ÉCOLE CENTRALE DE NANTES UNIVERSITY OF GENOA

MASTER ERASMUS MUNDUS
EMARO+ "European Master in Advanced Robotics"

2016 / 2017

Master Thesis Report

Presented by

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On 24.01.16

# UGV and UAV collaboration in an autonomous infrastructure scenario

Jury

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# Abstract

# Abbreviations

**UAV** Unmanned air vehicle

**UGV** Unmanned ground vehicle

**SLAM** Simultaneous localization and mapping

**VO** Visual odometry

**GVG** Generalized Voronoi graph

**LSD-SLAM** Large-scale direct monocular SLAM

**DSO** Direct sparse odometry

**KF** Kalman filter

**EKF** Extended Kalman filter

**UKF** Unscented Kalman filter

**IR** Infra-red

**IMU** Inertial measurement unit

**GPS** Global positioning system

**LIDAR** Light detection and ranging

**RGB** Red, green, blue

**RGBD** Red, green, blue, depth

**MAP** Maximum-a-posteriori [estimation]

**MR-SLAM** Multi-robot SLAM

**BoW** Bag of words

**BA** Bundle adjustment

**ICP** Iterative closest point

# Symbols

$R_i$ – Robot unit $i$

# Chapter 1

# Introduction

## Introduction

Autonomous infrastructure, even though not yet formally defined, has seen a high interest and development in recent years in certain fields related to security, data transmission [1] and transport. In the scope of global production, personal and products transport as well as services it is highly dependent on robot collaboration. Autonomy of the individual units is desired, since the possible working scenarios are usually non trivial. For very complex problems the collaboration of robots that have complementary capabilities could achieve group autonomy. The master thesis deals with an Unmanned Ground Vehicle (UGV) and Unmanned Air Vehicle (UAV) collaboration for a decentralized multi SLAM (Simultaneous Localization and Mapping) process with the help of visual servoing within the autonomous infrastructure aspect.

The proposed framework is a decentralized approach with units of different type. The robots conduct SLAM in an unknown environment, starting from an unknown location and store the map locally in memory. The relevant data is shared between units once in communication range and both local maps are optimized based upon virtual loop closures using Bundle Adjustment (BA) or similar techniques. In order to provide additional information and utilize rendezvous for data exchange, visual servoing and visual communication can be utilized. While the UAV follows the UGV marked with a QR code or similar marker, it can provide additional information from another perspective about the environment. It is of particular interest to involve these two types of robots, because of their different capabilities and very different points of view into the environment.

By using LEDs or other light source devices around the marker, an unidirectional communication between the mobile platform and drone could be established. This can help with establishing rendezvous points between the robots, once a unit is ready to optimize it's local map, it's memory is full or it requires assistance in establishing next move. In the last case the UAV could be instructed to perform an area sweep in order to supply additional map information. The LEDs also provide a possibility of pose estimation using DeMenthon's POSIT algorithm [19].

One possible problem in this approach is the communication of limited range between units. Therefore data transmission optimizing measures should be performed. The basic data will consist of key frames coming from the output of an monocular SLAM approach like Large-Scale Direct Monocular SLAM (LSD-SLAM) [10] or Direct Sparse Odometry (DSO) [11].

## Context of the work

An autonomous infrastructure is one with the capability of independent self-adjustment and self-maintenance. Today this term is mostly associated in robotics and in a very limited way, in general with aspects of security, data networking and transport. The master thesis formalizes the term therefore in more detail 2.

## Motivation

The reason are current developments in the technological sector as well as on the level of society. According to the United Nations Department of Economic and Social Affairs report human population will reach approximately 9 billion in the year 2050 and 11 billion by the end of the century with a probability of 80% . It can be observed that the current premise of the socio-economic structure is that of an ever growing economy with little regard to related physical processes.

