RAWSEEDS

Robotics Advancement through Web-publishing of Sensorial and Elaborated Extensive Data Sets

WorkPackage 3

Deliverable D3.2
Final Data Certification

Project no. 045144

Instrument: Specific Support Action

Thematic Priority: IST-2005-2.6.1 Advanced Robotics

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1. Executive summary

This document describes the activities performed in WP3 to validate the quality of the datasets obtained in the RAWSEEDS project. The effort in WP3 has been devoted to the design of the algorithms for data validation, their software implementation and the validation of the datasets obtained in WP2, that include Indoor, outdoor and mixed datasets. The datasets have been validated considering the four criteria defined in WP1: file format, timing, data overlap and data density and quality.

In general, the datasets obtained have very good quality. The problems reported in the previous validation: *"D3.1: Preliminary Data Certification"* have been properly addressed:

- The dataset documentation has been improved containing all the available sensor information. Particularly the relative position between sensors has been properly documented.
- The new camera calibrations performed have state-of-the-art quality.
- The critical timing and data loss problems have been corrected.

During the validations, a critical failure was detected in the trinocular sequences of the indoor datasets acquired between 2008-12-06 and 2008-12-09, and they were declared invalid (see section 6). The problem was fixed and new indoor datasets were acquired during 25-27 February 2009 in WP2. The new datasets have been validated in WP3 right in time to write this deliverable.

The results of the validation are summarized in the following section and detailed in section 4. The final outcome of the validation is:

- 1 indoor dataset rejected due to synchronization errors.
- 5 indoor datasets valid.
- 3 mixed datasets valid.
- 3 outdoor datasets valid.

Sections 5 and 6 present the analysis of the defects found in the datasets and describe the recovery action performed.

2. Summary of validation of datasets

The result of the validations is detailed in section 4 and is summarized in the following tables, where red cells represent validation failures, and yellow cells indicate minor defects that need to be corrected.

Sesion	**Mixed**		
Dataset	Bovisa 2008-09-01 Static	Bovisa 2008-10-06 Dynamic	Bovisa 2008-10-11a Static
Odometry	Valid(1)	Valid(1)	Valid(1)
IMU	Valid	Valid	Valid
SICK Laser	Valid	Valid	Valid
Hokuyo Laser	Not usable outdoors	Not usable outdoors	Not usable outdoors
Sonar Belt	Not available	Not available	Not available
Monocular Vision	Valid	Valid	Valid
Trinocular Vision	Valid(3)	Valid(3)	Valid(3)
Panoramic Vision	Valid	Valid	Valid(5)
GPS	Valid	Valid	Valid

Sesion	**Outdoor**		
Dataset	Bovisa 2008-10-04 Static	Bovisa 2008-10-07 Dynamic	Bovisa 2008-10-11b Static
Odometry	Valid(1)	Valid(1)(2)	Valid(1)(2)
IMU	Valid	Valid	Valid
SICK Laser	Valid	Valid	Valid
Hokuyo Laser	Not usable outdoors	Not usable outdoors	Not usable outdoors
Sonar Belt	Not available	Not available	Not available
Monocular Vision	Valid	Valid	Valid
Trinocular Vision	Valid(3)(4)	Valid(3)	Valid(3)(4)
Panoramic Vision	Valid	Valid	Valid
GPS	Valid	Valid	Valid

Sesion	**Indoor**					
Conditions	**Static Lamps**		**Static Daylight**	**Dynamic Lamps**	**Dynamic Daylight**	
Dataset	Bicocca 2009-02-25b	Bicocca 2009-02-27b	Bicocca 2009-02-27a	Bicocca 2009-02-26b	Bicocca 2009-02-25a	Bicocca 2009-02-26a
Odometry	Valid	Valid	Valid	Valid	Valid	Valid
IMU	Valid	Valid	Valid	Valid	Valid	Valid
SICK Laser	Valid	Valid	Valid	Valid	Valid	Valid
Hokuyo Laser	Valid	Valid	Valid	Valid	Valid	Valid
Sonar Belt	Valid	Valid	Valid	Valid	Valid	Valid
Monocular Vision	Valid	Failed(6)	Valid	Valid	Valid(7)	Valid
Trinocular Vision	Valid	Failed(6)	Valid	Valid	Valid	Valid
Panoramic Vision	Valid	Failed(6)	Valid	Valid	Valid	Valid
GPS	Not available indoors	Not available indoors	Not available indoors	Not available indoors	Not available indoors	Not available indoors

The reasons for the defects reported are:

(1) The odometry presents a bias towards the left hand side. ALUFR has developed a technique to recalibrate the odometry and compensate the bias in the datasets, that is described in Section 6. The dataset documentation should include the results of the calibration process to allow the users to improve the odometry.

(2) There are a few wheel slippages in specific points of the outdoor datasets Bovisa_2008-10-07 and Bovisa_2008-10-11b, which can cause problems to some current SLAM methods. However, this issue is representative of the difficulties that a SLAM algorithm must face in real-life applications. This is

further analyzed in section 6. The slippages should be documented.

(3) The left and right images of the trinocular camera are interchanged in all mixed and outdoor datasets. The filenames should be corrected.

(4) The Left and Top trinocular sequences in the outdoor dataset Bovisa_2008-10-11b have a gap of 12 seconds of frames lost. As the gap occurs at the end of the dataset, we consider the stream valid for trinocular SLAM. Another gap of 12 seconds appears in the Top camera in the middle of dataset Bovisa_2008-10-04. We consider the stream valid because it can be properly used for stereo SLAM. The gaps should be documented in the datasets.

(5) Panoramic vision has a gap of 3.5 seconds of frames lost in the mixed dataset Bovisa_2008-10-11a. We consider this stream valid because the error is found in the last part of the dataset and, according to our tests, it can be recovered with SLAM algorithms that use appropriate relocation techniques. The gap should be documented in the dataset.

(6) In the indoor dataset Bicocca_2009-02-27b, the timestamps of monocular and trinocular streams have periodic gaps of 1 second, but no frames were lost. This seems to be caused by the ptpd clock synchronization daemon that was used to synchronize the clocks of the different computers involved in the data acquisition. The timestamps have been manually corrected, eliminating the artificial timestamp gaps. However, the validation procedure has detected a significant residual error in the synchronization of monocular, trinocular and panoramic cameras: errors up to 200ms, standard deviation up to 70ms and drift in the case of panoramic. This indicates that the different computers were not correctly synchronized, and the dataset has been discarded.

