Map Matching for SLAM with Multiple Robots in Different Moments

André Felipe da Silva Oliveira[1], Diego de Oliveira Dantas[1], Doriedson Mendonça Corrêa[2], Areolino de Almeida Neto[3] and Will Ribamar Mendes Almeida[2]

[1]*Science and Technology Center, State University of Maranhão (UEMA), Av. Lourenço Vieira da Silva, São Luís, Brazil*

[2]*Department of Computer Engineering, CEUMA University (UNICEUMA), São Luís, Brazil*

[3]*Department of Informatics, Federal University of Maranhão (UFMA), São Luís, Brazil*

Keywords: Mapping, Robot Navigation, Map Matching, Map Merging, Map Fitting, SLAM.

Abstract: This paper proposes a method for matching of occupancy grid maps in image form, in which a new way of searching for similarities is developed. The maps used were obtained via SLAM. This work uses image processing techniques to extract map features and create an alphabet, by means of features relationships, for each map. Candidates for matching points are found from the comparison between members of the alphabets generated. After the comparison, the possible matchings are verified from candidate points, applying a metric of similarity. Thus, matching points that provide greater similarity are chosen as the best current points. These operations are repeated each time that a new updated map is provided. Thus, the similarity rates of the best points of the previous iteration are updated, and the new best matching points are calculated for the current iteration; in this way, the matching points that have the highest similarity ratio among the previous iteration and the current iteration are chosen as the best current points. The results obtained are promising, since in most tests performed, it was successful in finding the correct matching between the maps. A quantitative analysis was also performed on success cases, which demonstrated the efficiency of the method and the proximity of the map matching method with single robot mapping methods.

1 INTRODUCTION

For a mobile autonomous robot to perform a task, it is often necessary to have knowledge about the environment in which it is inserted, because through this knowledge the robot can make decisions and move more efficiently. However, a map of the environment is not always available, making it necessary to have a mapping process in the place, whether performed by the robot itself or not.

The mapping processes can be performed in various ways. A very common example in Robotics is the use of SLAM (Simultaneous Localization and Mapping) techniques, in which the robot maps the environment at the same time it is located. Mapping processes performed by different robots have been increasingly used in order to improve mapping speed and make the process more reliable. In this way, if one of the robots becomes unavailable, the others continue the process.

Many map matching works (Bresson et al., 2013), (Thrun and Liu, 2005), (Cunningham et al., 2012), (Koch et al., 2016), (u. N. Jafri and Chellali, 2013),(Jian et al., 2017), (Blanco et al., 2013), (Birk and Carpin, 2006) use robot-generated maps via SLAM. Thus, some of these works (Bresson et al., 2013), (Thrun and Liu, 2005), (Cunningham et al., 2012), (Jian et al., 2017), (Blanco et al., 2013) tend to focus their efforts on extracting features directly from the mapping process, relating matching directly to the mapping process itself. However, in this way, the matching process becomes highly dependent on the type of SLAM used and the specifics characteristics extracted of this SLAM.

There are several mapping techniques from SLAM with multiple robots. These techniques usually use extracted features during the individual SLAM of each robot of the team, so that through these features it is possible to find several types of associations.

This work proposes a method of map matching, which is used to compare geometric features extracted from the corners detected in the maps. This method was developed in order to work with occupancy grid

Oliveira, A., Dantas, D., Corrêa, D., Neto, A. and Almeida, W.
Map Matching for SLAM with Multiple Robots in Different Moments.
DOI: 10.5220/0007395902100217
In *Proceedings of the 11th International Conference on Agents and Artificial Intelligence (ICAART 2019)*, pages 210-217
ISBN: 978-989-758-350-6

type maps as image so that it does not rely on internal variables SLAM method used for mapping, making it therefore a more usefull method and easy portability.