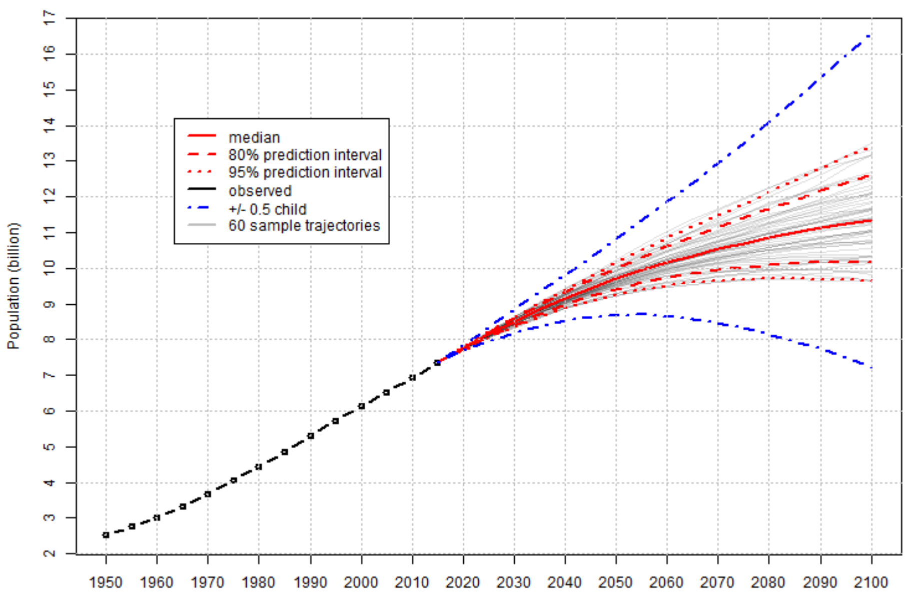



Figure 1.1: Total world population projection using Bayesian filtering

Robot collaboration offer a variety applications, from simple

Autonomous infrastructure Today's meaning and the context of the work Add sources probably from books: The Singularity Is Near Physics of the Future Mention: Technological singularity Civilization type I Resource based economy Possible application scenarios today Search and rescue 290916/Nathan Michael, Shaojie Shen, Kartik Mohta, Yash Mulgaonkar, and Vijay Kumar - Collaborative Mapping of an Earthquake-Damaged Building via Ground and Aerial Robots Mention the scenario proposed to Prof Sgorbissa

## Problem formulation

## Contribution and innovation

The master thesis project aims at developing and implementing a working distributed multi SLAM algorithm between different type of robots, in particular between UAV and UGV. Furthermore the proposed solution uses a distributed approach, where data communication is under a constraint related to the limited range of transmission. Additionally aspects like visual servoing for the purpose of optimization of the SLAM process and acoustic/visual communication are to be analysed and evaluated.

# Chapter 2

# Background theory

## Definitions

**Robot collaboration** Process of coordinated actions performed by robots towards a specified goal.

**Autonomy** The ability of making independent decisions.

**Unmanned vehicle** Vehicle designed without support systems for humans, capable of similar performance as a manned vehicle.

**Autonomous infrastructure** An infrastructure with the capability of independent self-adjustment and self-maintance.

To further formalize the term *autonomous infrastructure*, it can be classified by 4 levels:

0 The autonomy is local in very limited aspects, there is no autonomous chain. The majority of processes are human controlled and monitored.

1 Branches of the economy hold at least one full chain of product or services. Specific needs of the community are satisfied by the infrastructure. Autonomy is regional in limited aspects. The majority of processes are human controlled and monitored.

2 Major branches of the economy, like nutrition production and personal transport, hold full autonomous chains of product or services. Majority of the needs of the community are satisfied by the infrastructure with little human interaction, mostly limited to monitoring. Autonomy is national and pseudo-continental in many aspects, self-maintenance achieved.

3 Full economy autonomy, virtually no human interaction required. Complex dynamic demand is satisfied after infrastructure adjustment.

4 Planetary autonomy. Infrastructure predicts and adjusts itself for future developments.

## Simultaneous localization and mapping

The process of mapping of the environment and using it for localization, while at the same time localizing with the help of that map has been first defined as simultaneous localization and mapping problem in the 1986 [2]. It spreads into many other fields of research and is being further developed in the robotics field with respect to current open problems [5]. Artificial and natural features of the environment can be utilized for this purpose using a variety of sensors, whose measurements can be then fused and used for the localization and map building process.

SLAM is most often defined as a maximum-a-posteriori (MAP) estimation problem [5], that can be then expressed as probability distribution (2.1)

$$P(x_i, l_a | y_{0:i}, u_{0:i}) \tag{2.1}$$

where $x_i$ is the pose in the state vector at instance $i$; $l_a$ is a set containing the locations of all landmarks, $l = l_0, l_1, \ldots, l_n$ with $n$ being the number of landmarks; $y_{0:i}$ represents all measurements or observations of landmark locations $l$ up to time instance $i$; $u_{0:i}$ holds all the control inputs up to time instance $i$, ergo the history of control input $u$.

Additionally, often the formalism of factor graphs is used to express the relations among relevant variables [5].

## Sensors

A SLAM algorithm can utilize a wide variety of sensors and tools [5], including these shown in 2.1

Table 2.1: List of sensors compatible with current SLAM approaches

| Range | Odometry and direct localization | Vision | Sound |
|---|---|---|---|
| • Infra-red<br>• Laser<br>• LIDAR (Light Detection And Ranging)<br>• Sonar | • Encoder<br>• GPS – Global positioning system<br>• IMU – Inertial measurement unit<br>• Motion capture system | • Camera<br>– Monochrome<br>– RGB (color)<br>– Camera model<br>• RGBD (color and depth)<br>• Multi camera system<br>• Range camera<br>• Light field camera<br>• Event based camera | • Acoustic<br>• Sonar |

Some of these fields intersect. For example RGBD sensors use both, vision and distance from IR (infra-red) registered laser reflections. Some are restricted to limited spaces, for example a motion capture system.

