in Multi-Robot Mapping

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An important prerequisite for creation of an autonomous robot is the ability to create the map of the environment. While the use of robot teams becomes more and more widely used, the issue of robot coordination becomes one of the central questions to be addressed. If multiple robots are used for the exploration of the environment, their collected information has to be fused into one general global map. This problem is called map merging. In the case, when more than two robots map the environment, it is possible that the order of map merging can influence the quality of the result – the global map. However, most researches in the map merging field address the problem as if the recommended order of map merging were known. The goal of this paper is to prove that the merging order can greatly influence the resulting global map and discuss the consequences this knowledge makes in the mapping process.

Keywords – Map merging, robotic mapping, Hough Transform, conceptual model

I. Introduction

One of the fundamental problems in mobile robotics is the environment mapping problem. Robots need to be able to construct a map of the environment and to use it for the navigation. As the use of robot teams becomes more and more popular, the issue of robot coordination becomes important. If multiple robots are used for the exploration of the environment, their collected information has to be fused into one general global map. The fusion of the map information from multiple robots into one global map is called map merging [1].

When only two robots explore the environment, the choice of the map merging order is trivial, as only two maps are available. The situation becomes more complicated, when several robots explore the environment. Depending on the robot paths, some local maps may overlap and some may not.

There are two main sources of information used for robot map merging: relative positions of robots and heuristics [2]. If the relative positions are known or might be determined during the mapping, it is possible to acquire the relative reference frames of the local maps and, as a consequence, the choice of the map merging order becomes natural – the maps are merged, when there is a known overlap between them. If no relative positional information is available, it is impossible to know for sure, which local maps should be merged and what merging order should be chosen. Consequently, the map merging becomes unreliable. This problem is virtually unaddressed by robot map merging researchers, and the optimal map merging order is often assumed to be known.

The goal of this paper is to prove that the merging order can greatly influence the resulting global map and discuss the consequences this knowledge makes in the robot mapping process.

The structure of this paper is as follows. At first the related work is discussed in Section II. Then the map merging concept is introduced and several map merging approaches discussed in the Section III. In Section IV one of the map merging approaches is used for the merging of three maps by using the framework developed by the author. The influence of the map merging order in the creation of the global map is demonstrated. In Section V the conceptual map merging model in the context of mapping is presented, and it is discussed, how this model deals with the consequences of the map merging unreliability induced by the wrong choice of merging order. Finally, the conclusions are drawn and possible future work defined.

II. Related work

Map merging might be considered from two different viewpoints:

1) Map merging is considered a **physical fusion** of two robot maps – the search process in transformation space leading to one or more transformations to be evaluated. In some cases also the preprocessing of the maps is performed. In this case research subjects address the search strategies, feature spaces that are used for map comparison and the evaluation metrics of the map merging result.
2) Map merging is considered **in the context of the mapping**. The main advantage of this approach is that the results of map merging can be verified. However, in this case of the map merging reversion, the choice of the maps and other problems have to be addressed in addition to the research of physical map fusion.

Most of the researches in the map merging area address solely the physical fusion of maps [3],[4],[5],[6]. The map merging order in this case is not particularly important, as the input maps are chosen manually by researchers. While these approaches evaluate the map merging results by applying some kind of acceptance metrics, they do not guarantee reliable results.

A few researchers have addressed the problem of a reliable map merging [7],[8]. In [7] the problem of the reliable map merging is addressed as a decision where both the absolute likelihood (the similarity of the two maps for a particular transformation) and the relative likelihood (the similarity of the two maps for a particular transformation compared with other transformations) are taken into account. This work, however, does not consider a particular case where the acquired result is wrong and has to be reversed. Instead, the emphasis is put on the avoidance of inaccurate results.

In [8] it is admitted that it is natural to make mistakes when merging maps. Therefore, the merged maps need to be stored in a way that allows a simple discarding of incorrect hypothesis without losing the whole map or information acquired after map merging. It is proposed to store the maps of each robot in layers. Layer 0 stores the local map, Layer 1 – the maps created by merging Layer 0 map with other maps etc. The problem with this approach is that many maps have to be maintained simultaneously, and it can prove to be computationally unfeasible.