This paper is divided as follows: in Session 2 it is presented how the map matching was made, discussing the preprocessing applied in the maps, the process of extraction of features (corners), the creation of alphabets through the relationship geometric of these features, the comparison of these alphabets, the selection of the best feature to finally perform the matching of the maps; in Session 3 it is discussed the methodology used in the preparation of this work, considering the used machine configurations and the robot model used in SLAM process; in Session 4 it is discussed on the results obtained, in both qualitative and quantitative analyzes and in Session 5 it is presented the conclusion as well as future works.

2 MAP MATCHING THROUGH FEATURES RELATIONSHIP

This work sought to make the matching of maps performed by several robots. The matching between the provided mappings is done for each two maps, generating a final map at the end of the process.

The maps provided for the method are occupancy grid type (Elfes, 1989), which is characterized by an occupation matrix and, when treated in image form, represented in gray scale, where the black color expresses obstacles detected in the environment, the white color expresses regions mapped without obstacles, and the gray color represents unmapped regions.

The image format used in the method was Portable Graymap (pgm), because it is a portable format and has small dimensions, while also having a good scale conversion ratio to the original environment being mapped.

2.1 Map Matching

In order to match the individual maps obtained by a robot team and thus generate a final map, it is necessary to follow a sequence of steps.

Because the proposed method is based on map matching through the mapping process, it works so that the system receives maps of each new state that is provided or saved during the process. In the Algorithm 1, it can be observed the procedure, in which the system receives the states of each mapping and supplies them to the map matching function. This function returns the resulting matching and matching rate, which define how similar the map states are (relative to the selected matching points). After this step, it is checked if the matching rate is higher than the best matching rate thus far; if the matching rate is higher, then the best matching rate is updated along with the best matching 1. In this work, map 1 is represented by δ_1, while map 2, by δ_2, and mapping process 1 is represented by Δ_1, while mapping process 2, by Δ_2. The best current matching rate is represented by Ψ; while the current matching rate, by ψ. The best current matching is represented by Λ, while the current matching between the maps is represented by λ.

Algorithm 1: Map Matching of the mappings process.

```
Function MapMatchingMapping (Δ1, Δ2)
begin
    ψ = 0
    Ψ = 0
    δ1 = empty
    δ2 = empty
    Λ = empty
    while (exist maps in Δ1 or Δ2) do
        if (exist maps in Δ1) then
            δ1 = next map from Δ1
        end
        if (exist maps in Δ2) then
            δ2 = next map from Δ2
        end
        λ, ψ = MapMatching(δ1, δ2) if (ψ >
        Ψ) then
            Λ = λ
            Ψ = ψ
        end
        return Λ
    end
end
```

The matching process can be observed in the function exposed in the Algorithm 2, in which the procedure receives two maps as input. Thus, a sequence of procedures for obtaining matching is performed. Initially, the maps are preprocessed, so that the most obvious noises are smoothed and the main features of the maps are highlighted. After the preprocessing, the features of the maps are extracted and then, from geometric relationships among them, alphabets [1] are generated. By comparing the similarities of alphabet members, a set of points is considered to be a candidate for matching points among maps (mapping points). From these matching points, the best points are defined based on a metric of similarity and then the matching generated by points with greater similarity are returned with associated similarity rate. The map $delta_1$ converted to gray scale is represented by α_1, while the map $delta_2$ by α_2. The features extracted from the map α_1 are represented by β_1, while

[1] In this work, alphabet is considered a set of symbols with features that differentiate them from each other.

the map α_2, by β_2. The matrix that stores the compared alphabets is represented by γ. The current candidate points are expressed by ϕ, while the best current candidate points are represented by Φ. The highest evaluation of the Jaccard similarity metric is represented by Σ.

