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Praca dyplomowa

Planar segment-based global localization for autonomous agents

Globalna lokalizacja agenta w oparciu o segmenty płaszczyzn

Autor:	**Jan Rodzoń**
Kierunek:	**Informatyka**
Opiekun pracy:	**prof dr hab. inż. Bogdan Kwolek**

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Składam szczególne podziękowania mojemu Promotorowi, prof. dr hab. inż. Bogdanowi Kwolek za życzliwość, wszechstronne wsparcie, cierpliwość, cenne uwagi merytoryczne oraz poświęcony czas.

Streszczenie

Niniejsza praca bada obecne rozwiązania i architektury sieci neuronowych pod kątem lokalizacji agenta w oparciu o rozpoznawanie segmentów płaszczyzn na zdjęciach RGB. W ramach pracy wybrano oraz sprawdzono zastosowanie kilku najnowszych technologii opartych o sieci neuronowe w radzeniu sobie z rozpoznawaniem segmentów płaszczyzn w różnych warunkach życia codziennego.

Abstract

This thesis examines current neural network solutions and architectures in terms of agent localization based on recognition of plane segments from RGB images. The work selects and tests the application of several state-of-the-art technologies based on neural networks in dealing with the recognition of plane segments in various everyday conditions.

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1. Preface

We live in the era of automation. Everywhere robots are taking over the positions, which require not only repetitive actions but also more complicated tasks. In this environment, there are more and more machines that are operating within some contained spaces like commercial buildings or warehouses. There is also a growing market for indoor drone usage. Because of that, there is a need for a means of autonomous localization of these machines, which we will call generically agents in this work. Recent advances in computer vision and artificial intelligence come in handy and provide some models for localization based on planar segments.

1.1. Motivation

Unfortunately, when one tries to use or apply the latest state-of-the-art models and algorithms there are a lot of obstacles to it—starting from missing environment requirements, through outdated libraries, which have dropped backward compatibility, and finishing on overfitted models, which are good only within specific circumstances and are not applicable in ordinary indoor applications. This thesis aims to contribute to the field of agent localization and plane segmentation by reviewing the current development of plane segmentation and measuring its potential on data that is completely different from the training or testing one. Additionally, some of the latest models are difficult to get started. In this work, I also try to ease the workload required to get these projects going for future contributors or researchers.

1.2. Content of this work

The content of the chapters in this thesis is organized as follows:

1. **Chapter 2: Plane Segmentation Development** 2

   This chapter goes through the recent development in plane segmentation. It compares different approaches and techniques to tackle this problem bringing up relevant literature.

2. **Chapter 3: Problem Description** 3

   This chapter explains the problem of agent localization and the difficulties in applying it in everyday use. It also covers the obstacles of running the latest state-of-the-art projects to deepen the research in this matter.

3. **Chapter 4: Implementation** 4

   This chapter shows the actions taken to get the related projects up and running and to evaluate their usefulness in indoor applications, including data preparation and processing.

4. **Chapter 5: Results Evaluation** 5

   This chapter presents and compares the results of the selected models. It also shows how to get the related projects going after the contribution.

5. **Chapter 6: Conclusions** 6

   This chapter concludes the results and shows potential directions for future work.

2. Plane Segmentation Development

2.1. RGB-D Approach

As the whole artificial intelligence field has been developing rapidly over the past few years, plane segmentation is no exception. In the previous century, it was almost unimaginable to parse the film in real time and interpret the frames. Furthermore, it seemed that the depth component was necessary to find plane segments in the pictures. Since the RBG-D sensors were only available in the form of expensive machines like time-of-flight cameras or scanning 3-D laser range finders, [1] there were no possibilities for a broad usage of this technology, and thus, it saw little interest. Nevertheless, there were multiple approaches to recognizing planar sections in the pictures.

2.1.1. Rabbani Classification

Rabbani [2] categorized contemporaneous plane segmentation algorithms into three main categories:

1. **Edge-based segmentation**

   This approach comprises two stages:

   - Edge detection

     It involves scanning the depth map for points in which there are some changes in the local surface properties (like gradients or normals) above a designated threshold.

   - Point grouping

     This part groups together points inside borders detected in the previous step.

   One of the first successful applications of this method was done by Bhanu et al. [3] Another more recent work with promising results was published by Sappa et al. [4]

2. **Surface-based segmentation**

   Algorithms of this type try to merge points with similar local surface properties. Generally, there are two approaches:

   - Bottom-up

     It begins by selecting some starting points and expanding from them using some predefined similarities. It is worth noting that the selection of these initial points is crucial as the results are dependent on them - i.e., you don't find segments without starting points within them.