III. The Map Merging Concept and Approaches

In the context of this paper the map merging is the search for transformation of one map against the other map. It is assumed that no relative positional information of the robots is known. Consequently the relative reference frame of the maps is not available.

Another assumption is that the environment is represented as occupancy grid maps. The occupancy grid map can be described as N×M matrix, where each cell represents the probability of the corresponding environment part being free or occupied [9]. If the value of the cell is equal to zero, then it is assumed that no information is available about the particular part of the environment.

To merge two occupancy grid maps, a transformation is required. The formal definition of the map transformation is the following [10]: Let t_x,t_y and θ be three real numbers. The transformation associated with t_x,t_y and θ is the function defined as follows:

$$TR_{t_x,t_y,\theta} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} cos\theta & -sin\theta & t_x \\ sin\theta & cos\theta & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \quad (1)$$

The transformation in equation (1) corresponds to a counterclockwise rotation of θ around the origin, followed by a translation [t_x, t_y].

The goal of the map merging is to find such transformation that the dissimilarity between two maps would be as small as possible [10]. In an ideal case robots would have explored the whole environment and created identical maps. In the real world applications it is not true. The robots might have explored different parts of the environment and the common parts may look different due to the sensor noise. In some cases there might be no overlap between the maps. However, due to the complexity of map merging, when the reference frames of the maps is unknown, most authors assume that the maps are precise and contain no significant global distortions [3],[4],[6],[5].

Further in this section several existing map merging approaches are shortly addressed.

A. Map Merging by Using Adaptive Random Walk

The map merging approach developed by Carpin and Birk [3] is one of the first attempts at map merging, when no relative positions of the robots are known. The only assumption this approach makes about the maps is that the maps are sufficiently precise.

The approach uses the Adaptive random walk algorithm [3] to stochastically search the transformation space for the best transformation.

```
k = 0; t_start = s_start; //Initial transformation
Σ_0 = Σ_init; μ_0 = μ_init; //Initializing Covariance matrix
and Mean vector
c_0 = Δ(m_1, T_tstart(m_2)); //Computing initial
dissimilarity function value
while (k < numSteps) do
  Generate new sample s = t_k + v_k;
  c_s = Δ(m_1, T_s (m_2));
  if (c_s > c_k) or (RS(t_k,s)=s) then
  //The sample is only considered if it improves the
  previous function value or is RandomSelected [3]
    k = k + 1; t_k = s; c_k = c_s;
    μ_k = Update(t_k,..,t_k-M);//Updating Mean vector
    Σ_k = Update(t_k,..,t_k-M);//Updating Cov matrix
  else
    discard the sample s;
```

The best transformation is the transformation with the lowest dissimilarity function value [3]. It is computed for each step of the search algorithm.

The main problem with this map merging approach is that it is stochastic and only guarantees convergence when the number of steps approaches infinity [3]. In real life applications there will always be a finite number of iterations, and it is entirely possible that given identical starting parameters, the algorithm will return different results. Also this map merging approach is not applicable to real time environments, as the computation time greatly increases with the map size due to the necessity to compute the dissimilarity metric in each step of search algorithm. For example, for 1000×1000 sized maps the merging time can take as much as 20 minutes [3].

B. Map Merging via Hough Transform

Another map merging approach developed by Carpin is the map merging via Hough Transform [4]. This method requires that the local maps of the robots are structured – straight lines are necessary for successful operation of the approach.

The main idea is the extraction of the Hough Specters [4] from the local maps of robots, and the search for cross-correlations between these two specters. A Hough specter shows the most common directions of the straight lines in the maps. The cross-correlation maximums of the Hough specters represent the rotation part of the transformation hypotheses. To find the translations along the X and Y axis, two additional specters are extracted from each map – X and Y specters. These specters are basically the projections of the maps along the axis and the correlation between them shows the possible translations.

Unlike Adaptive Random Walk approach, the map merging via Hough Transform is a determined transformation search algorithm. It is also able to find multiple transformation hypotheses in much shorter time than Adaptive Random Walk.

The disadvantage of this approach is that a rather large overlap between the maps is necessary.

C. Other Map Merging Approaches

Out of the existing map merging approaches only one [3] makes no assumptions about the existence of some kind of features in the robot maps. Map merging via Hough Transform [4] uses straight lines as features, and most other map merging approaches use more complicated features to find the correspondences between the maps.