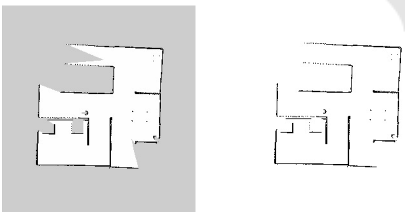
Algorithm 2: Map Matching.

```
Function MapMatching (δ1, δ2)
begin
    α1 = PreProcess(δ1)
    α2 = PreProcess(δ2)
    β1 = ExtractFeatures(α1)
    β2 = ExtractFeatures(α2)
    L_{c_{i,1}} = GenerateAlphabet(β1)
    L_{c_{z,2}} = GenerateAlphabet(β2)
    γ = CompareAlphabet(L_{c_{i,1}}, L_{c_{z,2}})
    φ = CandidateMatchingPoints (γ)
    Φ, Σ = BestMatchingPoints (φ, α1, α2)
    λ = Matching(Φ, δ1, δ2)
    return λ, Σ
end
```

2.1.1 Preprocessing the Maps

Preprocessing of maps is a fundamental step, as it smoothes the noise and highlights the features of the maps.

The map is converted to grayscale, and then binarized (Lopes, 2012), so that only whites and blacks remain on the map. A example can be observed in Figure 1 (a) represents the map to the system, and Figure 1 (b) expresses the map after being binarized.

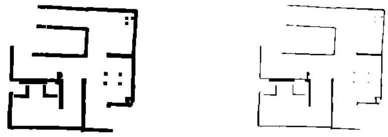


(a) Map provided. (b) Binary map.

Figure 1: Example of binarization of a map.

In order to close the discontinuities of walls that are common in occupancy grids maps type and thus to avoid wrong detections of corners , a sequence of two erosions (das Graças Medeiros et al., 2002) is applied to "thicken" the collisions of the map and then join the points belonging to the wall, in order to promote the continuities thereof. The result of the application of two erosions in Figure 1 (b) can be observed in Figure 2 (a), where it is verified that erosions promote the closure of spacing on the walls of the map.

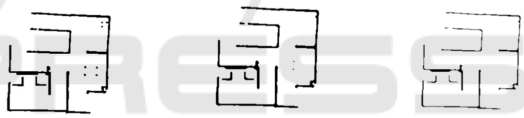
After closing the undue spacing on the walls of the map, it is necessary to return the walls to their original thicknesses, so a sequence of two dilations (das Graças Medeiros et al., 2002) is applied to "sharpen" the walls of the map. The result of the dilations applied in Figure 2 (a) can be observed in Figure 2 (b) and, comparing the result of Figure 2 (b) with the result of Figure 1 (b), it can be seen that a large part of these discontinuities have been corrected.



(a) After two erosions. (b) After two dilations.

Figure 2: Example of erosion and dilation applied to a binary map.

In order to remove features originated from non-relevant objects such as chair and table legs, a sequence of erosion, median blur (Gonzalez and Woods, 2010) and dilation is performed. The result of these operations applied to the image in Figure 2 (b) can be observed in Figure 3.



(a) Erosion. (b) Median Blur. (c) Dilation.

Figure 3: Example of a sequence of erosion, median blur and dilation.

2.1.2 Features Extraction

The SLAM maps are poor in features, so we chose one of the most obvious features, which are the corners. As a corner detector, the Good features to track (Shi and Tomasi, 1994), which is an extension of the Harris corner (Harris and Stephens, 1988) method, has a strong invariance of rotation and noise. Good features to track were used because it selects corners in a distributed form throughout the image, limiting the maximum number of corners to be detected and these reduce the complexity in the process of generation and comparison of alphabets.

The Good features to track technique is applied right after the preprocessing of the mappings. In the figure 4 it is possible to observe the corners that were detected in the map of the Figure 3 (c).

With the detection of these corners, a list L_m is generated for each map of each robot with N_m corners detected in each map, where m represents the map, N

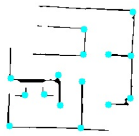


Figure 4: Detection of corners using the technique Good features to track.

the number of corners and L represents the list as seen in the expression 1.

$$L_m = (c_{1,m}, c_{2,m}, c_{3,m}, \ldots, c_{N_m,m}) \qquad (1)$$

2.1.3 Generation of the Alphabet

The alphabet is treated as a set of symbols with its own characteristics. Each symbol is defined by a particular corner and the characteristics of the symbol are determined by the set of geometric relationships with others belonging to the same map.