## Architecture

The architecture of a typical SLAM system shown in figure (2.1). It consists of a back-end and a front-end. The input is the data from sensors and the output is usually a Maximum-a-posteriori (MAP) estimation , the current standard SLAM formulation [5]. There can be feedback coming from the back-end to the front-end.

## Representations

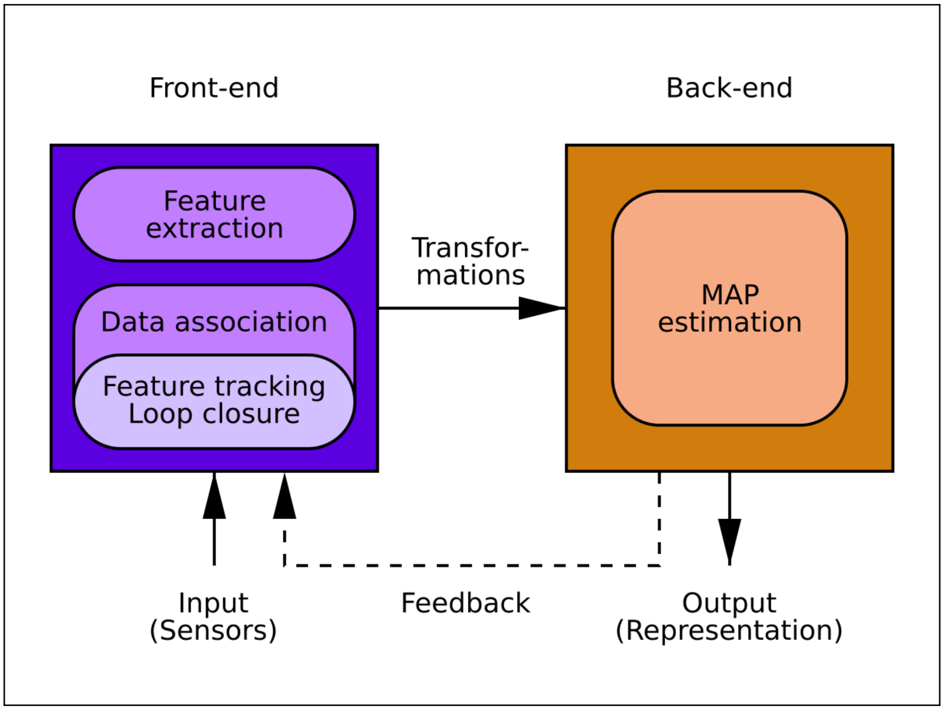



Figure 2.1: SLAM architecture consisting of a back-end and a front-end with sensors data as input and a map as output[5].

## Visual SLAM

Visual SLAM (V-SLAM) corresponds to solutions of the SLAM problem using vision sensors as the main tool . Cameras are often combined with other types of sensors in order to increase the confidence of measurements. This variant of the SLAM problem often can be formulated as mapping environment and determining camera pose at given instance, ergo trajectory of poses across data stream.

As with conventional SLAM approach, one of the more important aspects is the information certainty, which can be increased by revisiting already explored areas. This can be interpreted by the system as a loop closure, once detected.

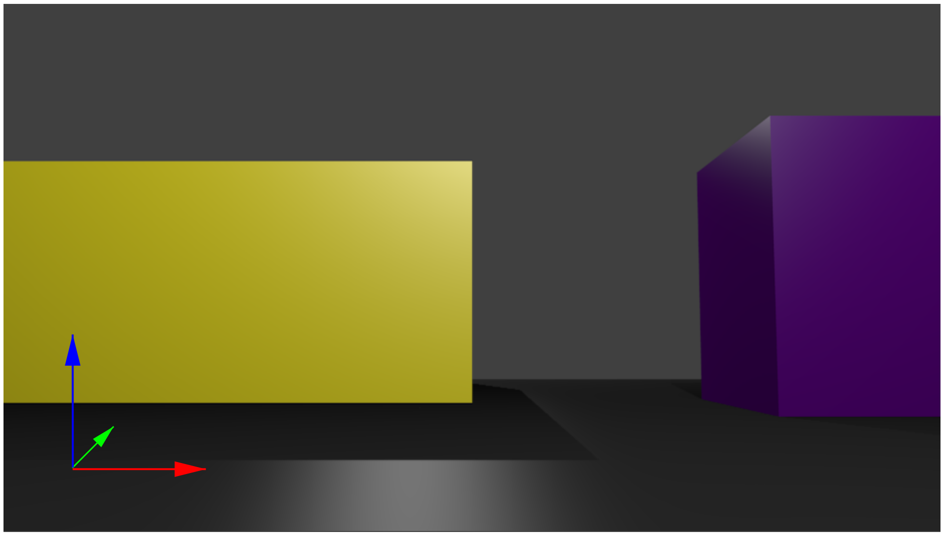
The scale ambiguity is a problem in monocular SLAM systems. However, formulation used by approaches like Large-Scale Direct SLAM (LSD-SLAM) that operate on *sim(3)*, which allows to detect the scale drift [10]. *Sim(3)* can hold 3 dimensional similarity transforms **S** consisting of rotation matrix **R**, defined as:

