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Frederike Dümbgen
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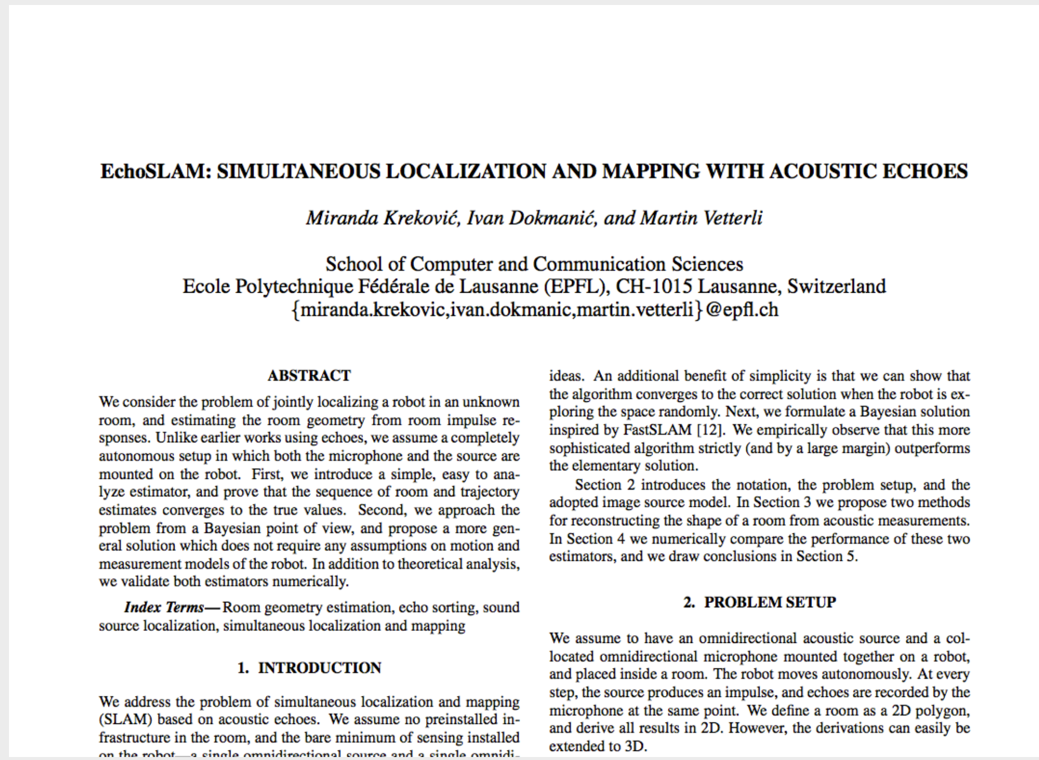
Experimental Setup of Sound Emitting and Processing Robot for Acoustic-Based SLAM Applications

Introduction

Motivation – Echolocation for Navigation



EchoSLAM: SIMULTANEOUS LOCALIZATION AND MAPPING WITH ACOUSTIC ECHOES

Miranda Kreković, Ivan Dokmanić, and Martin Vetterli

School of Computer and Communication Sciences
Ecole Polytechnique Fédérale de Lausanne (EPFL), CH-1015 Lausanne, Switzerland
{miranda.krekovic,ivan.dokmanic,martin.vetterli}@epfl.ch

ABSTRACT

We consider the problem of jointly localizing a robot in an unknown room, and estimating the room geometry from room impulse responses. Unlike earlier works using echoes, we assume a completely autonomous setup in which both the microphone and the source are mounted on the robot. First, we introduce a simple, easy to analyze estimator, and prove that the sequence of room and trajectory estimates converges to the true values. Second, we approach the problem from a Bayesian point of view, and propose a more general solution which does not require any assumptions on motion and measurement models of the robot. In addition to theoretical analysis, we validate both estimators numerically.