(7) In the indoor dataset Bicocca_2009-02-25a, there is a sequence of frames during 35 seconds that are alternatively dark and over-saturated, when the robot was traversing a crystal corridor. This issue was caused by the functioning of the auto exposure control in the low-cost monocular camera used. In our tests visual SLAM here seems more difficult than usual, but doable. In any case, users not interested in developing SLAM algorithms able to work in such extreme situations can also use for monocular SLAM the sequence obtained by one of the cameras of the trinocular system, that are more expensive, and have a more reliable auto exposure control. The issue should be documented in the dataset.

3. Data validation methodology

The datasets have been validated considering the criteria defined in WP1, that are summarized here:

1) File format: All the files will be checked to be readable, in compliance with the file format specification and complete according to the dataset description.
2) Timing: Each sensor acquisition must carry the timestamp of the instant when it was acquired. Timing characteristics such as mean acquisition frequency (F), mean period (T) and maximum time interval (Tmax) between two consecutive acquisitions of the data streams are computed from the different sensors. This information is usable to verify data lost along the sensor sequence: if Tmax values are higher than 2T, data lost can be critical for SLAM tasks and the corresponding dataset will be considered as failed. The synchronization between all elements will be checked using the IMU timestamps as time base. Following the recommendations from the reviewers, the synchronization is verified in several points throughout each dataset by computing the mean delay with respect to IMU time base and the standard deviation of the delay.
3) Data overlap: To be able to track environment elements to perform SLAM, any pair of successive data acquisitions from each sensor must have a significant overlap.
4) Data density and quality: The density and quality of the data acquired must be adequate to perform SLAM. This will be verified by applying classical feature extraction techniques throughout the dataset. For example, this allows us to detect problems with motion blur, dark images, etc. However, there are areas of the environment where there is a real lack of features, for example where a camera is facing a blank wall. This is not a defect of the data collection, but an intrinsic difficulty for mapping the environment.

The validation methodology for each sensor is described next.

1) Odometry
   a) Data is verified to be in compliance with the file specification and timestamped. Odometry data is processed to automatically select several portions of the trajectory with high angular velocity, where the synchronization of the rest of sensors will be verified.
   b) The quality of the data is cross-validated by comparing with the results obtained from laser odometry.

2) IMU:
   a) Data is verified to be in compliance with the file specification and timestamped.
   b) In WP1 we planed to use the timing of the odometry as reference to validate the synchronization of the rest of sensors. However, we have found that the IMU provides more precise time and angular velocity values, and will be used as time base for the validation of the rest of sensors. The synchronization of IMU and odometry is verified in the portions of the trajectory found to have high angular velocity. The angular velocities obtained by the robot odometry and the IMU are compared by cross-correlation.

3) SICK Laser:
   a) Data is verified to be in compliance with the file specification and timestamped.
   b) Data overlap is verified by performing scan-matching between successive scans. The matchings are used to compute the robot motion (laser odometry).
   c) The synchronization is verified in the portions of the trajectory found to have high angular velocity. The angular velocities obtained by laser odometry and the IMU are compared by cross-correlation; the laser delay corresponds to the maximum of the cross-correlation.
   d) Data density is validated running the software developed by ALUFR and UNIZAR. Scan matching and other two different approaches are used to process the data: the first approach is based on a Rao-Blackwellized particle filter [Grisetti et al, TRO 2007], [Stachniss et al, IROS 2007]; the second is a constraint network-based approach that models poses of the robot during data acquisition as nodes in a graph. Using efficient optimization techniques developed in this project [Grisetti et al, RSS 2007], [Grisetti et al, IROS 2007], [Grisetti et al, ICRA 2008], [Grisetti et al, TITS 2009], we obtained mapping results that are the basis for the subsequent analysis.

4) HOKUYO Laser:
   a) Data is verified to be in compliance with the file specification and timestamped.
   b) Data overlap is verified by performing scan-matching between successive

scans. The matchings are used to compute the robot motion (laser odometry). Due to the short sensor range, this is only possible in some portions of the trajectory.

c) The synchronization is verified in the portions of the trajectory found to have high angular velocity. The angular velocities obtained by the laser odometry and the IMU are compared by cross-correlation; the laser delay corresponds to the maximum of the cross-correlation.

d) The main limitation of this sensor is its short range (4 meters). Data density and quality are validated by detecting the number of valid returns in each scan throughout the trajectory.

5) Sonar Belt

a) Data is verified to be in compliance with the file specification and timestamped.

b) Data overlap is verified by analyzing the frequency of acquisition of data.

c) To validate data quality and timestamps synchronization, we have plotted the sonar returns obtained in selected parts of the robot trajectory and inspected them manually, comparing with the laser scans obtained by the SICK sensor at the same positions.

6) Monocular Vision:

a) Data is verified to be in compliance with the file specification and timestamped. File format: It is verified that all image files are readable.

b) Timing:

i. The mean and maximum times between frames is computed to check if there is data loss. We validate if the number of lost frames can be critical for SLAM evaluations. One or two lost frames are admissible and probably do not represent an important defect for SLAM solutions making valid a dataset.

ii. Angular velocities provided by monocular SLAM estimation and the IMU are compared by cross-correlation. The delay of the monocular data with respect to the IMU corresponds to the maximum of the cross-correlation.

a) Data overlap:

i. It is first verified by visual inspection of the image sequences. Then the sequences are processed to obtain FAST corners [Rosten and Drummond, ICCV 2005], track them on the sequence and perform pure visual SLAM, without using the robot odometry. The software has been developed by UNIZAR, it uses a single map where point features are coded in Inverse Depth [Civera et al, TRO 2008], and data association based on JCBB [Neira and Tardós, TRO 2001]. The Inverse Depth and JCBB combination first proposed by [Clemente et al, RSS 2007] has been selected because it has shown a remarkable ability to produce robust monocular SLAM maps with respect to clutter and moving objects.

ii. Several frames have insufficient exposition. This is a result of to the normal functioning of the internal exposure control of the low-cost monocular camera used and makes the sequences more difficult to use for monocular SLAM algorithms. We call them "dark" frames; they are detected and enumerated.

b) The synchronization of the vision data is verified by selecting several portions of the trajectory with high angular velocity. The angular velocities obtained by pure visual SLAM and the IMU are compared by cross-correlation.

c) Data density and quality:

i. It is validated by running the FAST [Rosten and Drummond, ICCV 2005] corner extractor throughout the image sequence. This allows to detect parts of the dataset with low feature density, or images with blur due to camera motion.

ii. Low feature density areas are identified and visually inspected.

iii. Camera calibration is a critical issue for a visual SLAM dataset. The calibration sequences have been verified to check if they follow the guidelines of proposed calibration method "Camera Calibration Toolbox for Matlab" by [Bouget et. Al, 2008] (See Section 5). The calibration quality is further verified by running visual SLAM software on the dataset.

