

Semester Project

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Map Fusion for Collaborative UAV SLAM

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ETH zürich



Autonomous Systems Lab

Map Fusion for Collaborative UAV SLAM

Andreas
Ziegler

Acronyms

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Map merging

Approaches
Results

Culling

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Optimization

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- ⑦ Outlook

SLAM Simultaneous Localisation and Mapping.

UAV Unmanned Aerial Vehicle.

KF KeyFrame.

KFM KeyFrame Match.

BA Bundle Adjustment.

PGO Pose Graph Optimization.

LM Levenberg-Marquardt.

DL Powell's dog leg.

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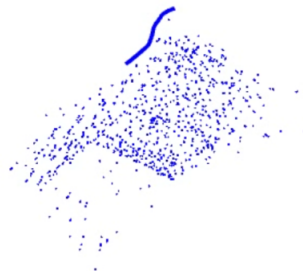
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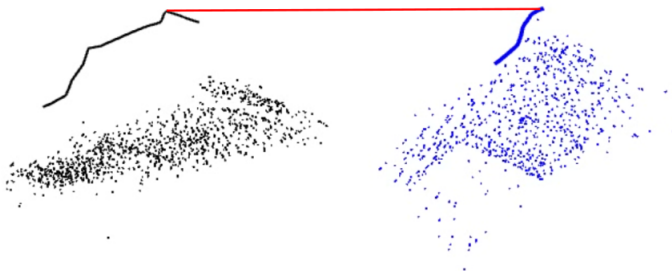
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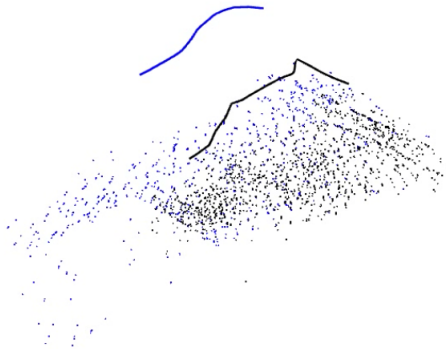
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KeyFrames (KFs): The most “representative” poses

Introduction - What is a KeyFrame Match (KFM)?

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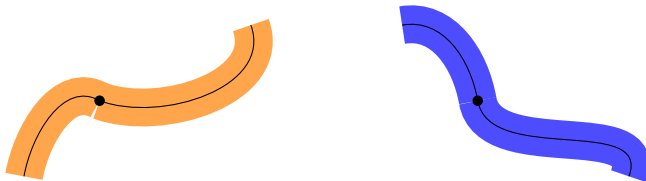
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KeyFrames (KFs): The most “representative” poses

Two clients each with own landmarks and KeyFrames (KFs)



Introduction - What is a KeyFrame Match (KFM)?

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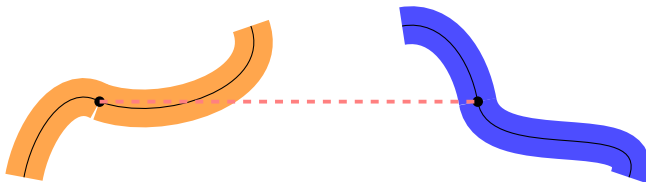
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KeyFrames (KFs): The most “representative” poses

KeyFrame Match (KFM): Two KeyFrames (KFs) observing the same location



Introduction - What is a KeyFrame Match (KFM)?

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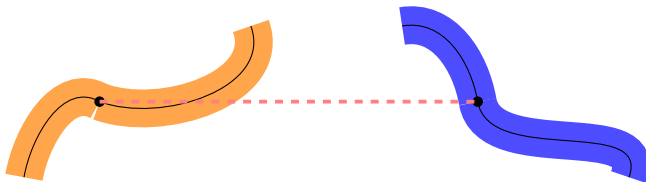
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KeyFrames (KFs): The most “representative” poses

KeyFrame Match (KFM): Two KeyFrames (KFs) observing the same location → Can obtain transformation

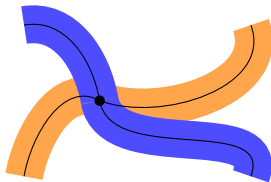


Introduction - What is a KeyFrame Match (KFM)?