$$\mathbf{S} = \begin{bmatrix} sR & t \\ 0 & 1 \end{bmatrix} \tag{2.2}$$

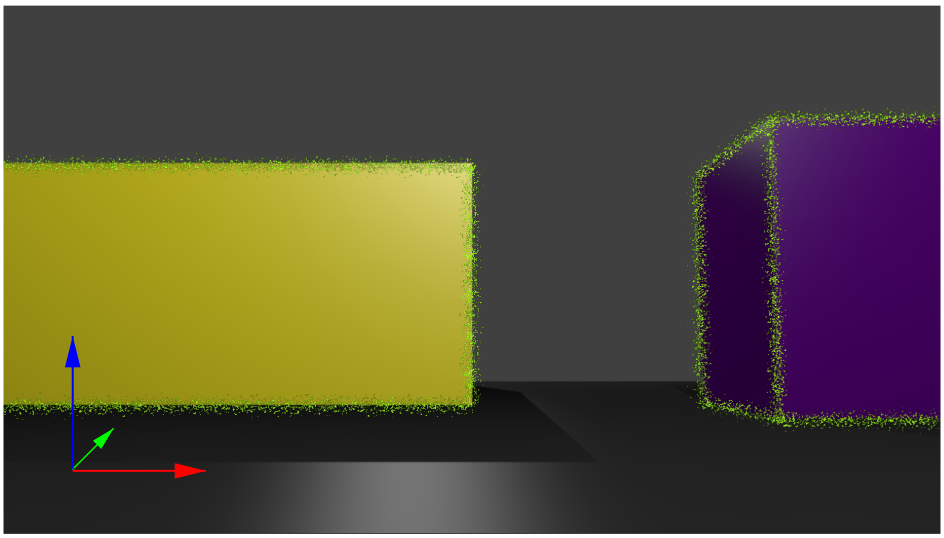
Multi SLAM Merging maps Rendezvous Virtual loops

### Monocular

### Stereo vision



(a) Raw frame with and indicator of the current unite pose.



(b) Processed frame with an sparse approach detecting edges of objects.

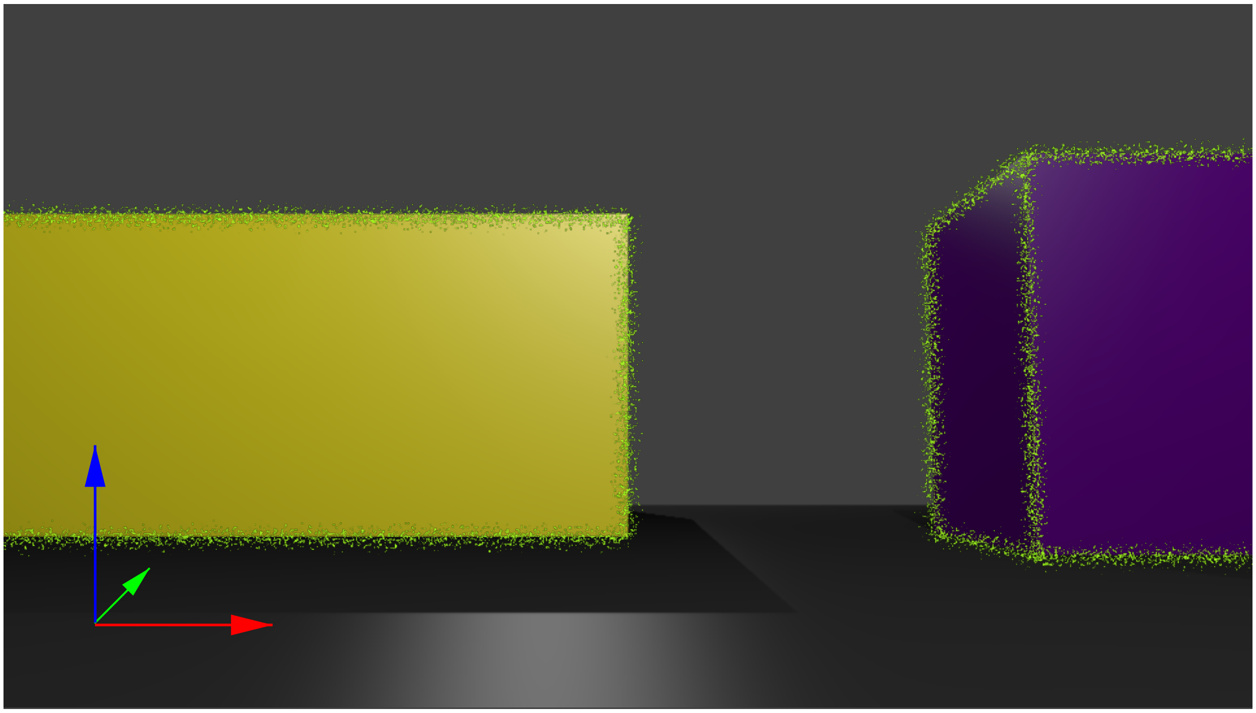
Figure 2.2: Visual SLAM using camera as sensor and a sparse/feature based approach for processing.