   - Top-down

     It starts by associating one big plane with all of the points in the picture. Then, it cuts it into smaller pieces until it achieves a predefined fitting threshold.

   One of the most prominent uses of this approach is published by Xiang et al. [5] They utilize the bottom-up approach, as it is far more often used than the top-down technique.

3. **Scanline-based segmentation**

   This approach treats rows or columns of pixels as scanlines. It takes advantage of the fact that each scanline projection over a 3D surface creates a 3D line. Ultimately, the technique consists of two stages:

   - Line segments extraction

     This stage involves processing scanlines to find line segments.

   - Line segments grouping

     In this step, the extracted line segments are grouped with the neighboring ones based on their similar surface properties to form plane segments.

   One of the first publications regarding this technique is made by Jiang et al. [6] giving a groundbreaking performance at the time. Natonek [7] utilized a similar approach for robots just two years later having promising results.

As we can see, these various techniques try to tackle the plane segmentation problem from different quarters, but most implementations require a large amount of computation. This fact renders them inconvenient for real-time agent localization, because they are not able to process multiple frames per second.

2.1.2. RGB-D Affordability

Plane segmentation started drawing more attention at the beginning of the 2010s with the availability of inexpensive RGB-D sensors (e.g. Microsoft Kinect). [1] With the lower price came higher availability and more promising research results. Multiple algorithms arose during the popularization of this topic. One of the early works with successful SLAM with Kinect 3D sensor was presented by Taguchi et al. [8] They have incorporated the RANSAC [9] algorithm (a widely used technique in the PCL library [10]) with planes and points as primitives. Then, multiple other promising methods arose, like:

- Published by Salas-Moreno et al. [11], which uses PCA to find plane candidates
- Developed by Michael Kaes [12], which uses infinite planes and least-squares for mapping, combined with minimal representation.
- Brought by Hsiao et al. [13], which uses keyframe-based approach and is viable on CPU-only devices.

All of them utilize some variation of plane extraction from the depth property with a veraiety of optimizations.

2.1.3. RGB-D To Point Cloud Mapping

For every RGB-D algorithm, it is essential to correctly calculate the real point coordinates based on the pixel location in the image. It defines the mapping between the camera and the world. It includes the focal length and the principal point (often the image center). To perform the computation, we need to know the camera matrix (i.e., camera intrinsic parameters):

$$C = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \tag{2.1}$$

where:

- f_x is the focal length on x-axis
- f_y is the focal length on y-axis
- c_x is the principal point x-axis coordinate
- c_y is the principal point y-axis coordinate

Then, for each pixel with 2D coordinates $p(u, v)$ we can calculate the world point $P(\mathbf{X}, \mathbf{Y}, \mathbf{Z})$ as follows:

$$\begin{cases} \mathbf{X} = \frac{(u-c_x)\cdot\mathbf{Z}}{f_x} \\ \mathbf{Y} = \frac{(u-c_x)\cdot\mathbf{Z}}{f_x} \\ \mathbf{Z} = d_p \end{cases} \tag{2.2}$$

where:

- d is the depth component in RGB-D image for pixel $p(u, v)$
- u is the pixel p x-axis coordinate
- v is the pixel p y-axis coordinate

The pixel projection mapping can be visible in the Figure 2.1

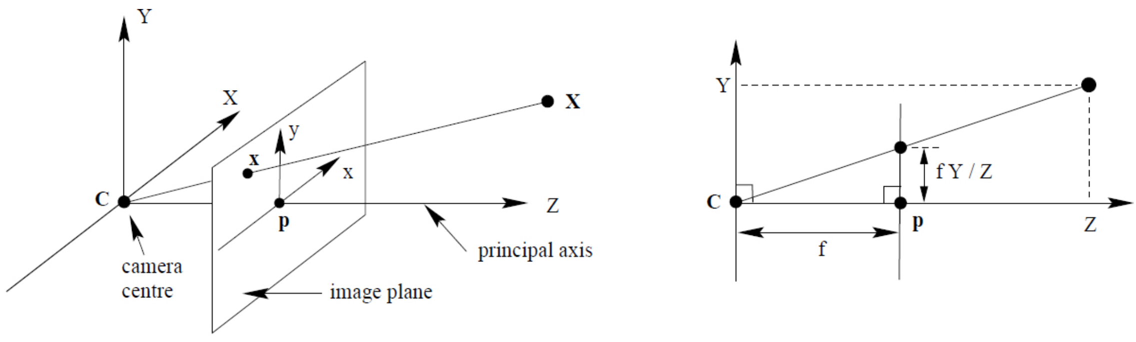

Figure 2.1.: Pinhole Camera Model pixel projection. [14]

The resulting set of 3D points is called a Point Cloud. [15] In addition, the Point Cloud is organized, meaning that the adjacent points are spatially placed next to each other. Also, the memory layout corresponds to the same ordering, which speeds up the steps of many algorithms like searching for nearest neighbors.