KeyFrames (KFs): The most “representative” poses

KeyFrame Match (KFM): Two KeyFrames (KFs) observing the same location

With the transformation \rightarrow maps can be aligned

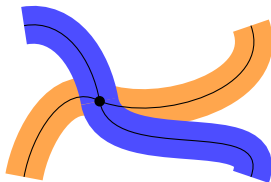


Introduction - What is a KeyFrame Match (KFM)?

KeyFrames (KFs): The most “representative” poses

A KeyFrame Match (KFM) contains:

- Two KeyFrames (KFs) (One per map)
- The transformation ($T \in \text{Sim}(3)$) between them



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- A multi agent SLAM system based on ORB-SLAM2 should be extended

[Mur-Artal and Tardos, 2016]

- A multi agent SLAM system based on ORB-SLAM2 should be extended
- So far, as soon as a KeyFrame Match (KFM) was detected, maps were merged

[Mur-Artal and Tardos, 2016]

- A multi agent SLAM system based on ORB-SLAM2 should be extended
- So far, as soon as a KeyFrame Match (KFM) was detected, maps were merged
- Using multiple KFMs to guarantee no false map merging

[Mur-Artal and Tardos, 2016]

- A multi agent SLAM system based on ORB-SLAM2 should be extended
- So far, as soon as a KeyFrame Match (KFM) was detected, maps were merged
- Using multiple KFMs to guarantee no false map merging
- Using multiple KFMs to obtain an optimal map alignment

[Mur-Artal and Tardos, 2016]

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Old approach:

- As soon as a KFM was detected, maps were merged

Map merging - New approach

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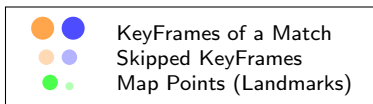
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Find $n(= 3)$ KeyFrame Matches (KFMs)



Map merging - New approach

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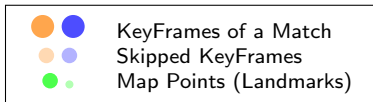
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Find $n(= 3)$ KeyFrame Matches (KFMs),
Skip $m(= 5)$ KeyFrames (KFs)



Map merging - New approach

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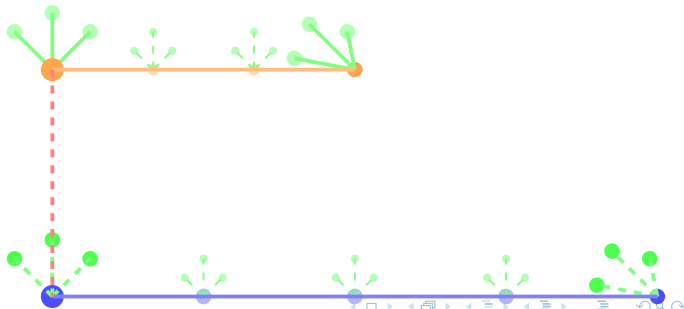
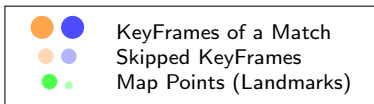
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Find $n(= 3)$ KeyFrame Matches (KFMs),
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Map merging - New approach

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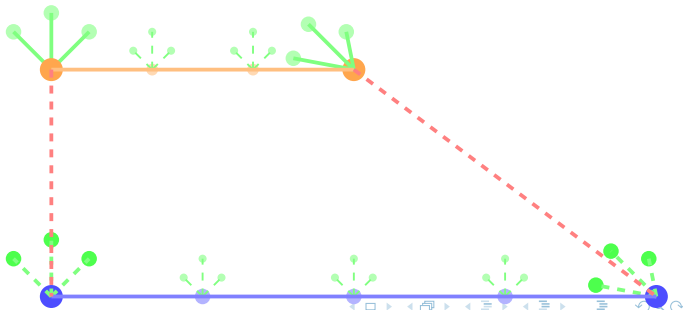
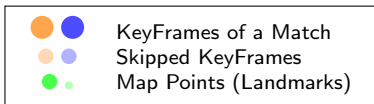
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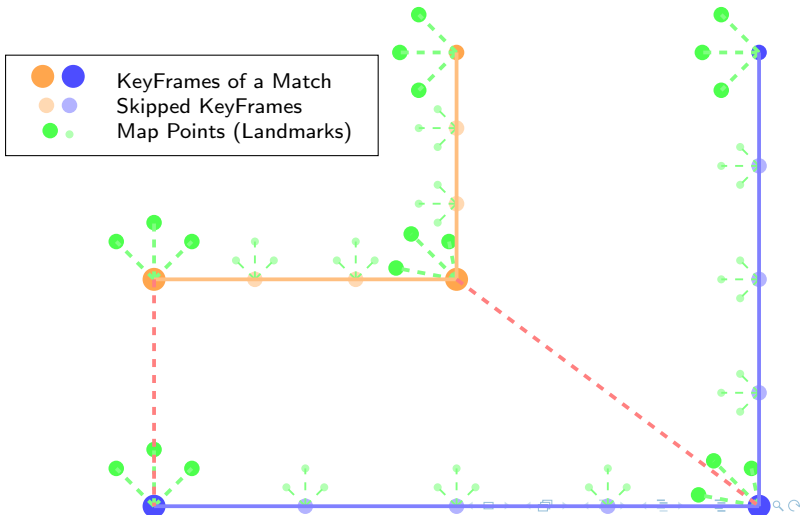
Outlook