## Collaborative SLAM

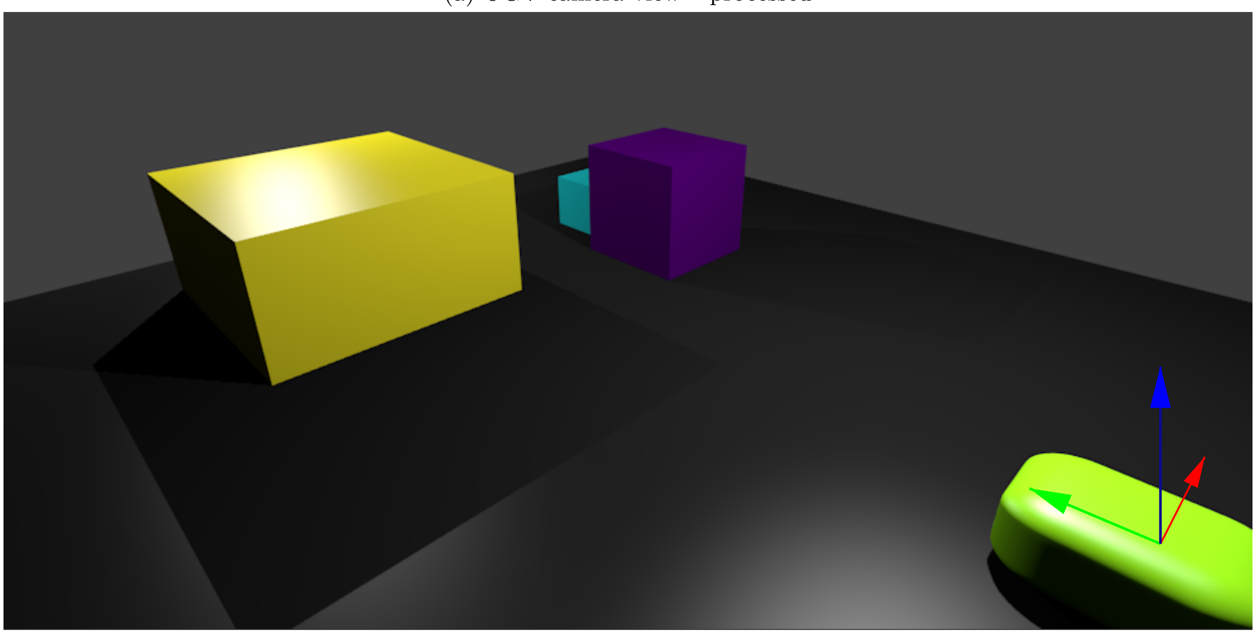
In contrast to multi robot SLAM (MR-SLAM), that can be defined as SLAM performed by multiple units, a collaborative SLAM has an active effort to *actively* use capabilities of all units in order to solve the SLAM problem.

## Data fusion

Data fusion - as a side note Filtering Bayesian filter Kalman filter Extended Kalman filter Particle filter Smoothing?



(a) UGV camera view – processed



(b) UAV camera view – raw

Figure 2.3: Collaborative visual SLAM scenario with UGV and UAV units.

– UGV, – Obstacles

## Active perception

Active perception or sensing can be defined as an application of control theory, such that reasoning, decision making and control are used for optimization of acquisition of desired data [3].

### Structure from motion

## Visual servoing

Visual servoing Chaumette Visual Servo Control I and II Derivations? Aim of VS Basics Change of frames Kinematic screw Interaction matrix Robot Jacobian 2D visual features 3D visual features

## Exploration and rendezvous tasks

The process of exploration, ergo visiting unmapped or unknown places in the environment, has been in focus of robotics for a long time [5]. It can be combined with the process of exploitation, ergo revisiting places in environment. Active SLAM is a variant, where the decision making process has been integrated in such manner that the robot and data acquisition are controlled with the goal of minimizing the uncertainty of localization and created map. A suitable approach prioritizes both aspects in a balanced manner [21].

The rendezvous aspect applied to multi SLAM deals with multiple units meeting at a specified location. This can be used in distributed SLAM approaches. At the rendezvous instance the acquired data is shared between the units.

The approach proposed by [17] is combination of exploration and rendezvous task using cost of reaching a location and reward for its characteristics. The cost of reaching the target location is proportional to the distance between the unit and the location, while the reward for reaching the target location is proportional to the estimated gain of relevant information, ergo map at the location.

Assumptions of the method include local sensing information only with a communication range limit. To overcome the latter limitation, a group of hierarchical or role-based robots starting from unknown location, can use it's explorer units to gather data, while constantly sharing information to the main data centre through relay units [14]. The approach from [17] however, deals with the rendezvous problem [20], that derived from the field of game theory and is specified as a search problem. It is defined as meeting at pre-specified time at a rendezvous location in an unknown environment without any communication. The described approach is grid-based, overcomes the range limit of communication and performs minimization of combined exploration and rendezvous time.