2.1.4. RGB-D State of the art

One of the best algorithms regarding agent localization was proposed by Zhang [1] et al. Their technique is based on scanlines. The high-level overview of the algorithm can be seen in the Figure 2.2.

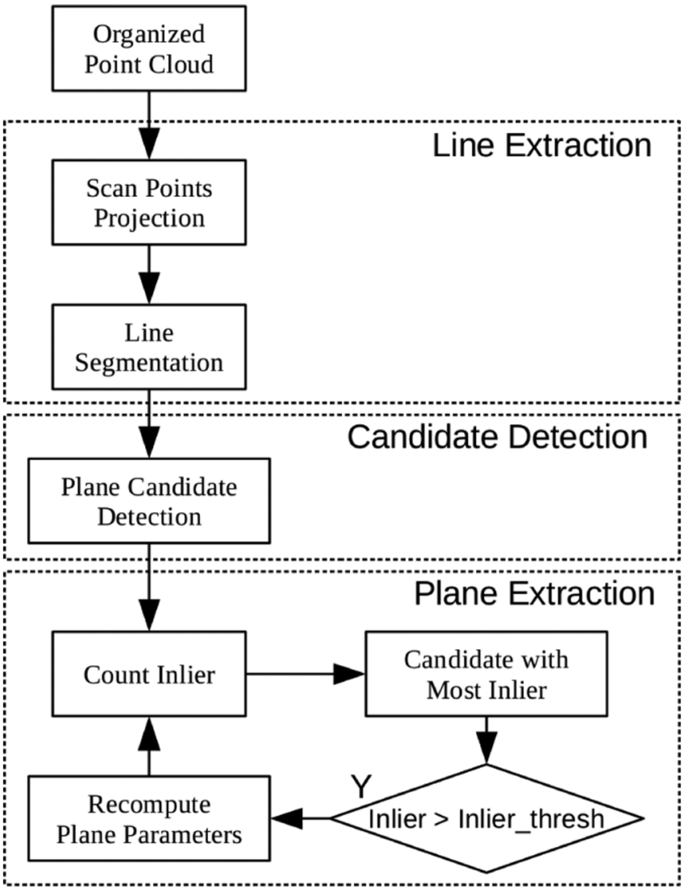

Figure 2.2.: Flowchart of the plane segmentation approach. [1]

There are three main stages of the algorithm:

1. **Line Extraction**

   The method, instead of looking for line segments on all possible scanlines, selects a few scanlines periodically, e.g., every thirty rows. It is worth mentioning that it is possible to select either rows or columns, and we can adjust the interval size to achieve a compromise between accuracy and performance.

   - Scan Points Projection

     Each selected line is treated as a 2D laser scan for the purpose of segmentation. Then, for each pixel on these lines, the projection is calculated according to the equation 2.2 from the RGB-D To Point Cloud Mapping section. 2.1.3

- Line Segmentation

  To extract line segments, the following algorithm is used:

  Algorithm 1: Line Regression [1]

  1 Initialize sliding window size N_f.
  2 Fit a line to every N_f consecutive points.
  3 Compute a line fidelity array. Each element of the array contains the sum of Mahalanobis distances between every three adjacent windows.
  4 Construct line segments by scanning the fidelity array for consecutive elements having values less than a threshold.
  5 Merge overlapped line segments and recompute line parameters for each segment.

  This algorithm was initially proposed in a study by Arras and Siegwart. [16] It yielded good results without much computational complexity.

2. **Plane Candidate Detection**

   For each line segment, a plane candidate is calculated in the following way:

   - Selection of points for local normals

     The more points are selected, the more accurate the result, but with the cost of computational complexity. The middle point for each line segment is a good compromise, which is confirmed empirically in the article.

   - Calculation of local normals

     For each selected point, the smoothing region is chosen as a square with a fixed size (for example 20 pixels). Then, for each region, the principal component analysis (PCA [17]) algorithm is executed, which gives us the local normal.