Index Terms— Room geometry estimation, echo sorting, sound source localization, simultaneous localization and mapping

1. INTRODUCTION

We address the problem of simultaneous localization and mapping (SLAM) based on acoustic echoes. We assume no preinstalled infrastructure in the room, and the bare minimum of sensing installed on the robot—a single omnidirectional source and a single omnidi-

ideas. An additional benefit of simplicity is that we can show that the algorithm converges to the correct solution when the robot is exploring the space randomly. Next, we formulate a Bayesian solution inspired by FastSLAM [12]. We empirically observe that this more sophisticated algorithm strictly (and by a large margin) outperforms the elementary solution.

Section 2 introduces the notation, the problem setup, and the adopted image source model. In Section 3 we propose two methods for reconstructing the shape of a room from acoustic measurements. In Section 4 we numerically compare the performance of these two estimators, and we draw conclusions in Section 5.

2. PROBLEM SETUP

We assume to have an omnidirectional acoustic source and a collocated omnidirectional microphone mounted together on a robot, and placed inside a room. The robot moves autonomously. At every step, the source produces an impulse, and echoes are recorded by the microphone at the same point. We define a room as a 2D polygon, and derive all results in 2D. However, the derivations can easily be extended to 3D.

Introduction

Goal – Experimental Framework

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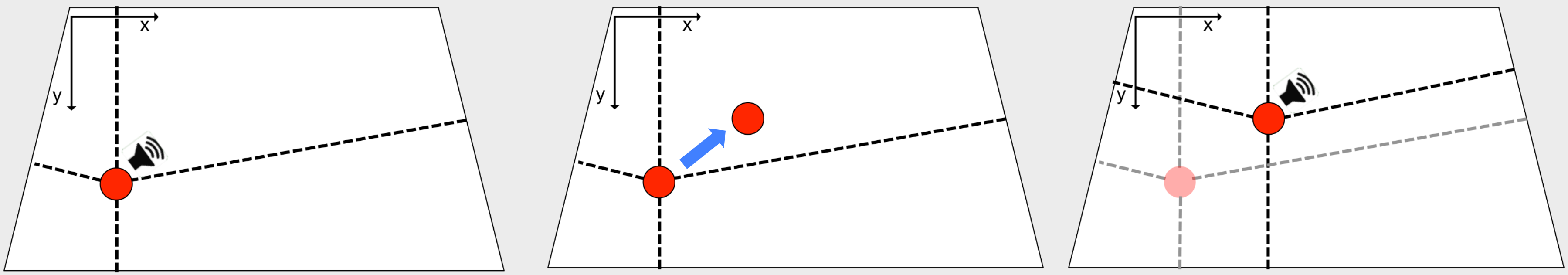
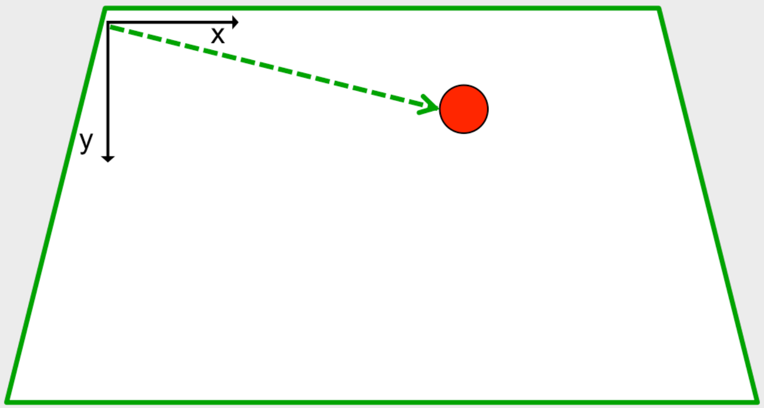