7) Trinocular Vision:

a) Data is verified to be in compliance with the file specification and timestamped. File format: It is verified that all image files are readable.

b) The synchronization of the vision data is verified by selecting several portions of the trajectory with high angular velocity. The angular velocities obtained by the the pure stereo SLAM and the IMU are compared by cross-correlation.

c) Data density and quality are validated by running the Harris corner extractor throughout the image sequence. This allows to detect parts of the dataset with low feature density, dark or missing frames, or images with excessive blur due to camera motion.

d) Camera calibration is even more critical in the case of a multi-camera SLAM dataset. The calibration sequences and the calibration results provided with the datasets have been manually inspected to verify their quality levels.

e) We have also performed 3D scene reconstruction with Photomodeler using selected frames from the trinocular sequence. This allows to verify that the three images are correct and correspond with the calibration data provided.

8) Panoramic Vision:

a) Data is verified to be in compliance with the file specification and timestamped.

b) Data overlap is verified by visual inspection of the image sequences.

c) The frequency of the images is checked to detect lost frames. For this deliverable we have obtained angular velocity from the panoramic images and compare it to the IMU angular velocities using cross-correlation.

d) Data density and quality will be validated by running SURF feature extractor [A. C Murillo et al., ICRA 2007], [H. Bay et al., ECCV 2006] throughout the image sequences. This will allow us to detect parts of the dataset with low feature density, black or missing frames, or images with excessive blur due to camera motion.

9) GPS:

The operation of the GPS system was validated in WP2. The results obtained were described in the additional deliverable AD2.3. The additional validations performed in WP3 are:

a) Data is verified to be in compliance with the file specification and timestamped.

b) Data density and quality are validated by plotting the robot positions obtained from GPS and verifying that they cover sufficiently the outdoor parts of the trajectory.

4. Data validation results

The datasets available and the sensor streams provided in each dataset are:

Sesion	Indoor					
Conditions	**Static Lamps**		**Static Daylight**	**Dynamic Lamps**	**Dynamic Daylight**	
Dataset	Bicocca 2009-02-25b	Bicocca 2009-02-27b	Bicocca 2009-02-27a	Bicocca 2009-02-26b	Bicocca 2009-02-25a	Bicocca 2009-02-26a
Odometry	Yes	Yes	Yes	Yes	Yes	Yes
IMU	Yes	Yes	Yes	Yes	Yes	Yes
SICK FRONT	Yes	Yes	Yes	Yes	Yes	Yes
SICK REAR	Yes	Yes	Yes	Yes	Yes	Yes
HOKUYO FRONT	Yes	Yes	Yes	Yes	Yes	Yes
HOKUYO REAR	Yes	Yes	Yes	Yes	Yes	Yes
SONAR BETL	Yes	Yes	Yes	Yes	Yes	Yes
FRONTAL	Yes	Yes	Yes	Yes	Yes	Yes
TRINOCULAR	Yes	Yes	Yes	Yes	Yes	Yes
PANORAMIC	Yes	Yes	Yes	Yes	Yes	Yes
GPS						
CALIBRATION	Yes	Yes	Yes	Yes	Yes	Yes
FILEFORMAT	Yes	Yes	Yes	Yes	Yes	Yes
SENSOR POSITION	Yes	Yes	Yes	Yes	Yes	Yes

Sesion	Mixed			Outdoor		
Dataset	Bovisa 2008-09-01 Static	Bovisa 2008-10-06 Dynamic	Bovisa 2008-10-11a Static	Bovisa 2008-10-04 Static	Bovisa 2008-10-07 Dynamic	Bovisa 2008-10-11b Static
Odometry	Yes	Yes	Yes	Yes	Yes	Yes
IMU	Yes	Yes	Yes	Yes	Yes	Yes
SICK FRONT	Yes	Yes	Yes	Yes	Yes	Yes
SICK REAR	Yes	Yes	Yes	Yes	Yes	Yes
HOKUYO FRONT	Yes	Yes	Yes	Yes	Yes	Yes
HOKUYO REAR	Yes	Yes	Yes	Yes	Yes	Yes
SONAR BELT						
FRONTAL	Yes	Yes	Yes	Yes	Yes	Yes
TRINOCULAR	Yes	Yes	Yes	Yes	Yes	Yes
PANORAMIC	Yes	Yes	Yes	Yes	Yes	Yes
GPS	Yes	Yes	Yes	Yes	Yes	Yes
CALIBRATION	Yes	Yes	Yes	Yes	Yes	Yes
FILEFORMAT	Yes	Yes	Yes	Yes	Yes	Yes
SENSOR POSITION	Yes	Yes	Yes	Yes	Yes	Yes

The datasets correspond to indoor, outdoor and mixed trajectories. Each dataset can be identified with the name of the environments, and the date in which it was acquired (yyyy_mm_ddX), where X specifies the run, if more than one took place in the same day. The table also indicates the characteristics of the traversed environment such as light conditions (lamps / daylight) or the presence of moving people around (static / dynamic). In the following sections we summarize the results obtained during the validation process of the listed datasets. The structure of this document has been chosen to present the validation results in accordance to static and dynamic sessions for each kind of dataset (indoor, mixed, outdoor). The results are presented in more detail for the first datasets. In the rest of cases, only the most important novelties discovered are detailed.

4.1. *Validation of Indoor-Static sessions*

In the following, we first present the main time characteristics of the datasets, and then present the most important details of the validations performed for each sensor stream.

4.1.1. Basic time properties

The following tables summarize the main timing characteristics of the data streams obtained from the different sensors (F: mean acquisition frequency, T: mean period, Tmax: maximum time interval between two consecutive acquisitions, Delay: mean delay with respect to IMU time base, std Delay: standard deviation of the delay). Cells highlighted in yellow represent data loss or synchronization issues, cells marked with '--' could not be computed.