### Mapping and exploration

For each unit the mapping process is performed in the grid-based approach. From the acquired data Hilditch's algorithm [13] is used to generate a skeleton structure similar to generalized Voronoi graph (GVG) [9]. The main difference between the two methods is the construction, where GVG uses the edges to close the graph. The reason for using Hilditch's algorithm is that it can create a skeleton structure with a limited sensor range that each unit has. The structure of the skeleton shown in (2.5a) is stored as a graph, where the nodes, representing potential rendezvous points, are then used for exploration. In particular the described approach uses depth-first traversal. Using flood-fill algorithm [15] the adjacent nodes are determined as well as the filled area is calculated. Path planning is performed by an A* search algorithm [12].

### Rendezvous

The set of meeting locations is specific for the environment, where each rendezvous place is extended from the conventional point to a finite area. For the problem statement three rendezvous strategies are proposed:

- asymmetric sequential,

- symmetric sequential,
- and exponential.

Each of the rendezvous strategy characterizes a landmark by determining it's distinctiveness measure and ranks it among other landmarks. Three ranking criteria summarized in were proposed.

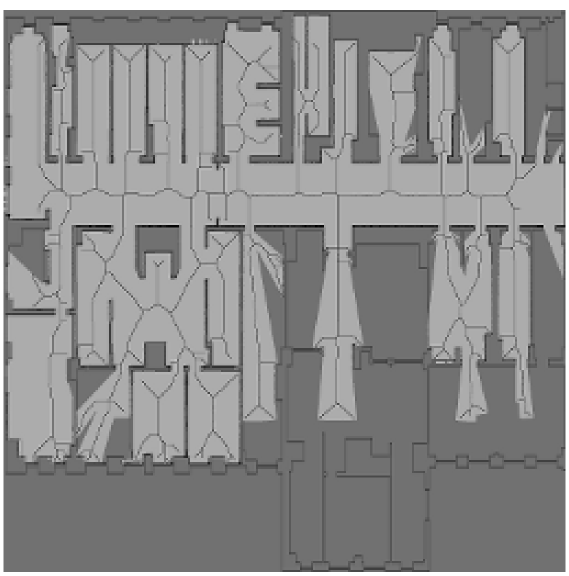
Table 2.2: Ranking criteria and formulations.

| Ranking criteria | Formulation |
|---|---|
| Area | $rank(l_i^R) = area(l_i^R)$ |
| Distance | $rank(l_i^R) = \frac{area(l_i^R)}{distance(l_i^R)}$ |
| Sigmoid distance | $rank(l_i^R) = \frac{area(l_i^R)}{sigmoid(l_i^R)}$ |

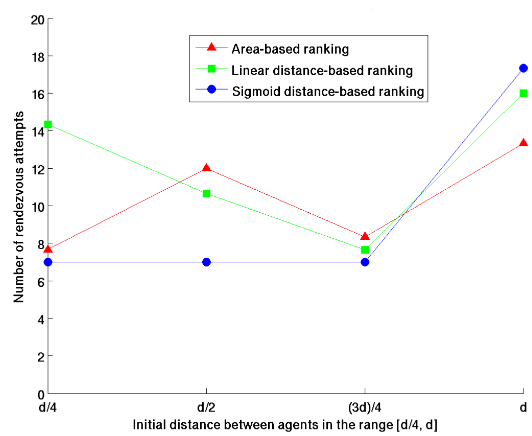
The rendezvous process itself consists of sequential attempts $a_i$ performed at time instances $t(a_i)$ by robots $R \in 1, 2$ at a selected location $l_i^R$ that is determined by each unit based on acquired data. If $l_i^1 = l_i^2$ at time instance $t(a_i)$, then robots 1 and 2 met at the same location, which concludes the rendezvous process, otherwise the robots continue performing previous actions until the next rendezvous time instance $t(a_{i+1})$.

#### Test results

The provided test results shown in (2.5b) clearly state that the sigmonoid distance based rendezvous strategy obtains best results, ergo minimal number of rendezvous attempts in minimal time for all studied scenarios.



(a) Generated skeleton structure with nodes representing potential rendezvous points.




(b) Test results for the examined rendezvous strategies.

Figure 2.5: Rendezvous and exploration approach [17].