In order to relate a corner $c_{i,m}$ to another $c_{j,m}$, it has been defined that the euclidean distance d among them is subject to the following condition: $\forall d_{i,j} \mid D_{max} \geq d_{i,j} \wedge D_{min} \leq d_{i,j} \wedge D_{max} \geq D_{min} \wedge i \neq j$. In addition, that D_{max} and D_{min} are the parameters that define the maximum and minimum distances, respectively, of relationship among the corners.

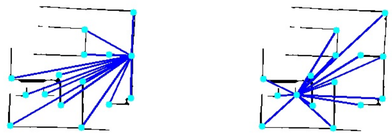
To relate the corners, for each corner $c_{i,m}$ within the list of corners L_m, the distance from that corner is calculated for all other $c_{j,m}$ of the same list, where $j \neq i$. The corners within the range defined by D_{max} and D_{min} are added to a list $L_{c_{i,m}}$ which represents the alphabet and is related to the corner $c_{i,m}$, as seen in the Expression 2, where the value $T_{L_{c_{i,m}}}$ represents the size of the list $L_{c_{i,m}}$, that is, the number of other corners with which $c_{i,m}$ relates.

$$L_{c_{i,m}} = (c_{1,m}, c_{2,m}, c_{3,m}, \ldots, c_{T_{L_{c_{i,m}}},m}) \qquad (2)$$

After relationship among the corners, it is required to calculate the second characteristic of each member of the alphabet. The angle formed by the vectors defined by the corners $c_{i,m}$ is calculated for all the members $c_{j,m}$ of its list $L_{c_{i,m}}$. The calculation of all the possible combinations within each list is achieved and thus the alphabet is obtained that will be used for comparison between the maps.

Each $c_{i,m}$ along its angles and calculated distances relative to all other corners within a range of distances delimited by D_{max} and D_{min} are a letter of the alphabet. The purpose of delimiting these distances is to prevent errors accumulated with the distance among the corners interfering in the matching process.

Based on the Figure 5, one can observe visually how the form of two alphabet members generated by using the corners detected in Figure 4 looks.



(a) Member 1. (b) Member 2.

Figure 5: Members of an alphabet generated.

2.1.4 Comparison of Alphabet Members

In this step, a comparison is made among the members of the alphabets, in which a comparison is made based on the characteristics of distances and angles related to each member.

Firstly, we compute each distance $d_{i,j}$ and $d_{z,k}$ related to each alphabet $L_{c_{i,1}}$ and $L_{c_{z,2}}$, if these distances are similar (or within a margin of error ε), we look for other similar distances $d_{i,y}$ and $d_{z,q}$, and if similar distances, we seek to relate the angles. For the relationship among the angles, the angle formed among the distances in each map, angle $a_{i,j,y}$ for the distances $d_{i,j}$ and $d_{i,y}$ and the angle $a_{z,k,q}$ for the distances $d_{z,k}$ and $d_{z,q}$, if the angles $a_{i,j,y}$ and $a_{z,k,q}$ are similar (or within a margin of error ν), then the matrix $\gamma[i][z]$ s incremented in the positions for each member of the alphabet i and z.

2.1.5 Selection of Candidates for Matching Points

After calculating the similarity among the corners of each map, one must select the candidates for matching points among the maps. This selection is performed by searching for corners with greater similarities in the matrix γ.

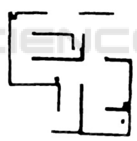
A maximum number *candidates_number* of candidates for matching points ϕ is established. For each candidate $\phi_{a,1}$, a position of greater value is associated within γ, so that positions do not recur among candidates. After defining the first matching point for each candidate, the second point is defined, where $\phi_{a,2}$ receives the position with the highest value within γ and the associated distances are similar ($d_{i,j} \approx d_{z,k}$ are similar, i and z are related to $\phi_{a,1}$ and j and k are related to $\phi_{a,2}$). Thus, the candidates for matching points to be tested in the next stage are selected.