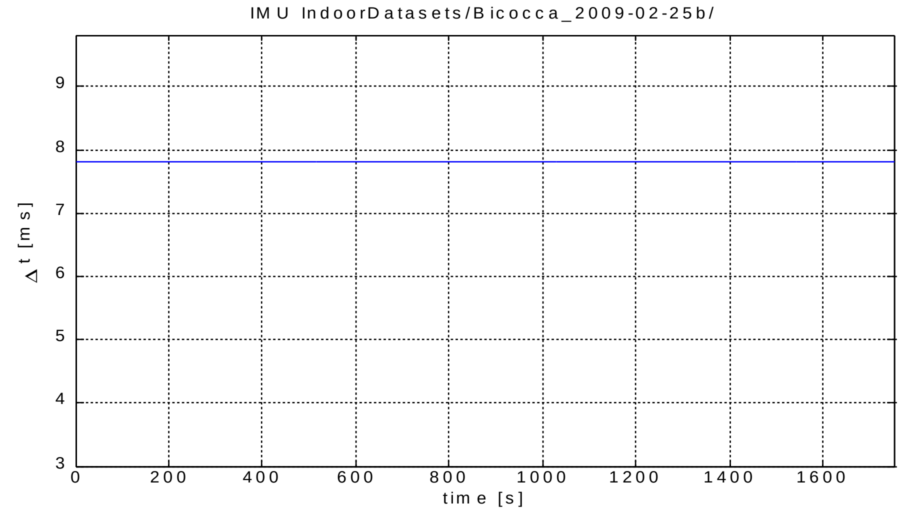
Indoor / Static_Lamps / Bicocca_2009-02-25b										
	IMU	Odometry	Sick R	Sick F	Hokuyo R	Hokuyo F	Frontal	Trinocular	Panoramic	Sonar
F (Hz)	127,97	47,63	76,93	76,93	10,09	10,06	29,96	15	14,97	12,5
T (ms)	7,8	20,99	12,99	12,99	99,01	99,38	33,37	66,65	66,78	79,97
Tmax (ms)	7,8	31,50	22,31	21,37	171,06	171,03	34,91	68,46	101,19	95,39
Delay (ms)	--	-148,33	-51,58	-45,83	--	--	4,0	-56,83	-3,2	--
std Delay (ms)	--	37,62	6,77	12,85	--	--	5,9	12,23	3,8	--

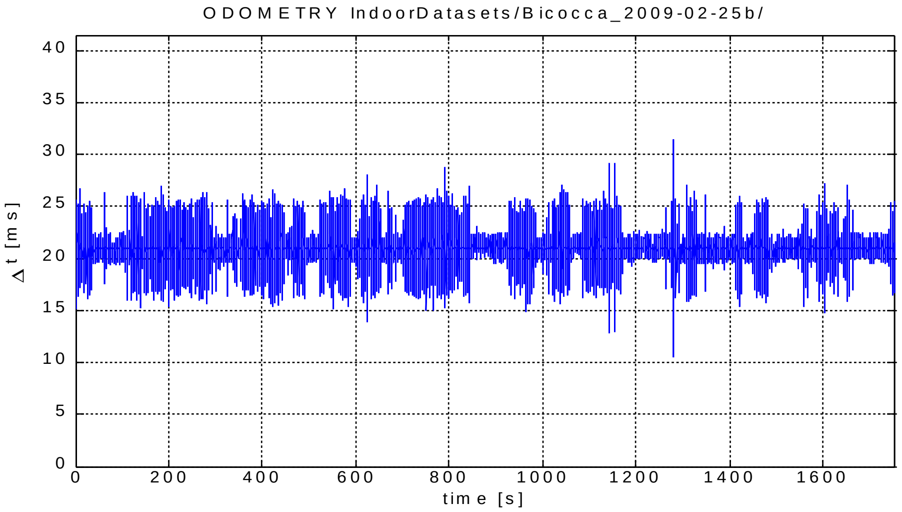
Indoor / Static_Lamps / Bicocca_2009-02-27b										
	IMU	Odometry	Sick R	Sick F	Hokuyo R	Hokuyo F	Frontal	Trinocular	Panoramic	Sonar
F (Hz)	127,97	47,63	76,93	76,93	10,10	10,06	30,17	14,86	14,97	12,5
T (ms)	7,8	20,99	12,99	12,99	98,99	99,31	33,13	67,27	66,77	79,95
Tmax (ms)	7,8	28,04	19,63	21,9	171,05	171,04	35,14	68,28	86,50	96,02
Delay (ms)	--	-146,55	-45,88	-44,11	--	--	-183.4	-123,00	61,9	--
std Delay (ms)	--	22,35	11,97	8,46	--	--	20,8	21,95	78,4	--

Indoor / Static_Daylight / Bicocca_2009-02-27a										
	IMU	Odometry	Sick R	Sick F	Hokuyo R	Hokuyo F	Frontal	Trinocular	Panoramic	Sonar
F (Hz)	127,96	47,62	76,92	76,92	10,09	10,05	29,95	15	14,97	12,5
T (ms)	7,8	20,99	13,00	13,00	99,02	99,44	33,37	66,65	66,79	79,97
Tmax (ms)	7,8	29,62	21,55	40,96	171,11	171,13	35,00	67,94	92,39	98,57
Delay (ms)	--	-163,14	-51,78	-50,00	--	--	4,5	-60,71	-4,4	--
std Delay (ms)	--	37,86	4,87	8,54	--	--	5,4	13,11	5,9	--

The delays will be discussed in more detail in the following subsections. With respect to the periods, if for a sensor stream Tmax is bigger than 2*T, most probably some data acquisitions have been lost. This can be seen more clearly in the following figures that plot the time separation between every pair of consecutive acquisitions. The following conclusions has been obtained from the validation results:

1. There are no critical data gaps.
2. The frequency of the sensors corresponds to the nominal frequency.
3. HOKUYO sensor present some oscillations.
4. In Dataset Biccoca_2009-02-07b, monocular, trinocular and panoramic cameras have significant synchronization errors that are analyzed in detail in section 6.3.