Lakaemper and others [5] require the map to contain data that can be simplified in a few geometrical lines. The map merging algorithm extracts distinctive features in one map and searches for similar features in the map of other robot. If similar structures are found, the maps are merged and the compatibility of other lines is tested to evaluate the map merging hypothesis.

Ho and Newman in [11] offer to supplement the metric information of the maps with information about the visual appearance of the environment. A camera is used to take images that are further assigned to the corresponding parts of robot maps. However, this approach is not applicable to robots without cameras or in the environments without distinctive visual features.

In [6] the key-points are identified in robot maps and used for map merging. These key-points are invariant to the scaling, rotation and translation.

IV. Experimental results

Out of the map merging approaches considered in Chapter III, the map merging via Hough Transform has been chosen for the experiments described in this chapter.

The map merging by using Adaptive Random Walk has been rejected due to its stochastic nature. It is impossible to determine, how the map merging order might affect the resulting global map, if a different result is possibly returned each time for more complicated map merging cases.

Some of the other map merging approaches, for example, geometric line extraction [5] and key-point extraction [6] are also reasonable alternatives for the experiments. However, each of the map merging approaches will succeed in some cases and fail in others. The main point of the experiments is not to compare all these approaches but to show that there are cases, when the map merging order can significantly influence the resulting global map.

A. The Framework Used for Map Merging

For the experiments the map merging framework developed by the author of paper [12] has been used. Currently the map merging framework is able to perform the following tasks:

- Merge the maps via Hough Transform [4];
- Merge the maps with Adaptive Random Walk [3] approach;
- Reduce the size of the maps;
- Align the maps against the X axis (used for map merging via Hough Transform);

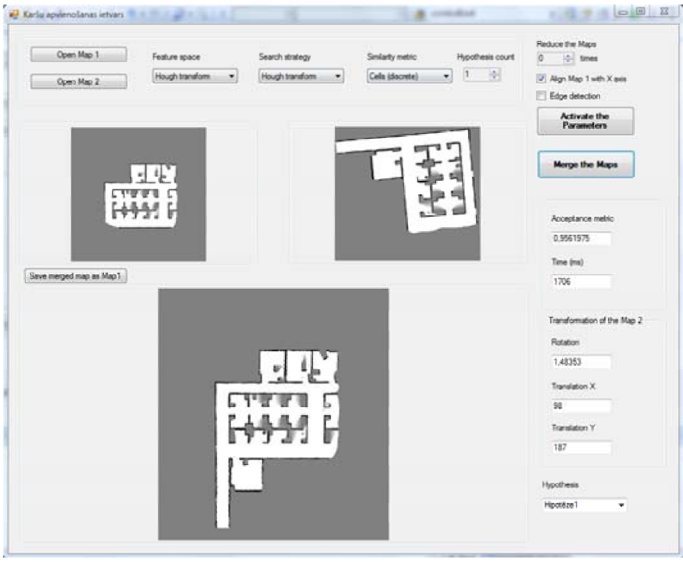

Fig. 1. An example of successful map merging with the framework developed by the author

- Compute a maximum of up to ten hypotheses for one run (available only for map merging via Hough Transform);
- Compute and display the acceptance metrics [3];
- Compute and display the computed transformation.

In the Figure 1, an example of map merging can be seen. First, it is necessary to choose two maps to be merged. After that it is possible to choose the map merging approach and acceptance indicator from the list of approaches implemented in the framework.

In addition to the basic map merging components, the map preprocessing techniques can be selected – the size of maps can be reduced selected times, map 1 can be aligned against the *X* axis (alignment can be expanded to both maps if necessary) and the edge detection can be performed on the maps.

In the example in Figure 1, Hough specter detection is selected as a feature space, Hough transformation is selected as a search strategy and discrete cell count is selected as a acceptance indicator. Additionally the map 1 is aligned against the *X* axis.

B. Map Merging Results with Different Merging Order

To demonstrate how the map merging order can influence the global map, a map created by a robot has been acquired from Robotics Data Set Repository (Radish) [13].