Visual localization
ground truth

Odometry
relative position

EchoSLAM
absolute position
and room geometry

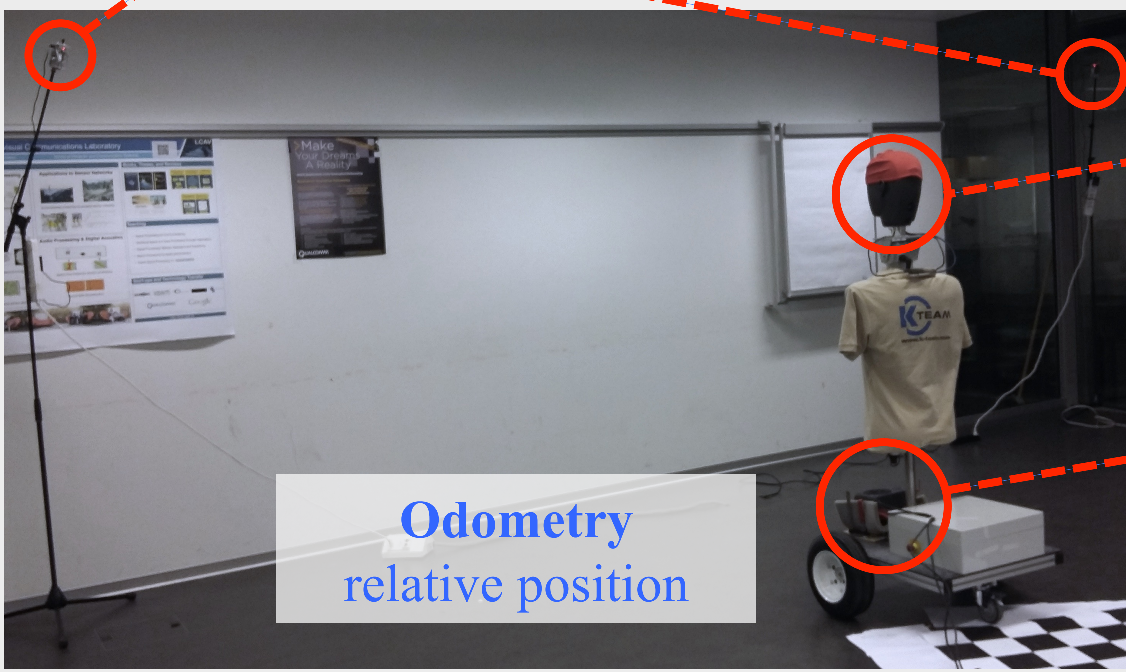


Experimental Setup

Overview

Visual localization
ground truth

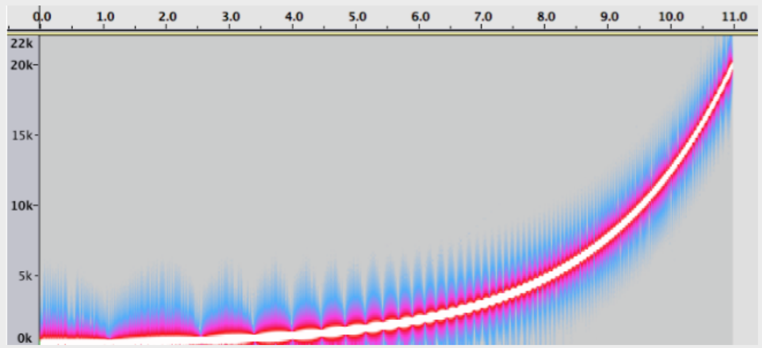
EchoSLAM
absolute position
and room geometry



Odometry
relative position

Room Impulse Response (RIR)
Experimental Procedure

Fig. 1: Spectogram of sine sweep used



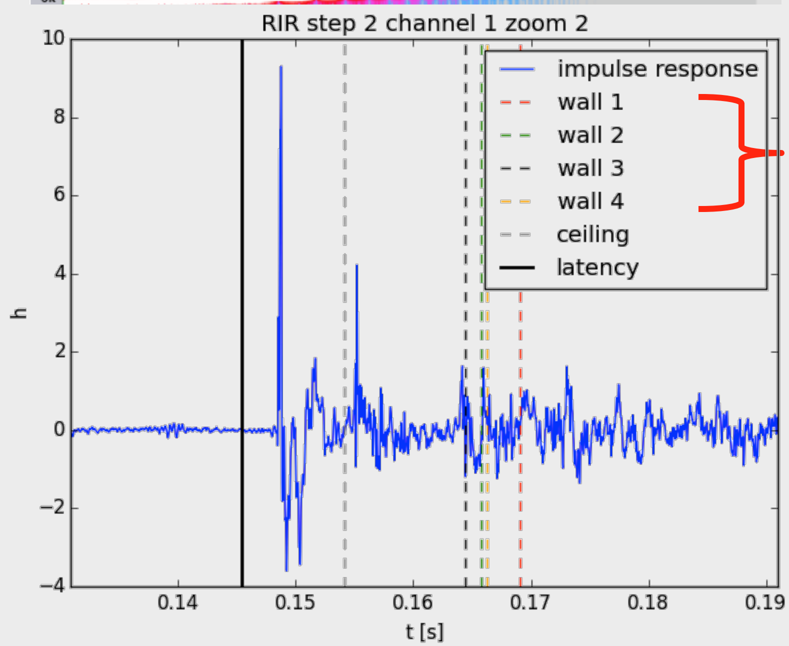
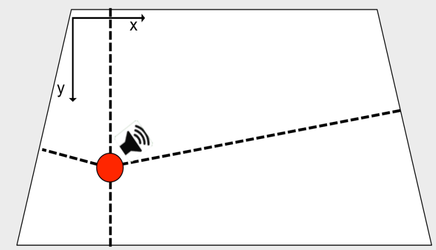