IMU IndoorDatasets/Bicocca_2009-02-25b/
Δt [ms]
time [s]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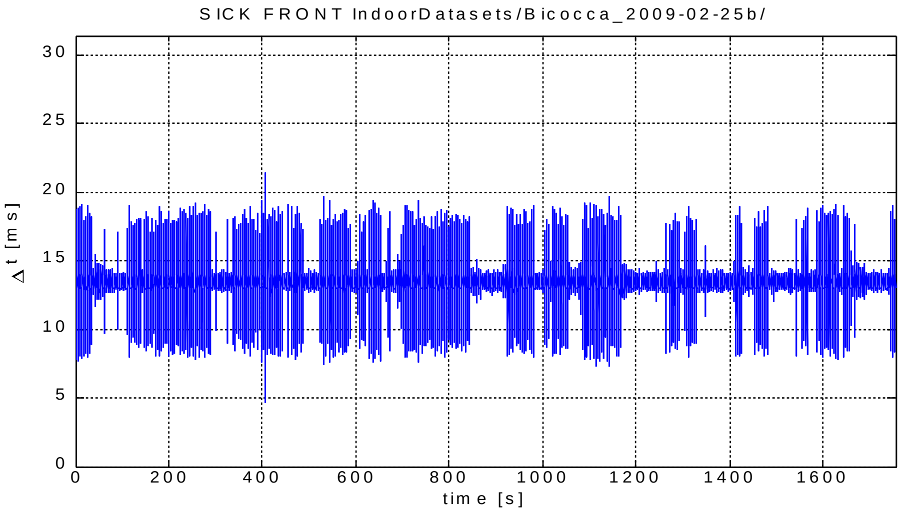
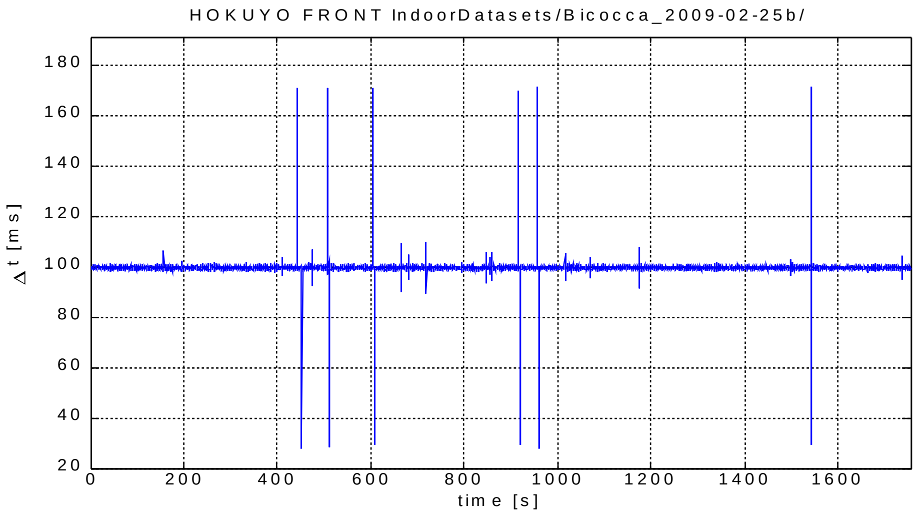
Δt [ms]
time [s]


SICK FRONT IndoorDatasets/Bicocca_2009-02-25b/
Δt [ms]
time [s]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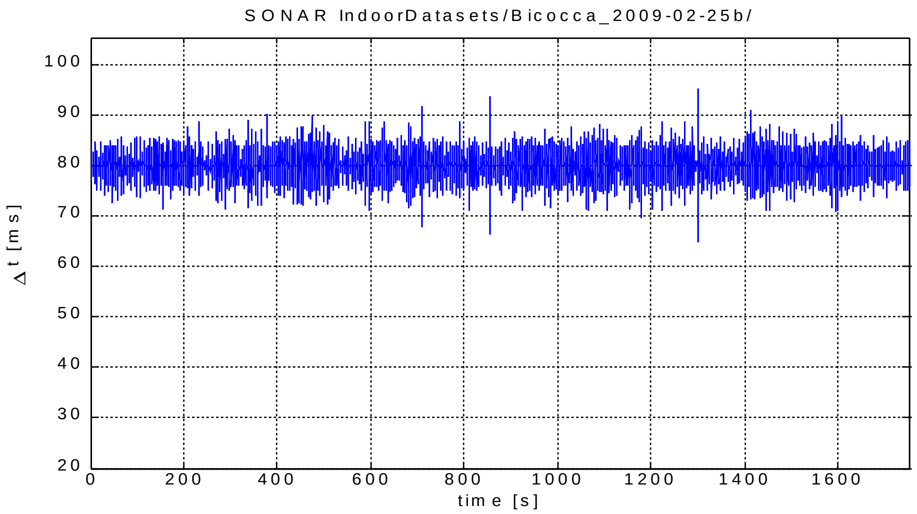
time [s]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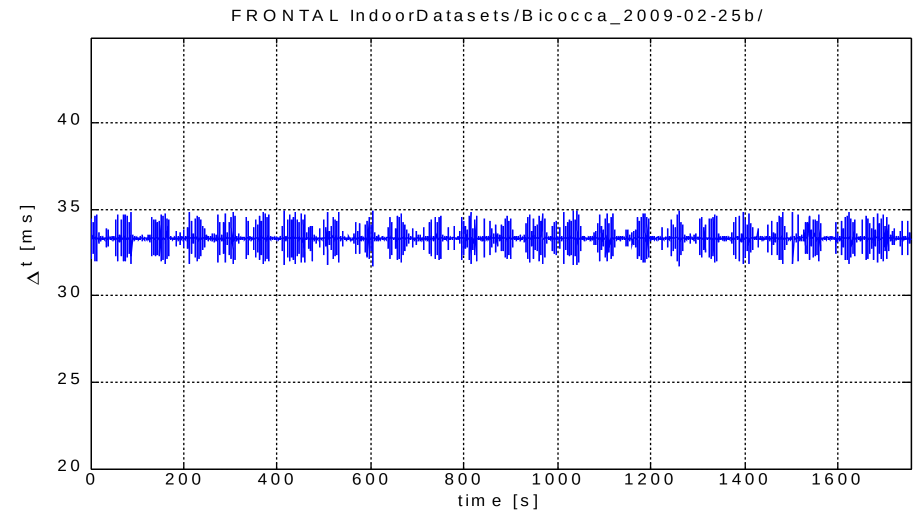
Δt [ms]
time [s]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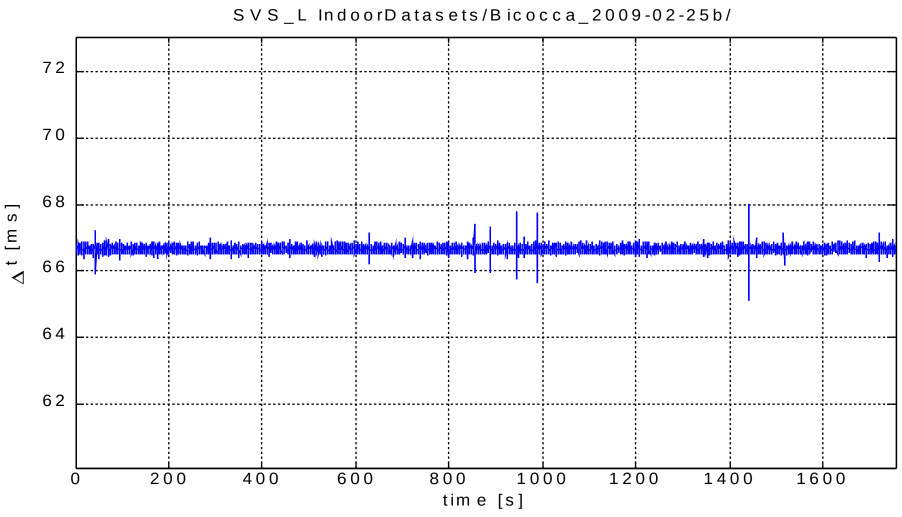
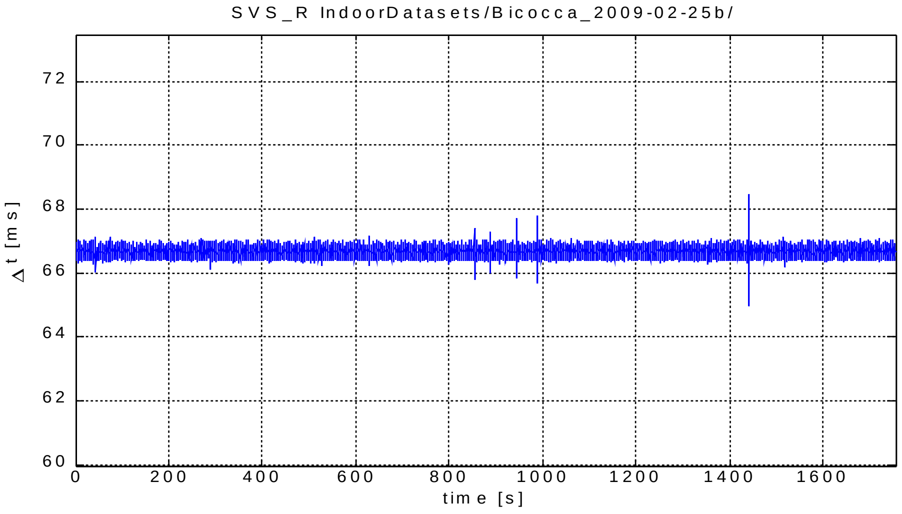
Δt [ms]
time [s]