   - Selection of plane candidates

     Lastly, the valid points regarding PCA are chosen as an inlier (part of the plane) from the smoothing region. Then, the local curvature is calculated, and the inliers with the normals with curvature less than a maximum threshold are selected as plane candidates.

   Example plane candidates result can be seen in the Figure 2.3

(a)

(b)

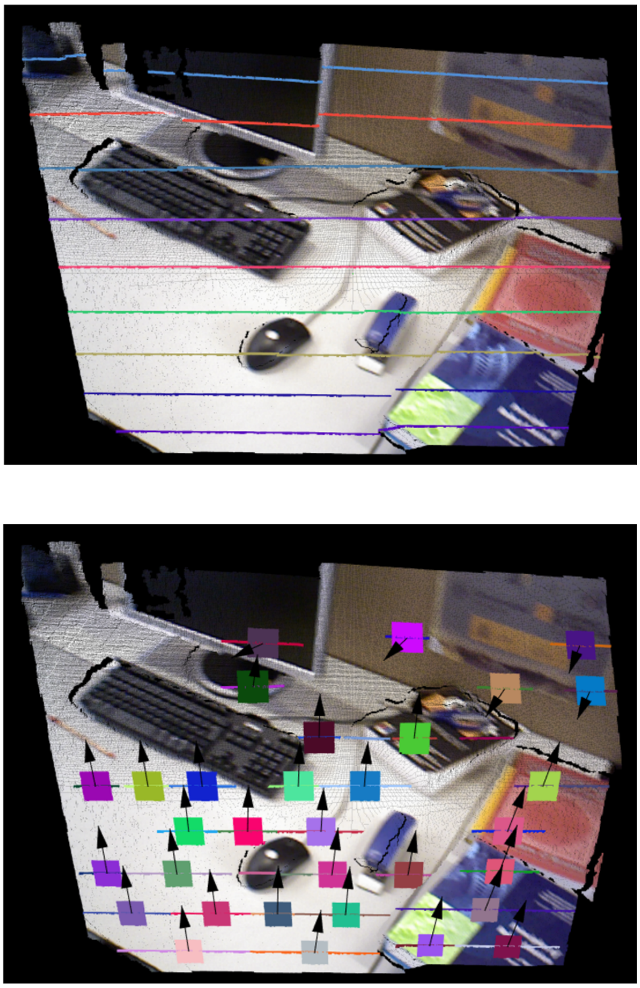

Figure 2.3.: Examle showing plane candidates calculation. [1] (a) Colored lines are scanlines (b) Each plane candidate is represented by part of the line segment (colored line), normal smoothing region (colored square) and local normal emerging from the middle point (black arrow)

3. **Plane Extraction**

   For plane extraction, the recursive algorithm is used, which is presented in the Algorithm 2 It takes every plane candidate and discards each with its inlier N_s smaller than the minimal threshold $N_{sthresh}$. Then, it calculates the quality of the inlier by counting how many neighbors within range d_n are closer to the plane than a distance threshold d_τ. The candidate is also invalidated if the number of valid points is smaller than the minimal threshold $N_{\xi_{thresh}}$.

Next, the biggest approved inlier $N_{\xi_{max}}$ is considered to be part of the plane segment from the final result. Ultimately, principal component analysis [17] is calculated again for the selected candidate $N_{\xi_{max}}$, and the actual inlier of the chosen plane segment is deducted directly from the point cloud. After adding the plane segment to the result set, the plane candidate $N_{\xi_{max}}$ is removed from the possibilities for the next iterations. This sequence of actions is repeated recursively until there are no valid plane candidates.

Algorithm 2: Recursive plane extraction [1]

Input: plane candidates $\hat{\xi}_i, i = 1, 2, \cdots, n$.
Output: plane segments $\xi_j, j = 1, 2, \cdots, m$.