# Chapter 3

# State of the art

Overview of current state of the art: 131016/Cesar Cadena, Luca Carlone, Henry Carrillo, Yasir Latif, Davide Scaramuzza, Jos´e Neira, Ian D. Reid, John J. Leonard - Past, Present, and Future of Simultaneous Localization And Mapping: Towards the Robust-Perception Age.pdf Add the other review

## Simultaneous localization and mapping

Simultaneous mapping and localization Aspects on efficient map building - key frames, high abstract formalism Multi SLAM with same type robots Open problems Multi SLAM with different type of robots

### Standards in SLAM architecture

### Representations

=Representations - Metric reasoning Landmark based

Boundary and spatial-partitioning dense representations Comparison between sparse and dense methods/feature based and direct feature based methods - depend on feature type - rely on specified thresholds for detection and matching -> ambiguity - dealing with incorrect matches - not optimized for precision + optimized for speed dense methods + in scenes with poor texture, motion blur and defocus can outperform feature based methods - require high computing power - differentiate between structure and motion not possible at the same time => To overcome these shortcomings use semi-dense using dense approach on pixels with high gradients + less computation power wrt dense methods semi-direct + most efficient (proven by [113]) (efficient in what terms?) + allow for joint estimation of structure and motion

High level object based representations Object based reasoning SLAM++, Salas-Moreno [272] Civera [71] Dame [84]

Not yet utilized solid representations Parametrized Primitive Instancing (PPI) Sweep representations Constructive solid geometry Feature based models in CAD Dictionary based models Already some experience in robotics and CV Affordance based models Generative and procedural models Scene graphs [155]

Semantic representations

Open problems Multi SLAM with different types of robots V High level expressive representations in SLAM No general and tractable framework for optimal representation choice Adaptive and automatic representations adjusting to given task and complexity of environment

## Solutions

SLAM problem solutions are spread over a variety of approaches. , mostly concentrated around

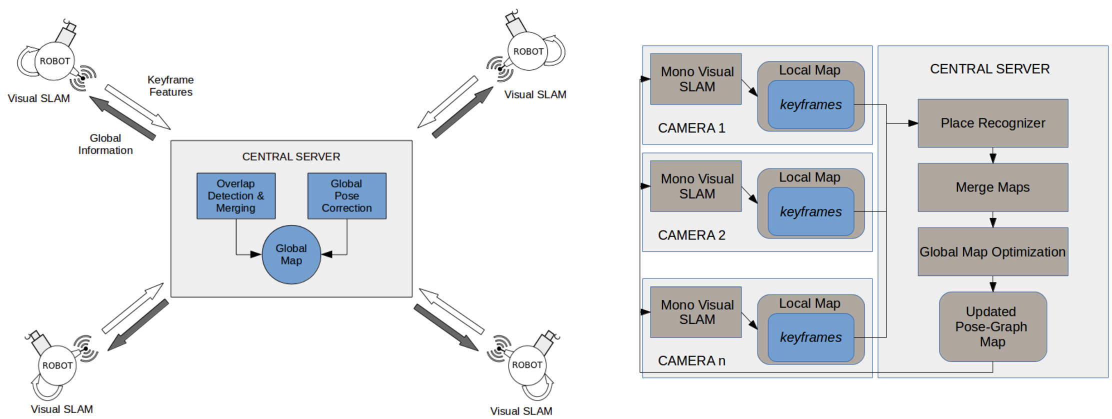
## Collaborative SLAM

”The multi-robot exploration task is a well-addressed problem in the field of robotics.” [17]

## Collaborative Visual SLAM Framework for a Multi-Robot System

The collaborative visual SLAM is a centralized approach, where each unit equipped with a monocular vision system performs visual SLAM individually and is structured according to Figure 3.1 [8].

The algorithm used for monocular SLAM estimates 7 degrees of freedom, including the scale of the scene using the group $sim(3)$. The environment is mapped to a pose graph of key frames that hold a depth map obtained by a semi-dense approach based on LSD-SLAM [10]. A central server runs a place recognition software that constantly monitors transferred data from mobile units (3.1a). In case of an overlap detection, that is performed in appearance space by comparison of extracted visual features from the key frames with the help of Bag of Words (BoW) technique, the map merging algorithm is executed. RANSAC version of the traditional Horn’s algorithm is utilized for the initial transformation estimate between matched key frames from the overlap detection block (3.1b). Optimization is performed using the calculated estimate as a starting point for similarity transformation estimation, that is additionally processed using and iterative closest point (ICP) algorithm. As next step map merging is conducted into a global map with an additional constraint between the two matched key frames. Finally optimization using bundle adjustment is performed on the global graph and information in form of updated poses is communicated to mobile units as feedback. The robots then perform optimization of the localization of the unit, based on the newly received and already stored information.