SVS_L IndoorDatasets/Bicocca_2009-02-25b/
Δt [ms]
72
70
68
66
64
62
0
200
400
600
800
1000
1200
1400
1600
time [s]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Δt [ms]
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68
66
64
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60
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600
800
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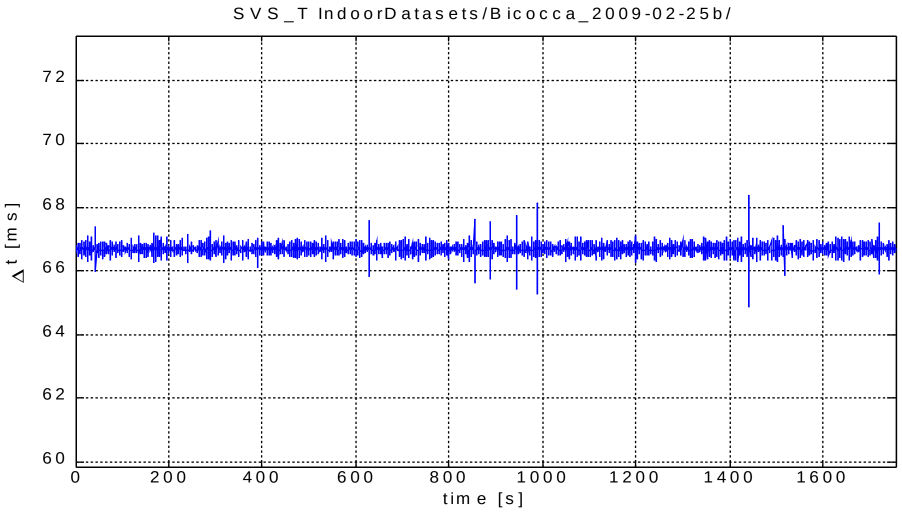
1200
1400
1600
time [s]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Δt [ms]
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68
66
64
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60
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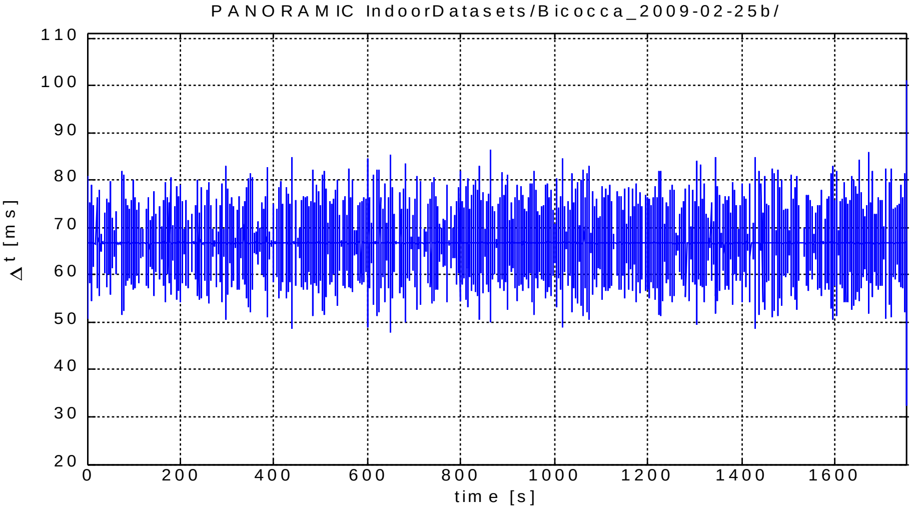
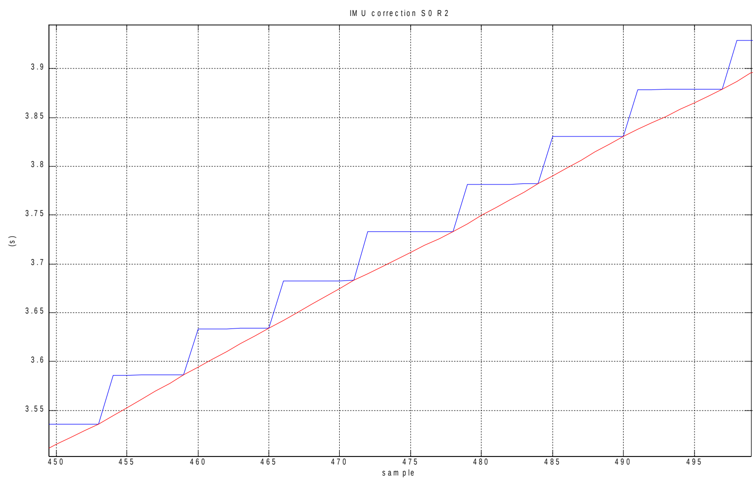
1200
1400
1600
time [s]