while *number of valid plane candidates* $\neq 0$ **do**
  initialize maximum inlier number $N_{\hat{\xi_{max}}} \leftarrow 0$, corresponding plane parameters $\hat{\xi_{max}} \leftarrow invalid$.
  for $i = 1$ ***to*** n **do**
    if $\hat{\xi}_i$ *is invalid* **then**
      count number of valid points N_s in normal smoothing region
      if $N_s > N_{sthresh}$ **then**
        count number of valid points $N_{\hat{\xi}_i}$ by point-plane distance threshold d_τ and neighbor distance threshold d_n
        if $N_{\hat{\xi}_i} > N_{\hat{\xi_{max}}}$ ***and*** $N_{\hat{\xi}_i} > N_{\hat{\xi_{thresh}}}$ **then**
          $N_{\hat{\xi_{max}}} = N_{\hat{\xi}_i}$
        end
      else
        $\hat{\xi}_i \leftarrow invalid$
      end
    end
  end
  if $N_{\xi_{max}} > N_{\xi_{thresh}}$ **then**
    recompute plane parameter $\hat{\xi_{max}}$ using all the inlier
    save result plane $\xi_j \leftarrow \hat{\xi_{max}}$
    delete inlier in point cloud data
  else
    break
  end
end

2.2. RGB Approach

With the recent boom in artificial intelligence, especially in neural networks, the scientific community has realized, that it is possible to get rid of all depth scanners and extract information about plane segments from simple RGB images, similar to our brain. The first successful attempt using a neural network to detect plane segments from a plain RGB was PlaneNet brought by Liu et al. [18] It took advantage of the recent advancement in neural network technology - Dilated Residual Network (DRM) [19], which was published just a year prior. This success drew much attention to the topic, and since then, there have been multiple enhancements and progressions. Based on the PlaneNet, SlamCraft was introduced by Rambach et al. [20] - a SLAM framework, which proved, that monocular SLAM systems are feasible with adequate neural network untilization. Yu et al. [21] tackled the problem from a different perspective. They have proposed a two-stage algorithm using an encoder-decoder approach and achieved promising results. A big step forward was the introduction of PlaneRCNN by Liu et al. [22] They used mask R-CNN [23] - a recent innovation in a neural network to computer vision. The state-of-the-art advancements are brought by Yaxu Xie et al. in the form of PlaneSegNet [24]. This framework achieves great results and was proved SLAM-worthy by Shy et al. in the form of Structure PLP-SLAM [25], which uses PlaneSegNet for plane segmentation.

All of the methods addressed in Section 2.2 use some variation of neural networks. Why is that the case? Well, many years ago, Kurt Hornik, Maxwell Stinchcombe, and Halbert White proved mathematically that multilayered feedforward neural networks are universal approximators. [26] So why haven't they been widely spread and entangled in multiple tasks? Training a neural network is highly resource-intensive. To train a neural network, huge amounts of data and computation are required, and thus, the hardware capabilities prevented the scientific community from satisfactory results. With the era of GPUs, the situation has changed and we can see the presence of neural networks almost everywhere. In the section 2.2.1 the basic principles of neural networks are presented.

2.2.1. Neural Networks

2.2.2. RGB State of the art - PlaneSegNet

The current state-of-the-art RGB plane segmentation is represented by PlaneSegNet proposed by Yaxu Xie et al. [24] The architecture is based on the YOLACT++ instance segmentation framework published by Bolya et al. [27] with added optimizations in some of the modules. The general overview of the framework can be seen in Figure 2.4. The architecture is quite complex and consists of:

- Encoder

  Produces a group of multi-scale feature maps P_3, P_4, P_5, P_6, P_7.

  – Backbone Network It is a deep residual network based on the ResNet by He et al. [28]

  – Feature Pyramid Feature Pyramid Network structure based on the work of Lin et al. [29]

- Residual Feature Augmentation

  Apart from the standard connection, layer C_5 of the backbone is connected to the prediction layer P_5 through the Residual Feature Augmentation brought by Guo et al. [30] It improves the context of the spatial placement of the features.

- Prediction Head For each layer of the Feature Pyramid Network, it produces c class confidences, four bounding box regressors, and k mask coefficients.

- Fast Feature NMS

  The most significant innovation brought by PlaneSegNet. It aims to enhance overlapping instances detection reliability. It is discussed more in detail in the Subsection 2.2.2.

- ProtoNet

  It is a convolutional neural network. It takes the feature maps from the P_3 layer and predicts k channels for prototype masks.