Fig. 2: RIR of channel 1 obtained by deconvolution



Room Impulse Response (RIR)
Experimental Results

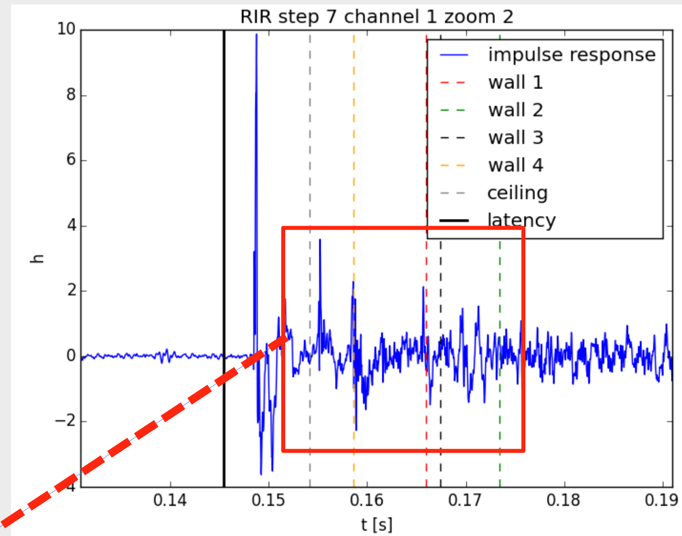
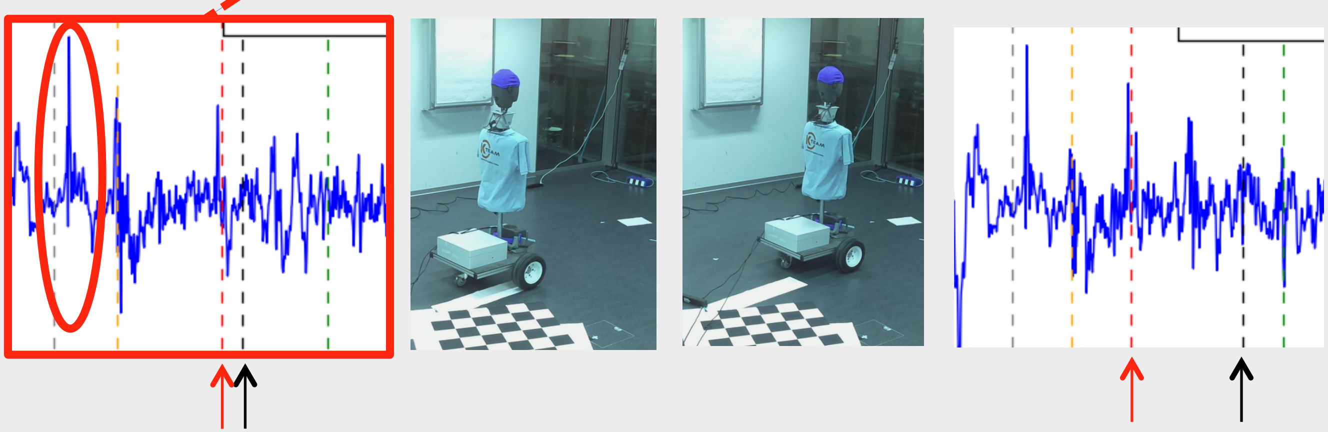
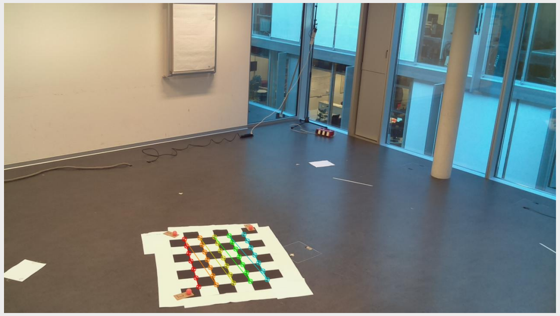