2.1.6 The Best Matching Points

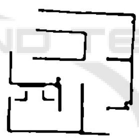
After the candidate selection phase for matching points, it is necessary to choose among them, that is, the ones that fit the best. This choice is made through attempts to fit among the maps, using the candidate points as fitting points.

In this way, the map δ_2 is translated and rotated on the map δ_1, so that the points (corners) $c_{i,1}$ and $c_{z,2}$ referring to $\phi_{a,1}$, and also the points $c_{j,1}$ and $c_{k,2}$, referring to $\phi_{a,2}$, are respectively aligned.

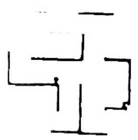
After fitting candidate points, it is possible to measure which of the fittings has the highest degree of similarity and, therefore, greater reliability. For this, the Jaccard similarity metric σ (Jaccard, 1912), (Milsztajn and de Geus, 2015) is applied between the maps δ_1 and δ_2, exemplified by Figure 6 (a) and (b). This metric requires that two operations should be performed among the maps, the first one is an intersection $inter$, exemplified by Figure 6 (c), and the second one is a union uni, exemplified by Figure 6 (d). In the result of these operations, the number of black pixels at the intersection $inter$ and the union uni is counted, and then the amount of black pixels of $inter$ is divided by uni. In this way, we obtain the similarity metric for each pair of candidates for matching points; the pair that has greater similarity is chosen as the current best matching points.



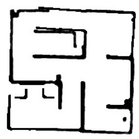
(a) Map 1.



(b) Map 2.



(c) Intersection.



(d) Union.

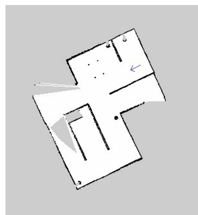
Figure 6: Example of union and intersection application on two maps.

2.1.7 Matching among the Maps

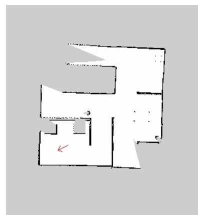
As maps 1 and 2 have already been aligned in the process of choosing the best matching points , a new image is generated that will receive the characteristics of both maps δ_1 and δ_2. This transfer of characteristics follows the following rules:

- Gray color is the first one to be transferred to image;
- White color is the second one to be transferred to image and overlaps with gray color;
- Black color is the third one to be transferred to image and it overlaps with gray and white colors.

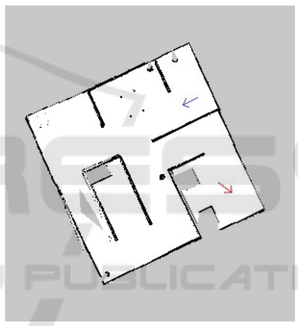
So, we have the new "matching" map λ generated. An exemplification of the result of the matching can be observed in Figure 7 (c), where one can observe the map obtained from a matching of maps in Figure 7 (a) and (b).



(a) Global map reference 1.



(b) Global map reference 2.



(c) Global reference in Matching.

Figure 7: Global reference in the matching among two maps.

The global reference of the map δ_1 remains the same as the mapping process. The global reference of the map δ_2 receives the same translation and rotation operations as δ_2 received. In Figure 7 (a), the global map reference is referenced by the blue arrow, where the direction of the arrow represents the initial orientation of robot 1 and the base of the arrow is the initial position of the robot 1 that mapped δ_1. In Figure 7 (b), the global reference of the map is referenced by the red arrow, where the direction of the arrow represents the initial orientation of robot 2 and the base of the arrow is the initial position of the robot 2 that mapped the δ_2. Thus, when the translation and rotation operations are applied to δ_2, these same operations are also applied in the global reference of robot 2, so that the result in the matching can be observed in Figure 7 (c), where the global reference of robot 2 is adjusted to match the maps.