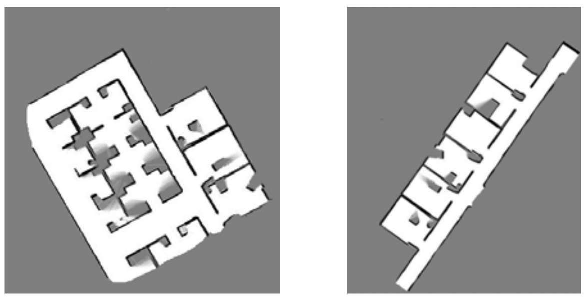

Fig. 2. Maps used for experiments – map_1 (left) and map_2 (right).

Fig. 3. Maps used for experiments – map_3.

This map has been divided into several maps that are randomly rotated, and three parts have been chosen for experiments (see Figures 2 and 3). These maps will be further denoted as map_1, map_2 and map_3.

All these maps have an overlap to demonstrate that sometimes the merging order is important not only in the trivial case, when only one map has a common part with both other maps. It is possible that the two maps have an overlap and can theoretically be merged but the overlap is too small to detect or there is not enough features used by the particular map merging approach.

For all map merging processes, the parameter of 10 map merging hypotheses was set. The acceptance indicator was computed for each hypothesis that shows the correspondence between equal and different cells in both maps. For example, the acceptance indicator of 1.0 shows that all the significant cells (not unknown) are equal in both maps for the particular transformation.

At first the attempt to merge maps map_1 and map_2 has been made. The best acceptance indicator from 10 hypotheses was 0.844 and the merging attempt failed (see Figure 4). The merging of map_1 and map_3 has also been unsuccessful. The best acceptance indicator for this merging was 0.828 (see Figure 5). Both these merging processes failed due to the characteristics of the particular map merging approach used – map merging via Hough transform. As we can see in Figures 4 and 5, the approach successfully found the rotation and translation against one of the axis.

However, the translation against the other axis failed due to several reasons:

- Inability to distinguish between different top rooms, because they are approximately the same size, in the case of map_1 and map_2.

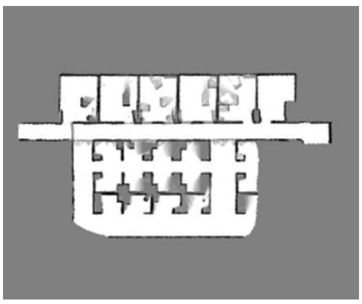

Fig. 4. The failed merging of map_1 and map_2 (best hypothesis acceptance indicator 0.844)

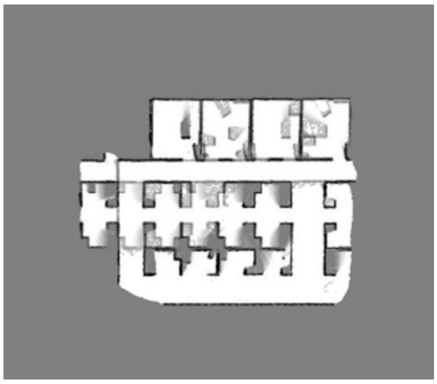

Fig. 5. The failed merging of map_1 and map_3 (best hypothesis acceptance indicator 0.828)

- Tendency of the algorithm to find the largest correlation between two maps, in the merging of map_1 and map_3. In this case only two top rooms are common in maps. However, the algorithm tries to combine as much walls together as possible and consequently attempts to merge maps as if three top rooms were common in both maps.

Although it is possible that another map merging approach would be able to merge the cases [map_1, map_2] and [map_1, map_3] successfully, no current approach is perfect in a way that it would be able to successfully merge two maps every time, when an overlap is present.

The next map merging attempt made was map_2 and map_3, and it was a successful merge (see Figure 6) with the acceptance indicator 0.943 (the acceptance indicator is not 1.0 mostly due to the approximations in the map rotations). Unlike the previous map merging attempts, this time the local maps have had sufficient overlap (four common top rooms) and no features that appear to be similar even if they actually depicted different parts of the environment (in this case one map contains all the similarly sized top rooms).