Find $n(= 3)$ KeyFrame Matches (KFMs),
Skip $m(= 5)$ KeyFrames (KFs)



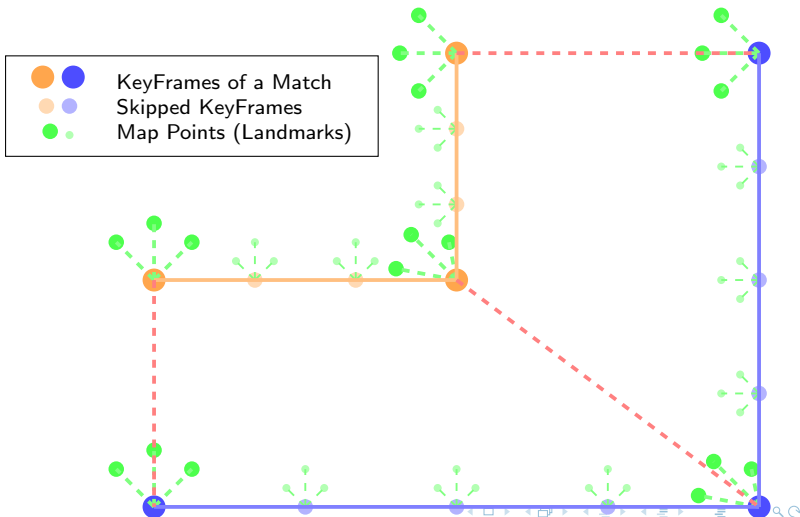
Map merging - New approach

Find $n(= 3)$ KeyFrame Matches (KFM), Skip $m(= 5)$ KFs

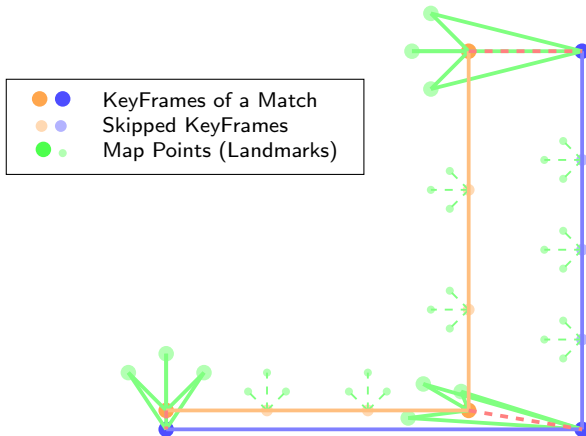


Map merging - New approach

Find $n(= 3)$ KeyFrame Matches (KFMs)



Merge the two maps and fuse map points



Map merging - Results - skipping of KeyFrame (KF)

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Co-visibility graph

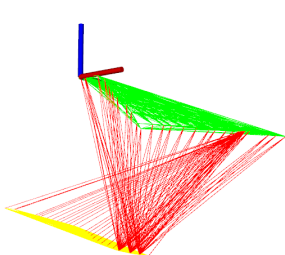
Connections/Edges between KeyFrames (KFs) which observe the same map points (landmarks)