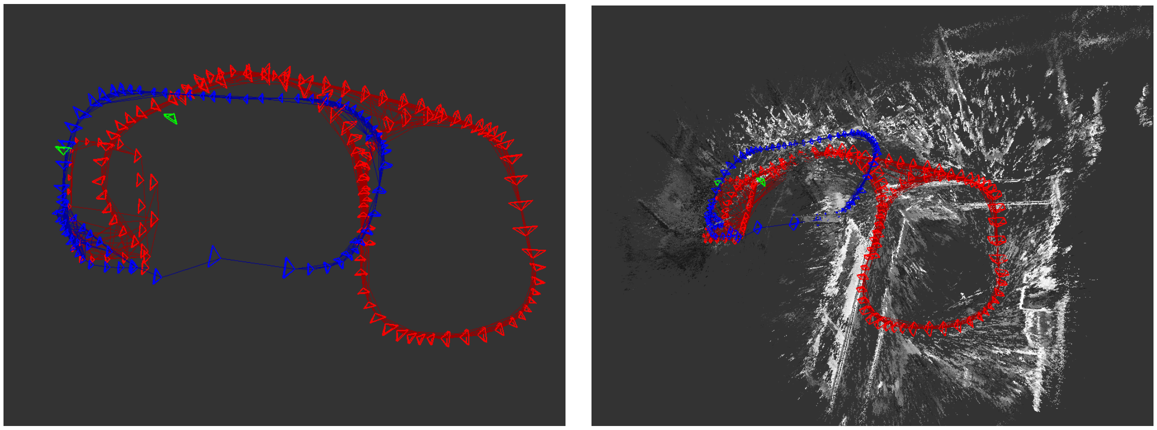



(a) Centralized approach architecture (b) Procedural scheme

Figure 3.1: Structure of the collaborative visual SLAM approach [8].

## Collaborative Visual SLAM

Work for the collaborative visual SLAM is based and a continuation of [8][7][6].



(a) (b)

Figure 3.2: Results of the collaborative visual SLAM approach [8].

## Distributed and Decentralized Cooperative Simultaneous Localization and Mapping for Dynamic and Sparse Robot Networks

One approach of a collaborative SLAM is the distributed and decentralized approach for dynamic and sparse robot networks [16]. It defines the distributed aspect as sharing of computation load among available units and decentralized as that each unit estimates just it's own state comprised of all poses and landmark positions. This approach does not focus on specific aspects of communication and provides a guarantee that all robots can recover the centralized equivalent estimate.

## Scalable Multi-Device SLAM

[18] Crowd-sourced mapping from multiple devices Scaling problem of SLAM maps Simultaneous global map update from many sources

## Co-operative Localisation and Mapping for Multiple UAVs in Unknown Environments

[4]

### CoSLAM: Collaborative Visual SLAM in Dynamic Environments

[23]

### Multi-robot simultaneous localization and mapping using D-SLAM framework

[22]

## Open problems

Main problems/aspects robust performance, high level understanding, resource awareness, task-driven inference.

## Visual servoing

### Visual communication

# Chapter 4

# Proposed work

## Experimental setup

## Collaborative SLAM

Previous work of Nived and Nicole as basis ”Collaborative Visual SLAM Framework for a Multi-Robot System” Propose a decentralized approach on that Min 7 DOF (position, orientation, scale) Other DOFs? Introduce visual communication in aspect of rendezvous

## Problem statement

### Assumptions

Assumptions Start work with a pair of UGV and UAV, then expand to 3 units, then swarms of both. UGV unit is equipped with high computational power hardware and the energy consumptions aspects are of no concern/negligible UAV unit is equipped with low computational power hardware, low memory capacity and programmed to perform with relatively small amount of computations Decentralized approach assumes exchange of map information between 2 units at a time Experimental hardware might/will be different from these assumptions There will be a limit of data accumulated by drones What about UGVs?

## Scenarios

Scenarios Search and rescue Map environment and look for points/features/objects of interest Map dynamic environments Might be too much here

## Map characteristics

Map quality/characteristics Allows for active SLAM Performance and quality index definition Proportional to number of frames in a given area Inversely proportional speed of the unit/optical flow magnitude?

Proportional to number of features Proportional to angle/rotational sweep Potential field approach 4 levels with ability to add more, so a general approach For two robots: Map from robot A Coverage of area Performance and quality index Map from robot B Coverage of area Performance and quality index Local A-B map Coverage of area Performance and quality index Areas of interest after merger Merging offline even though it's a decentralized approach Global map Performance and quality index Estimate Potentially difficult areas/Areas of interest Determined how? NN or AI a possible approach? Motion planning based on current state of global map

## Algorithm

Collection of data for specific points/features/objects of interest

Multi SLAM Merging maps Rendezvous Random or specified places Visual communication Communicate that unit is ready to merge maps Memory is full, needs optimization Emergency scenario Virtual loops

# Work plan

Table 4.1 shows the proposed work plan based on milestone tasks.

Table 4.1: Work plan schedule for the master thesis.

| Timeline → | 2016 | 2017 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Milestone task ↓ | **Dec** | **Jan** | **Feb** | **Mar** | **Apr** | **May** | **Jun** | **Jul** | **Aug** |
| State of the art | | | | | | | | | |
| Bibliography defence | | | | | | | | | |
| Milestone 1 | | | | | | | | | |
| Milestone 2 | | | | | | | | | |
| Milestone 3 | | | | | | | | | |
| Mid term presentation | | | | | | | | | |
| Milestone 4 | | | | | | | | | |
| Milestone 5 | | | | | | | | | |
| Milestone 6 | | | | | | | | | |
| Writing thesis | | | | | | | | | |
| Master thesis submission | | | | | | | | | |
| Master thesis defence | | | | | | | | | |

# Conclusions

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