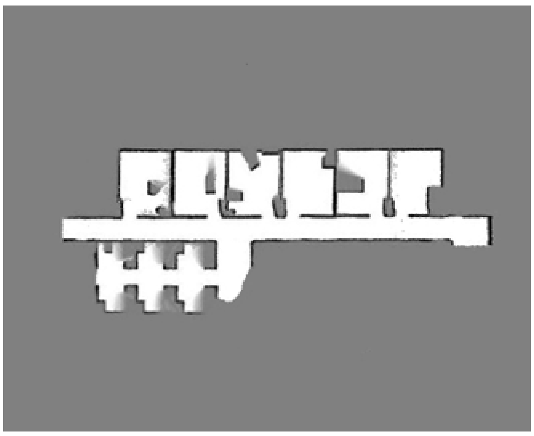

Fig. 6. The successful merging of map_2 and map_3 (best hypothesis acceptance indicator 0.943)

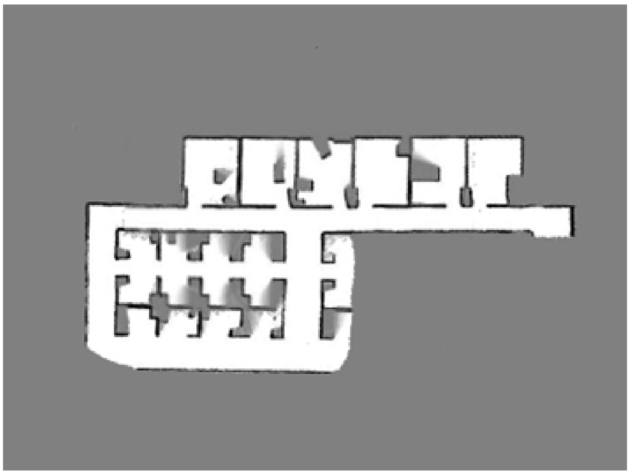

Fig. 7. The successful merging of map_{2+3} and map_1 (best hypothesis acceptance indicator 0.898)

Further the maps map_{2+3} and map_1 have been merged. The best acceptance indicator for this map was 0.898 due to a little error in the angle. However, the overall merging has been successful and the result can be seen in Figure 7.

If the map merging is continued with one of the unsuccessful merging results, for example, map_{1+2} (Figure 4) and map_3 (Figure 3), the result seen in Figure 8 can be acquired. It must be noted that the acceptance indicator (0.882) for this merging was only little lower than the acceptance indicator for the successful merging in Figure 7. In fact, the difference is so small that the robot without the help of a human cannot really tell if the particular merging is successful or not.

The experimental results show that the order of map merging can be very important for the acquisition of an accurate global map. Furthermore, the robots might have difficulties to distinguish between a successful and unsuccessful map merging result by acceptance indicator alone without the help of a human.

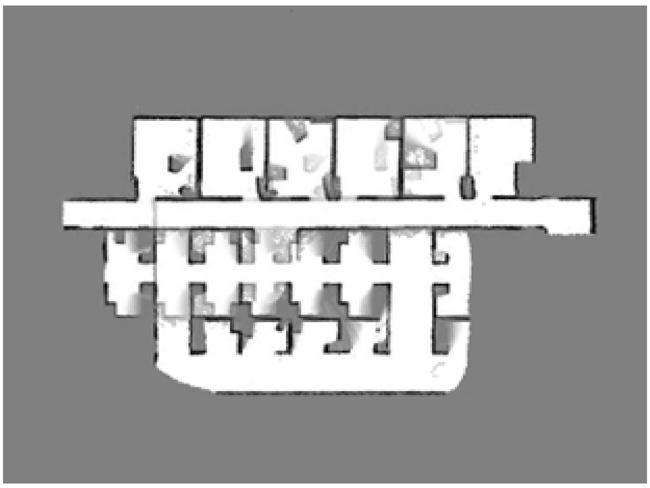

Fig. 8. The failed merging of map_{1+2} and map_3 (best hypothesis acceptance indicator 0.882)

V. The model for reliable map merging

If the robots exploring the environment are autonomous, it is not possible to rely on the human judgment. Therefore, there are two paths of action that robots can take:

- The robots merge their maps only when they are absolutely sure about their relative positions. It means that no map merging may be made, if robots are able to communicate but do not see each other, which is rather restrictive.
- The robots merge their maps, when they are able to communicate, however, the mechanism to reverse the map merging decision must be implemented.