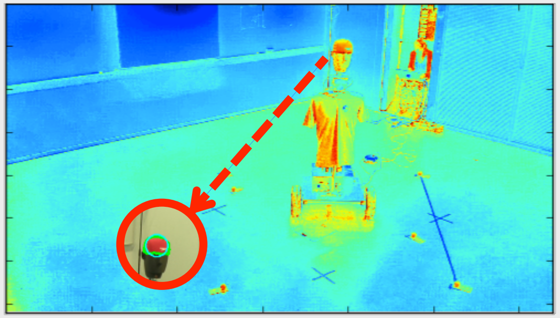
Fig. 1:
RIR at
position 7



Visual Localization

Experimental Procedure





given pictures of checkerboard

⟶ C and distortion coeff.

given positions X, Y, Z of N_{pts} = 5 x 7 points

⟶ R, **t**

given (u_j, v_j) for j cameras, ***Z optional***

⟶ X, Y, (Z)

$$s_i \begin{bmatrix} u_i \\ v_i \\ 1 \end{bmatrix} = C \begin{bmatrix} R & | & \mathbf{t} \end{bmatrix} \begin{bmatrix} X_i \\ Y_i \\ Z_i \\ 1 \end{bmatrix}, \quad \text{for } i = 1 \cdots N_{pts},$$