Map merging - Results - skipping of KF

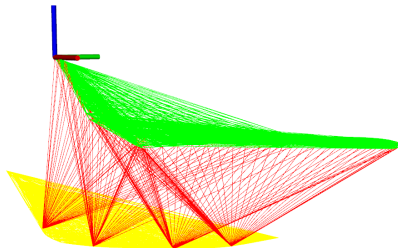
green: Covisibility graph of first map

yellow: Covisibility graph of second map

red: Covisibility between the KFM



(a) 1 KF skipped after a KFM was found



(b) 10 KF skipped after a KFM was found

Map merging - Results - Reduction of drift

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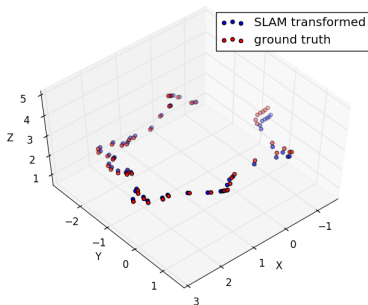
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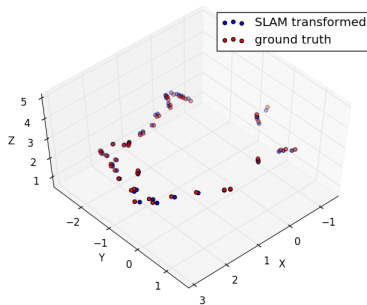
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Ground truth and SLAM transformed Map 1



(a) original approach

Ground truth and SLAM transformed Map 1



(b) new approach

Reduction of the error from $\text{rmse} = 0.13\text{m}$ to $\text{rmse} = 0.10\text{m}$

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Motivation

Perform KeyFrame (KF) culling to remove redundant information as bundle adjustment complexity grows with the number of KFs

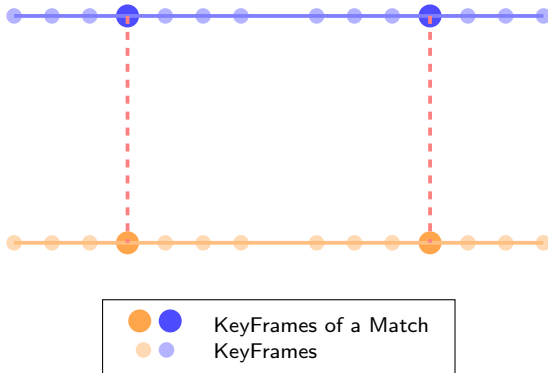
[Mur-Artal et al., 2015]

- Remove redundant KFs before map merging

- Remove redundant KFs before map merging
- Performs culling for every KFM separately

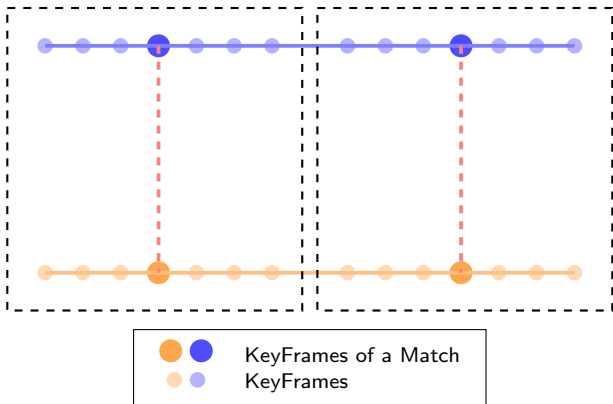
Culling - Remove redundant KF

- Remove redundant KFs before map merging
- Performs culling for every KFM separately



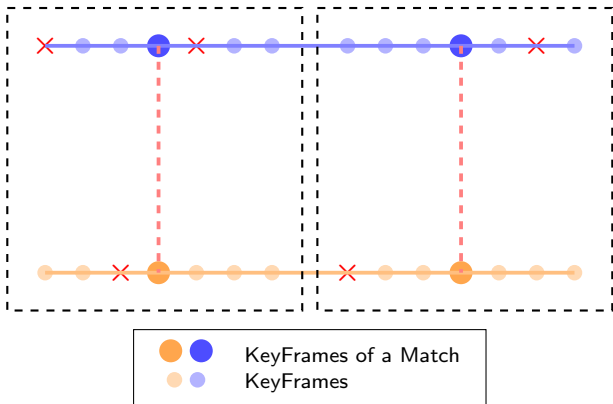
Culling - Remove redundant KF

- Remove redundant KFs before map merging
- Performs culling for every KFM separately



Culling - Remove redundant KF

- Remove redundant KFs before map merging
- Performs culling for every KFM separately



Culling removes $\approx 13\%$ of the KeyFrames (KFs)

Pose Graph Optimization (PGO)
Bundle Adjustment (BA)

Culling removes $\approx 13\%$ of the KeyFrames (KFs)

Culling	# KFM	# KFs skipped	PGO [ms]	BA [ms]
No	10	10	532.28	3659.48
Yes	10	10	178.83	1098.37

Table: Time measurements of PGO and BA without and with culling.