Few researchers have addressed the problem of a reliable map merging [7, 8]. In [7] the problem is addressed as a decision where both the absolute likelihood (the similarity of the two maps for a particular transformation) and the relative likelihood (the similarity of the two maps for a particular transformation compared with other transformations) are taken into account. This work, however, does not consider a particular case where the acquired result is wrong and has to be reversed. Instead, the emphasis is put on the avoidance of inaccurate results that consequentially leads to a possible loss of significant merges.

In [8] it is admitted that it is natural to make mistakes when merging maps. Therefore the merged maps need to be stored in a way that allows a simple discarding of incorrect hypothesis without losing the whole map or information acquired after map merging. It is proposed to store the maps of each robot in layers. Layer 0 stores the local map, Layer 1 – the maps created by merging Layer 0 map with other maps etc. The problem with this approach is that many maps have to be maintained simultaneously and it can prove to be computationally unfeasible.

To allow the robots to safely merge their maps, when they cannot determine their relative positions, the author has proposed a conceptual model that addresses the problem of reliable map merging and the map merging reversal [14]. The proposed map merging model differs from the existing map merging approaches in two ways:

- It addresses not only the physical map merging but the whole process of map merging in the context of mapping. It allows creating new hypotheses dynamically and also offers a simple way to discard them and return to a previous state without losing local information gathered by robots. To achieve this, the hypotheses are stored as transformations (see Figure 9). This representation of the hypotheses allows using the local maps for the creation of the global map or rejecting the hypotheses at any time without actually having to maintain multiple maps simultaneously.
- It distinguishes the local map merging from the global map merging. Local map merging addresses only the search of transformation between two given maps. This is the point of view taken by most map merging researchers. Global map merging focuses on the creation

of global map – how, when and which local maps should be merged to create the global map.

In Figure 10 the conceptual model can be seen. The Global map merging module is responsible for the maintenance of the global hypotheses to achieve the goal of creation of a global map. It decides when the map merging should be made and which maps should be merged by Local map merging module.

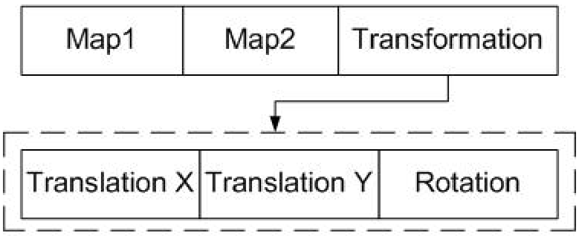

Fig. 9. The representation of map merging hypotheses

There are two possible tasks that the Local map merging module can receive – map merging by using heuristics or map merging by using the positional information of the robots. As the information available is different, each of these cases should use a different map merging approach.

The map merging module in Figure 10 depicts the map merging process when heuristics are used. Map merging approaches that use heuristics consist of at least three steps [12]: the identification of features in maps, the search and the evaluation of the result. The evaluation is an independent step that can be adapted to every map merging approach. On the other hand the feature identification and searching is often tightly interconnected within the bounds of one approach.

The map merging when robot positions are known is a much simpler task. In this case robot positions are used to determine the relative reference frames of robot maps. Even if the positional information is noisy, it is still useful for reducing the transformation search space.

In some cases an acceptable map merging transformation is not found. The common part of the maps may be too small or there might be no common part at all. In this case the map merging fails, and this information is passed back to the Global map merging module.

The Hypothesis verification module uses the computed map merging hypotheses and information from robots to determine if the map merging results are consistent or rollback should be applied. During the merging and further exploration typically two situations can happen:

- **The conflict arises**. The information coming from different robots is conflicting, indicating that one or more map merging hypotheses are incorrect. Maps of higher levels are created by hierarchically merging the lower level maps. Periodically the global map (or maps, if there are several highest level maps) is updated. It is gradually recreated from the lower level maps and each step is verified. If a conflict arises in a hypothesis, then this hypothesis is discarded. All the higher level hypotheses that depend on it are also rejected.
- **The meeting of two robots.** The meeting means that robots reach each other's sensor range and consequentially the relative positions can be determined. If two robots meet, they acquire new information that can be used for map merging – the relative positions of the robots. If these two robots have a common map merging hypothesis then it is possible to prove or reject this hypothesis. In case of rejection, all other hypotheses, which depend on it, are also rejected.