3 METHODOLOGY

3.1 Materials

For the development of this work was used a computer with the following machine configuration: Kaby Lake processor I7-7700HQ (6 MB cache up to 3.8 GHZ), a 32 GB DDR4 RAM (2133 MHZ) memory, a NVIDIA GEFORCE GTX 1050 GPU (4 GB GDDR5) video card, a 1 TB SSHD with 8 GB SSD, a 480 GB (500 MB / S) SATAE M.2 SSD. This was used with the Ubuntu 16.04 LTS 64-bit operating system.

As a robot manipulation system, the Robot Operational System (ROS) (ROS, 201) KINETIC version was used. As a robotic simulator, the V-REP was used. As generator of random environments, the V-REP map generator[2] (Jelinek, 2016) was used. As a system for mapping, the SLAM Gmapping (Grisetti et al., 2007) Toolkit was used. The Oracle VM VirtualBox software was also used for operating system virtualization.

3.2 Robotic Model

For simulation in the V-REP, the model of robot mecabot (Dantas, 2017)[3] was used.

For this work, the model used did not contain the robotic arm and the vision sensor it was replaced by a fastHokuyo laser scanner available on the V-REP. In this sensor it was introduced, via textit script, an error of 0.01 meters. It were also introduced a reading aperture of 240 degrees around the robot and a reading radius of 5 meters.

3.3 Methods

In order to carry out this work, it was necessary to use the materials described in the materials topic 3.1. So the software described was installed on an Ubuntu virtual machine, with the configuration of four processors and 16 GB of RAM.

Using the V-REP map generator connected with the V-REP, it was possible to generate and save scenes from ten random and different environments in-door. These environments were generated with the purpose of being mapped in order to generate a database for the tests of map matching.

With the V-REP integrated to the ROS, for each environment map generated previously, the mapping of these environments was performed through gmapping, the control of the robot was performed manually, via keyboard, through the teleop twist keyboard application [4].

Thus, the teleop twist keyboard application was performed applying a linear velocity of 0.8 m/s and an angular velocity of 1.61 rad/s via human control; five maps were also performed for each generated environments (for each environment, each mapping occurred with different poses). Thus formed a database of 50 mappings. In order to attempt a matching among maps, we have always explored an area in common among the mappings of the same environment. For each environment was created a possibility of ten matchings using two in two mappings referring to this environment. The database generated by gmapping is composed of mapping histories, and for each mapping and each time period of one second (if there is a change in map state), the state of the mapping at that instant is saved in image form.

The mappings were made by just one robot at a time and the matchings were performed, using combinations between these mappings, and simulating as if two robots were mapping at the same time.

After the generation of the database, for each environment, it inserts into the system implemented, based on the method proposed in this work, two processes of mapping at a time, in order to never repeat a combination. Thus, there are ten possible matching combinations for each environment, totalizing 100 matchings performed. This operation was performed with the following configuration of parameters in the system:

- $N = 30$, number of corners to be extracted from each map;
- $q = 0.2$, referring to the quality of the corners to be extracted from each map;
- D_{max} is half the greater distances among corners, taking into account the two maps being matched;
- $D_{min} = 18$, values in pixels;
- $\varepsilon = 1.1$, values in pixels;
- $\nu = 1.1$, values in degrees.

The results were evaluated qualitatively and in the cases of success a quantitative evaluation was applied. In this quantitative evaluation, the accuracy of the maps of each base environment was analyzed in comparison to the generated matching.

[2]Available in: https://github.com/Lukx19/Vrep-map-generator

[3]Robot model details available in: https://tede2.ufma.br/jspui/handle/tede/2062

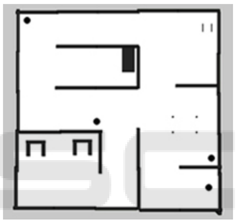
[4]The teleop twist keyboard is present in the ROS and through this at sends speed signals to the V-REP, which in turn applies these signals to the robot. Available in: http://wiki.ros.org/teleop_twist_keyboard

4 RESULTS OF EXPERIMENTS

The qualitative analysis defined only the attempted matching to have succeeded or not. From 100 matchings performed with two mappings, 79 were successful.