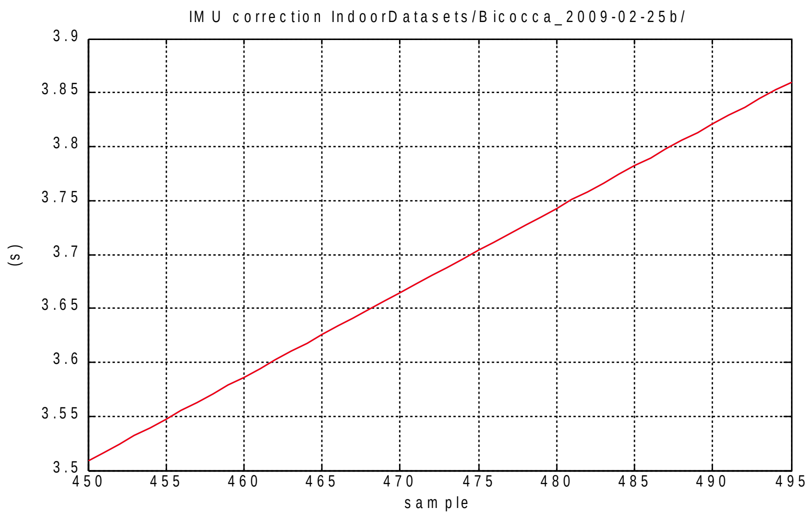

PANORAMIC IndoorDatasets/Bicocca_2009-02-25b/
110
100
90
80
70
60
50
40
30
20
Δt [ms]
0
200
400
600
800
1000
1200
1400
1600
time [s]

4.1.2. IMU

1) Data is verified to be in compliance with the file specification and timestamped. The nominal period for the IMU is 7.8ms (128Hz) which is checked during validation. Although the operation frequency of the sensor is very stable, timestamps are checked to rule out any probable source of error such as the produced by IMU data buffering in the computer. This defect was observed in old datasets in which jumps of 50ms were found (see blue plot in the first figure above). The problem was easily overcome with simple post-processing in the datasets performing a linear interpolation of the timestamps (red plot). The new datasets do not present jumps as shown in the second figure.

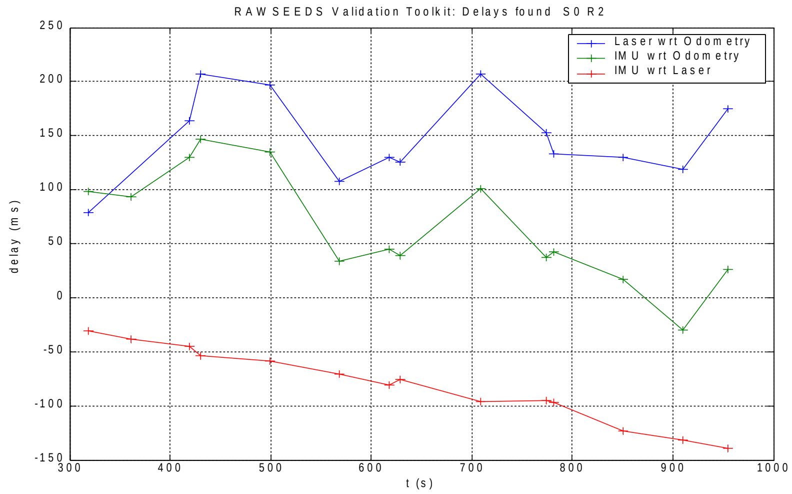


Old Dataset: Original IMU timestamps (blue) and corrected timestamps (red)

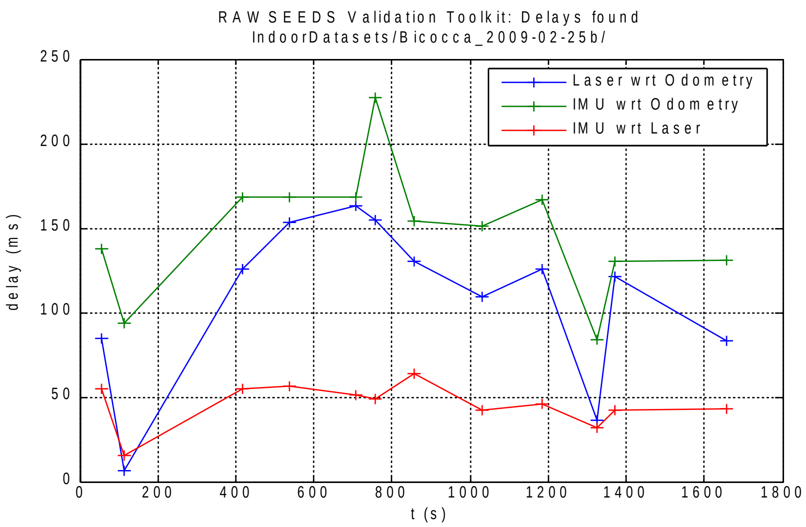


New Dataset: Original IMU timestamps (red)

The delays between laser, odometry and IMU are plotted in following figures. The times provided in IMU_STRETCHED do not present any continuous drift throughout the new dataset (see second figure). This problem was latent in old datasets as shown in the first figure, where it was necessary to improve timestamps with the proposed correct interpolation.



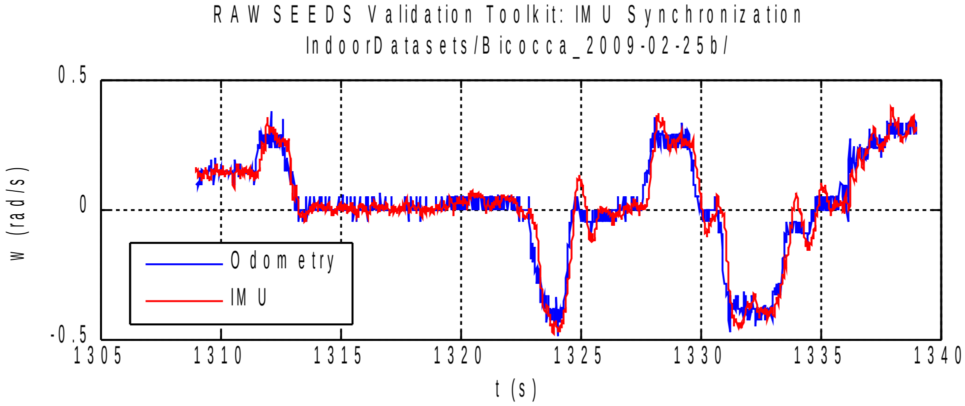
Old datasets: Delays between sensors with the interpolation provided in IMU_STRETCHED

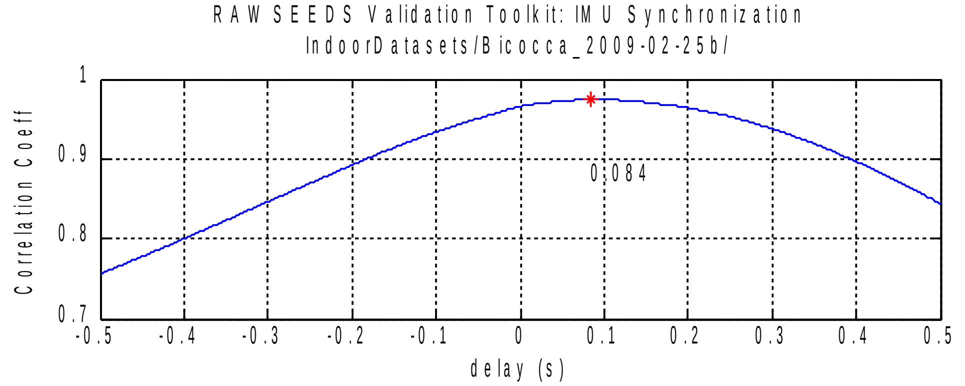


New Datasets: Delays between sensors without drift on delays.