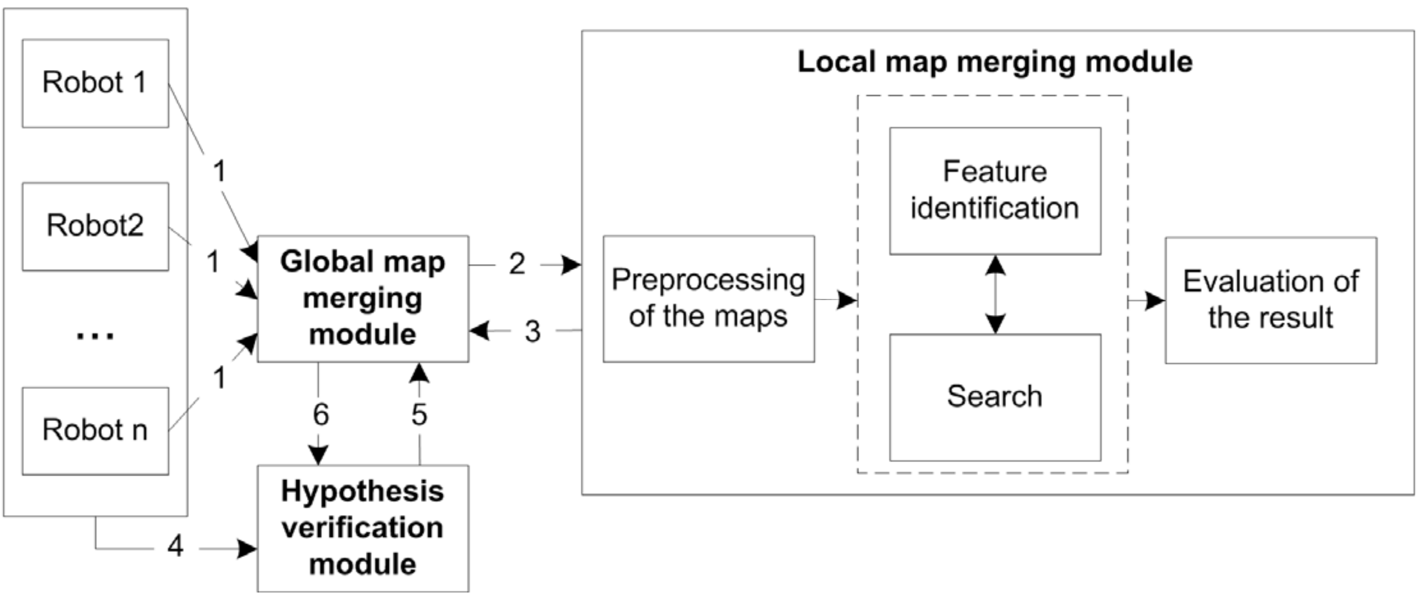

Fig. 10. The conceptual map merging model. Information flows represented in the Figure 10: 1) local maps of the robots and information about the relative position of the robots if the meeting occurs; 2) the maps to be merged and in some cases the relative position of the robots 3) and 6) map merging hypotheses (transformations) and messages about map merging failure; 4) local maps of the robots; 5) updated hypothesis structure

The model can be used to dynamically propose and reject map merging hypotheses without losing the information acquired after the map merging. When using the proposed hypothesis representation, it is not necessary to maintain local and global maps simultaneously. Instead, it is possible to acquire the global maps any time by using the local maps of the robots.

VI. Conclusions

In this paper the influence of the robot map merging order on the resulting global map was analyzed. From the available map merging approaches one approach was selected and it was experimentally shown that even when all the maps have common parts, the acquired global map can greatly differ depending on the order of map merging.

If multiple robots autonomously explore the environment and do not know their relative positions, it is not possible to know the correct map merging order without additional external information. The robots have to make this decision about the map merging order on their own and there are bound to be mistakes; it means that the map merging decision is unreliable.

It supports the assumption that the map merging model is needed that can provide a means to reverse the map merging, if it turns out to be incorrect. The conceptual model for reliable map merging is proposed by the author of the paper that can solve the problem of unreliability of the map merging.

The research can be continued by supplementing the conceptual model with the elaborated global map merging mechanism – how the local maps to be merged are chosen and the timing of merging. The model could also be implemented and tested in a real life multi-robot system.

VII. Acknowledgement

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