- Mask Assembly

  It assembles prototype masks based on the following linear combination equation:

  $$M = \sigma(P\mathbf{C_T}) \tag{2.3}$$

  where:

  – σ is a non-linear sigmoid function

  – P is a tensor of dimensions $h \times w \times k$ containing prototype masks

  – $\mathbf{C}$ is a matrix of dimensions $n \times k$ containing mask coefficients for the output of Fast Feature NMS 2.2.2

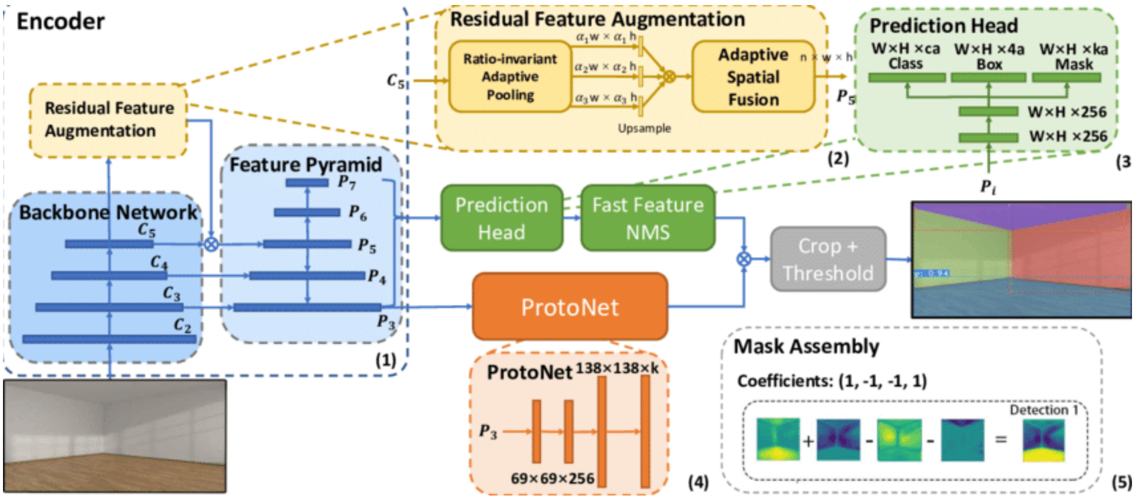

Figure 2.4.: PlaneSegNet Architecture. (1) Encoder (2) Residual Feature Augumentation (3) Prediction Head (4) ProtoNet (5) Mask Assembly [24]

The loss function

It takes into consideration each of the mask, confidence, and bounding box (localization) losses. It is represented with the following equation:

$$\mathscr{L}(x, C, B, M) = \frac{1}{N}(\mathscr{L}_{conf}(x, C) + \alpha\mathscr{L}_{loc}(x, B, B_{gt}) + \beta\mathscr{L}_{mask}(x, M, M_{gt})) \quad (2.4)$$

where:

- C is a confidence representation
- B is a bounding box (localization) representation
- M is a mask representation
- N is the number of positive matchings
- $\mathscr{L}_{conf}$ and $\mathscr{L}_{loc}$ are loss function taken from the single-shot detector presented by Liu et al. [31]
- $\mathscr{L}_{mask}$ is the pixel-wise binary cross entropy between the ground truth and predicted masks.

Fast Feature Non-maximum Suppression

It was observed, that strongly overlapping bounding boxes often don't belong to the same object. Because of that, usage of the classic NMS method brings unnecessary calculation overhead. To resolve this issue, a new method is introduced, Fast Feature Non-maximum Suppression. The technique is based on the research of Salcheider and Niels, who came up with Feature Non-maximum Suppression. [32] This method is described by Algorithm 3

Algorithm 3: Fast Feature NMS [24]

Input: $P \leftarrow Sort(Proposals)$ with Scores, $D \leftarrow \emptyset$
$X^{triu} \leftarrow GetPairwiseIoU(P)$
$K \leftarrow max(X^{triu})$ column-wise
if $K_i \leqslant N_1$ **then**
    $PUSH(p_i, D)$
else
    if $K_i \leqslant N_2$ **then**
        $C^{triu} \leftarrow GetCosineSim(p, D)$
        $S \leftarrow max(C^{triu})$ column-wise
        if $S_i \leqslant T$ **then**
            $PUSH(p_i, D)$
        end
    end
end
return D

3. Problem Description

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3.1. Problem 1

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3.2. Problem 2

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3.3. Problem 3

4. Implementation

5. Results Evaluation

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5.1. Running state-of-the-art projects

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5.2. Model usefulness evaluation

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6. Conclusions and future works

In the past several years, there have been many possible uses for RGB-D-based technologies. However, most of them focus on detailed scanning like Honti et al. [33] with little use for simultaneous localization and mapping (SLAM). Resuming, the more progress in neural networks, the more the scientific community moves away from RGB-D in favor of plain RGB.

6.1. Achieved goals and observations

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

6.2. Areas for development

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