Visual Localization
Experimental Results

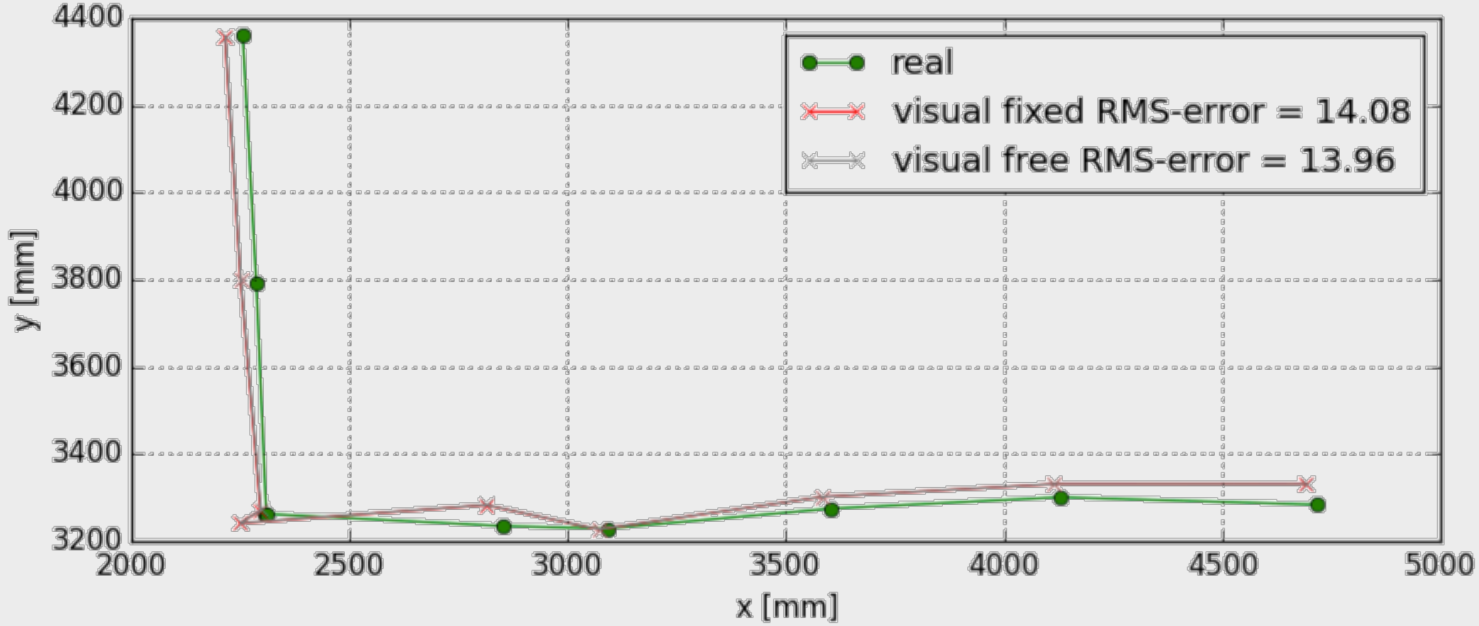
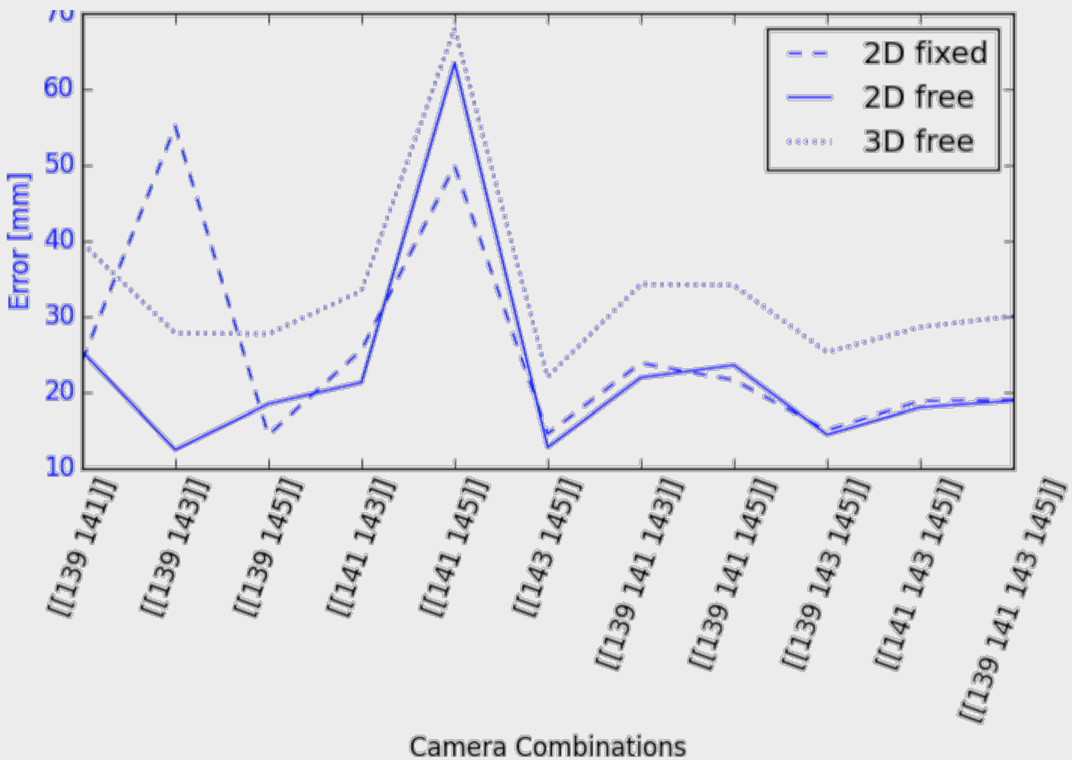