One examples of success can be seen in the Figure 8. The red color represents the mapping made by robot 1, the blue color expresses the mapping done by robot 2 and the green color represents the mapped locations in common.

Based on the Figure 8 (a), one can observe the format of the real environment. Thus, in Figure 8 (b), it is observed that the common areas, plotted by green color, tend to have a higher concentration in neighboring regions, while as far as the green color goes. The colors blue and red become more evident, demonstrating that, as it departs from the matching zone (green regions), the error of each mapping, used in the process, causes a loss of precision in matching. The same phenomenon can be observed in Figure 8 (c) and (d).

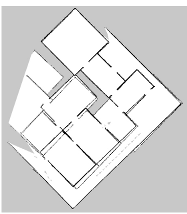


(a) Map of the environment 1.

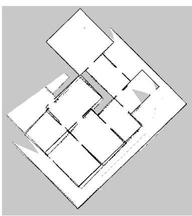
(b) Matching of the mappings 1 e 2.

Figure 8: Representation of environment 1 and one of their matchings.

The same process was applied to successful matching results (between two different mappings of the same environment), so that these results were matched to other mappings, always being performed two by two matching and thus providing a matching among three or more mappings. Thus, some success cases can be observed in Figure 9.



(a) Matching of the mappings 1, 2 and 4.



(b) Matching of the mappings 1, 2, 3, 5 and 4.

Figure 9: Matchings with more than two mappings related to the environment 2.

A quantitative analysis was performed with success cases. In this analysis the comparison of the original environments with the results of the matchings from which the number P_p of black pixels and the number P_b of white *pixels* were extracted, which coincided (black with black, white with white) between the original environment and the result of matching. The number P_{pc} of black pixels and the number P_{bc} of white pixels present in the results of the matching were also counted. Thus, for each obtained matching, it was applied the Equation 3. From this formula, the accuracy rate between the outcome of the matching and the original environment was obtained.

$$\frac{(Pp + P_b)}{(P_{pc} + P_{bc})} \tag{3}$$

The accuracy of each individual mapping was calculated. This calculation was performed using Equation 3, with the small change that the numbers P_p and P_b represented the values in relation to the individual mapping, instead of matching results. In this way, both individual mapping accuracies and matching results were used to calculate the means, median and standard deviation. These calculations were performed for two classifications: the first one representing only the individual mappings (thus representing the maps generated via gmapping) and the second one representing the results of the matchings.

Table 1: Quantitative result.

analysis	Gmapping	Proposed Method
Mean	0,929006	0,927027
Median	0,926777	0,931214
Standard Deviation	0,020205	0,021912

The quantitative results of matchings and mappings can be observed on the basis of Table 1. In these results, it was achieved that the mean, median and standard deviation differences were very small, being less than $0,01$, proving that the matching method provides approximate results to the individual gmapping mapping method. In addition, the averages and medians of precisions are considerably high (above 92%).

5 CONCLUSION

In this work, a mapping of SLAM maps with a single robot model was carried out and the mappings were performed at different times. These matchings were carried out on two maps. In order to enable the matchings, a technique of geometric relationship was developed among the corners that were detected in the mappings. This technique detected the three best corners for each two candidate points to fit among the maps. After this detection, the attempt of matching among these candidates is realized and then the generated maps are evaluated through a metric of similarity.

The quantitative analysis of matchings expressed the difference in precision between the mapping with only one robot and the result of the matching do not have considerable differences. Thus, matching can be considered a viable tool for mapping processes with more than one robot, but it remains to verify the navigability of both maps, which should be done in future work.