Pose Graph Optimization (PGO)

Bundle Adjustment (BA)

Culling removes $\approx 13\%$ of the KeyFrames (KFs)

Culling	# KFM	# KFs skipped	PGO [ms]	BA [ms]
No	10	10	532.28	3659.48
Yes	10	10	178.83	1098.37

Table: Time measurements of PGO and BA without and with culling.

Performance increases significantly when culling is enabled

Pose Graph Optimization (PGO)

Bundle Adjustment (BA)

Culling	# KFMs	# KFs skipped	<i>rmse</i> [m]
No	1	0	0.1311
Yes	1	0	0.2187
No	10	10	0.0961
Yes	10	10	0.0965

Table: *rmse* without and with culling.

Culling	# KFMs	# KFs skipped	<i>rmse</i> [m]
No	1	0	0.1311
Yes	1	0	0.2187
No	10	10	0.0961
Yes	10	10	0.0965

Table: *rmse* without and with culling.

Accuracy gets worse if not enough information is available.
No problem with multiple KeyFrame Matches (KFMs).

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Considerable computational benefits can be gained by substituting the Levenberg-Marquardt (LM) algorithm in the implementation of Bundle Adjustment (BA) with a variant of Powell's dog leg (DL) non-linear least squares technique [Lourakis and Argyros, 2005]

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DL optimizer handles trust region differently

- Tried Pose Graph Optimization (PGO) and Bundle Adjustment (BA) with the Powell's dog leg (DL) optimizer

- Tried Pose Graph Optimization (PGO) and Bundle Adjustment (BA) with the Powell's dog leg (DL) optimizer
- PGO: Slightly worse timing using the DL optimizer

- Tried Pose Graph Optimization (PGO) and Bundle Adjustment (BA) with the Powell's dog leg (DL) optimizer
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- BA: Better timing using the DL optimizer

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Conclusion

LM optimizer for PGO and DL optimizer for BA

Opt.	# KFMs	# KFs skipped	PGO [ms]	BA [ms]
LM/LM	10	10	178.83	1098.37
LM/DL	10	10	178.70	383.54

Table: Time measurements of LM and DL optimizer.

Pose Graph Optimization (PGO)

Bundle Adjustment (BA)

Opt.	# KFMs	# KFs skipped	PGO [ms]	BA [ms]
LM/LM	10	10	178.83	1098.37
LM/DL	10	10	178.70	383.54

Table: Time measurements of LM and DL optimizer.

Accuracy stays the same while the performance is increased

Pose Graph Optimization (PGO)

Bundle Adjustment (BA)

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- Multiple KFMs approach increases accuracy

- Multiple KFMs approach increases accuracy
- Skipping of KFs spreads KFMs over a bigger area

Higher accuracy

The use of KFMs from a bigger area serves PGO and BA with more information → higher accuracy

Higher accuracy

The use of KFM from a bigger area serves PGO and BA with more information → higher accuracy

- Culling removes redundant KFs → improved timing

Higher accuracy

The use of KFM from a bigger area serves PGO and BA with more information → higher accuracy

- Culling removes redundant KFs → improved timing
- Using DL optimizer for the BA also improves timing

Higher accuracy

The use of KFMs from a bigger area serves PGO and BA with more information → higher accuracy

Better timing

Culling and the use of the DL optimizer improves timing

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Outlook:

- Heuristic for best map alignment
- Extend area for KF culling

Limitation:

- # of KFMs and # of skips depends on data set

Outlook:

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Lourakis, M. I. A. and Argyros, A. A. (2005).

Is Levenberg-Marquardt the most efficient optimization algorithm for implementing bundle adjustment?

In *Proceedings of the IEEE International Conference on Computer Vision*, volume II, pages 1526–1531.



Mur-Artal, R., Montiel, J. M. M., and Tardos, J. D. (2015).

ORB-SLAM: A Versatile and Accurate Monocular SLAM System.

IEEE Transactions on Robotics, 31(5):1147–1163.



Mur-Artal, R. and Tardos, J. D. (2016).

ORB-SLAM2: an Open-Source SLAM System for Monocular, Stereo and RGB-D Cameras.