Fig. 1: Results using all cameras

Visual Localization
Experimental Results

Fig. 1: Position 3 –
Error vs. Camera combinations



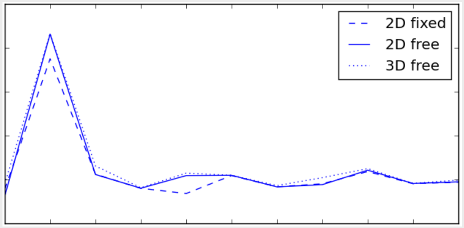


Fig. 2: Position 4

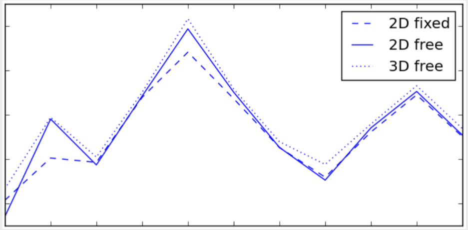


Fig. 3: Position 5

Robot Movement and Odometry

Procedure and Results

Fig. 1: Command blocks

```
0     f
2     s
0     f
2     s
0     r
3     s
```

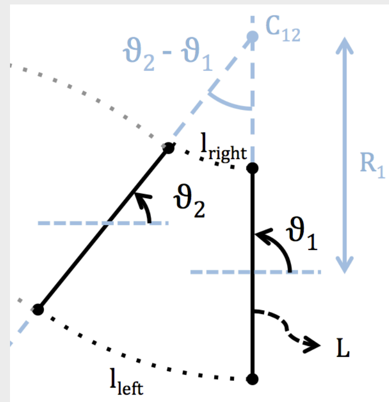


Fig. 2: Odometry geometry considerations

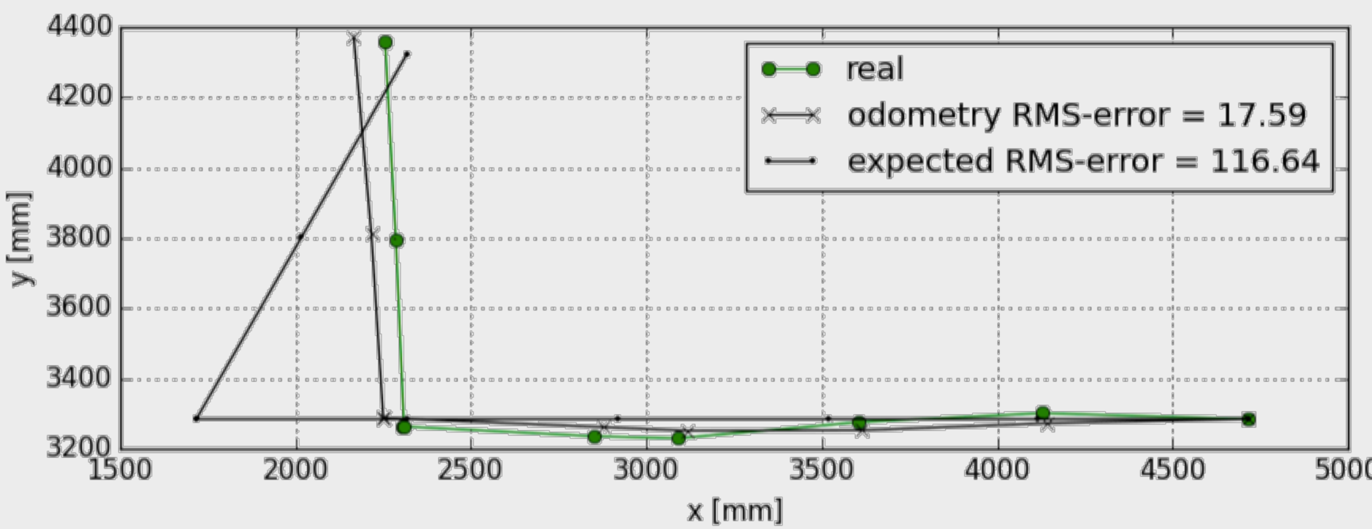


Fig. 3: Robot positions

Experimental Results
Summary

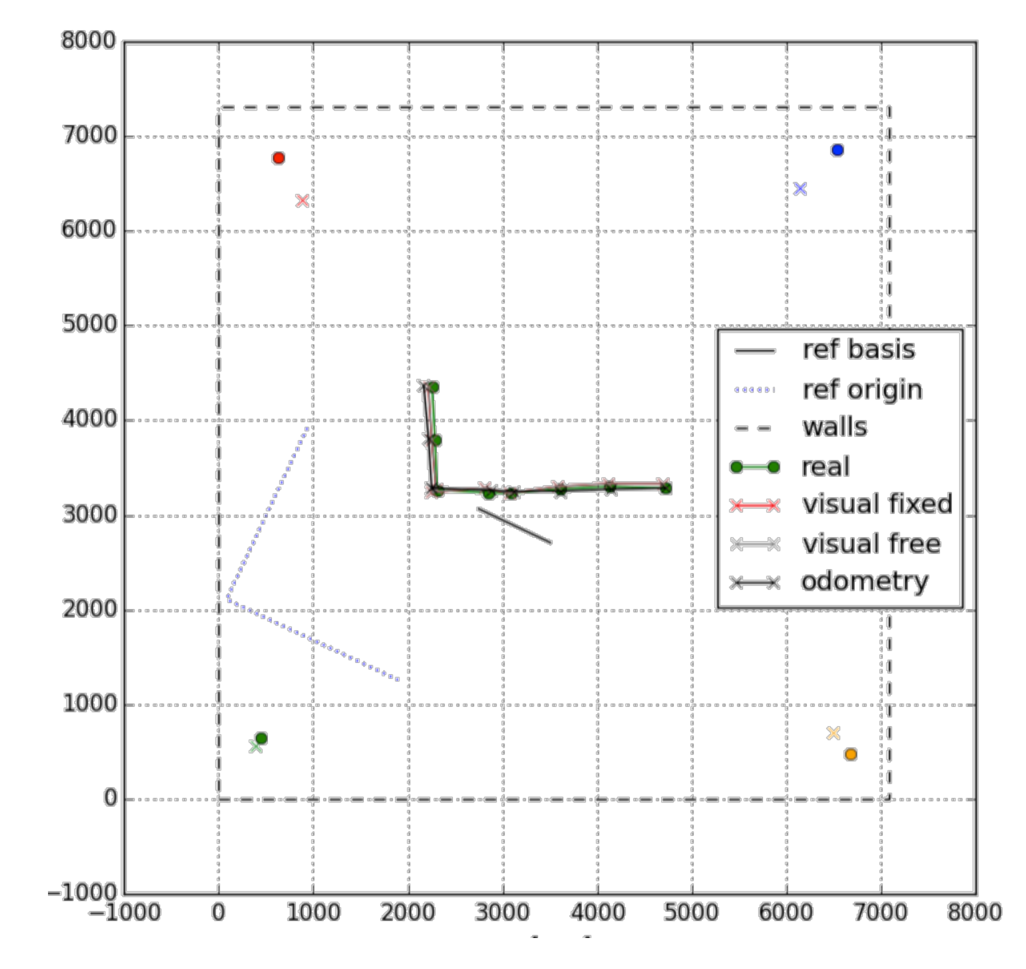


Fig. 1: Results using all cameras in room reference

Conclusion
Achievements

- Experimental framework (both **Hardware and Software**) tested and validated
  - Visual localization with precision up to 1 cm
  - Odometry analysis implemented
  - Room impulse response recording and deconvolution working
- Setup **instructions** and code **documentation** available online for later use

Conclusion
Suggested Improvements

- Smaller or more accurate **target point** for visual localization (checkerboard / *QR code*)
- Find criterion for **best camera combination**
- Add **fisheye** lenses for wider views
- More robust robot **movement** and **audio control**
- Improve **signal processing** for reliable echolocation (e.g. averaging)

Thank you

Experimental Setup
Visual Localization Procedure

- Governing equation

$$s_i \begin{bmatrix} u_i \\ v_i \\ 1 \end{bmatrix} = C \begin{bmatrix} R & | & \mathbf{t} \end{bmatrix} \begin{bmatrix} X_i \\ Y_i \\ Z_i \\ 1 \end{bmatrix}, \quad \text{for } i = 1 \cdots N_{pts},$$

- C and distortion coefficients obtained by **intrinsic calibration**
- Two different cases are treated:
  - Positioning of cameras (R, **t**) based on image-object space correspondances
  - Localization of point given its image in 4 cameras.
- Minimization of **reprojection error**