Through this method, good results were obtained, in order to make possible future tests in real robots and the continuity of the research. In order to improve the results obtained, it is suggested to apply probabilistic functions to verify if there is success or failure in the matching process, in addition to trying to increase the number of success cases.

ACKNOWLEDGEMENTS

The authors acknowledge FAPEMA, CAPES and CNPq for their financial support in the development of this work. Special thanks to CEUMA, UEMA and UFMA for their technical support.

REFERENCES

Birk, A. and Carpin, S. (2006). Merging occupancy grid maps from multiple robots. *Proceedings of the IEEE*, 94(7):1384–1397.

Blanco, J.-L., Gonzlez-Jimnez, J., and Fernndez-Madrigal, J.-A. (2013). A robust, multi-hypothesis approach to matching occupancy grid maps. *Robotica*, 31(5):687701.

Bresson, G., Aufrere, R., and Chapuis, R. (2013). Consistent multi-robot decentralized SLAM with unknown initial positions. *Information Fusion (FUSION), 2013*, pages 372–379.

Cunningham, A., Wurm, K. M., Burgard, W., and Dellaert, F. (2012). Fully distributed scalable smoothing and mapping with robust multi-robot data association. *Proceedings - IEEE International Conference on Robotics and Automation*, pages 1093–1100.

Dantas, D. d. O. (2017). Implementao de um sistema autnomo de construo de estrutura usando aprendizado por reforo. Master's thesis. DEPARTAMENTO DE INFORMTICA/CCET.

das Graças Medeiros, N., da Silva, E. A., and Nogueira, J. R. (2002). Segmentação morfológica de imagens utilizando o gradiente morfológico multi-escala. *Revista Brasileira de Cartografia*, (54).

Elfes, A. (1989). *Occupancy Grids: A Probabilistic Framework for Robot Perception and Navigation*. PhD thesis, Pittsburgh, PA, USA. AAI9006205.

Gonzalez, R. C. and Woods, R. E. (2010). *Processamento digital de imagens* . Pearson Prentice Hall.

Grisetti, G., Stachniss, C., and Burgard, W. (2007). Improved techniques for grid mapping with rao-blackwellized particle filters. *IEEE Trans Robot 23*.

Harris, C. and Stephens, M. (1988). A combined corner and edge detector. In *Alvey vision conference*, volume 15, page 50. Citeseer.

Jaccard, P. (1912). The distribution of the flora in the alpine zone. *New phytologist*, 11(2):37–50.

Jelinek, L. (2016). Vrep map generator. Accesso: 15-03-2018.

Jian, L., Chen, Z., Qiang, I., Heng, W., and Manzhen, M. (2017). Vision feature extraction algorithm for occupancy grid maps merging. In *Proceedings of the 2017 2Nd International Conference on Communication and Information Systems*, ICCIS 2017, pages 290–293, New York, NY, USA. ACM.

Koch, P., May, S., Schmidpeter, M., Kühn, M., Pfitzner, C., Merkl, C., Koch, R., Fees, M., Martin, J., Ammon, D., and Nüchter, A. (2016). Multi-robot localization and mapping based on signed distance functions. *Journal of Intelligent & Robotic Systems*, 83(3):409–428.

Lopes, F. M. (2012). Um modelo perceptivo de limiarização de imagens digitais.

Milsztajn, F. and de Geus, K. (2015). Segmentao de tecidos cerebrais em imagens tridimensionais do crebro.

ROS (201?). Documentation = http://wiki.ros.org/, note = Accessed: 2017-04-09,.

Shi, J. and Tomasi, C. (1994). Good features to track. In *1994 Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, pages 593–600.

Thrun, S. and Liu, Y. (2005). Multi-robot SLAM with Sparse Extended Information Filers. *The International Journal of Robotics Research*, 15:254–266.

u. N. Jafri, S. R. and Chellali, R. (2013). A distributed multi robot slam system for environment learning. In *2013 IEEE Workshop on Robotic Intelligence in Informationally Structured Space (RiiSS)*, pages 82–88.