4.1.3. Odometry

1) Data is verified to be in compliance with the file specification and timestamped.

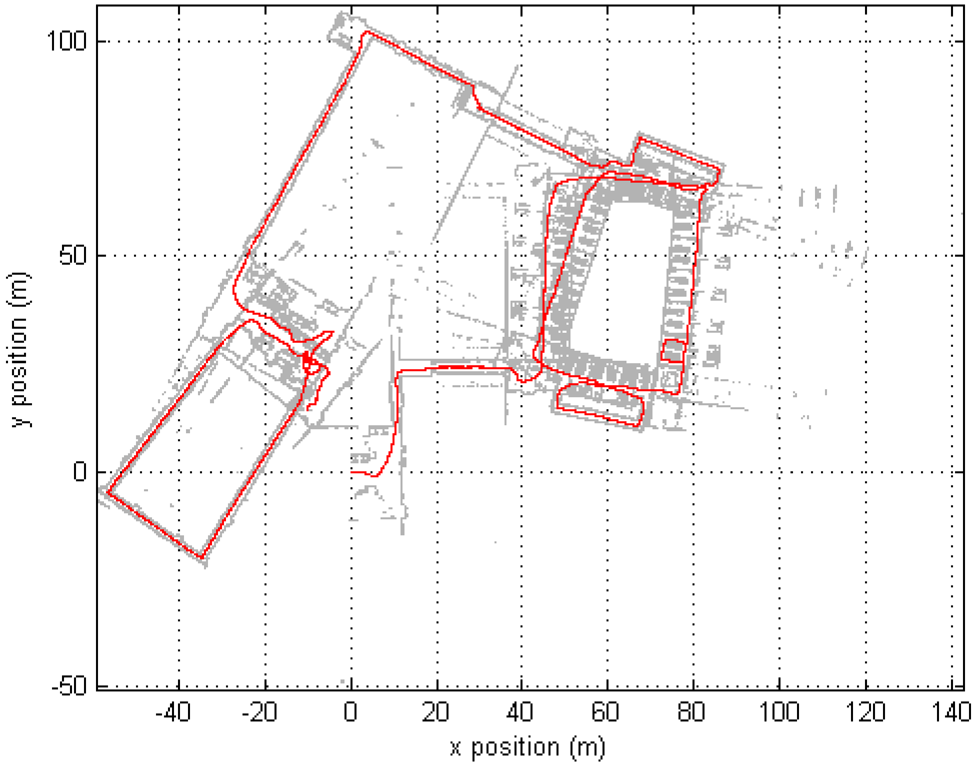




2) Timing and data quality are validated by comparing with the results obtained from IMU. The angular velocities obtained by the robot odometry and the IMU are compared by cross-correlation, as shown in the figure. The odometry has been found to run around 150ms ahead of time with respect to the IMU time base, with none oscillations throughout the dataset (see figure in the previous section). The constant part of the delay probably corresponds to a fixed offset in the clock of the computers involved. The suggested corrective action is to subtract the mean delay from the odometry timestamps. The variable part, with standard deviation smaller than 40ms, can easily be taken into account in the SLAM algorithms by increasing the odometry uncertainty.

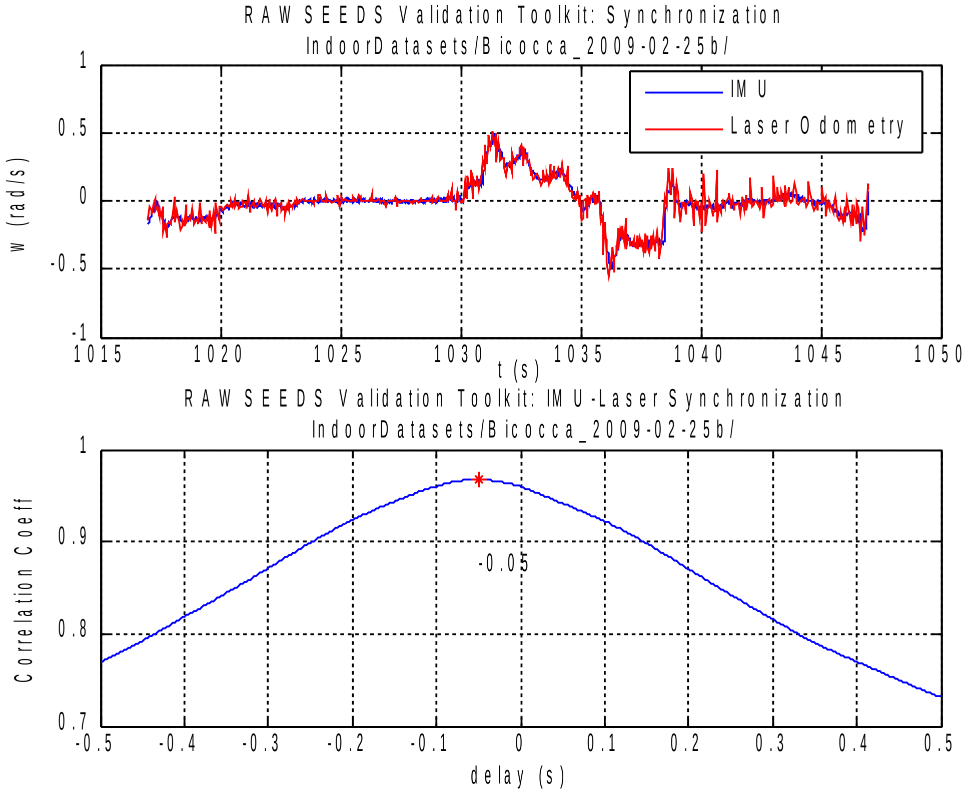
4.1.4. SICK Laser

1) Data is verified to be in compliance with the file specification and timestamped.
2) Data overlap is verified by performing scan-matching between successive scans. The matchings are used to compute the robot motion (laser odometry). An example of the results obtained is shown in the figure.



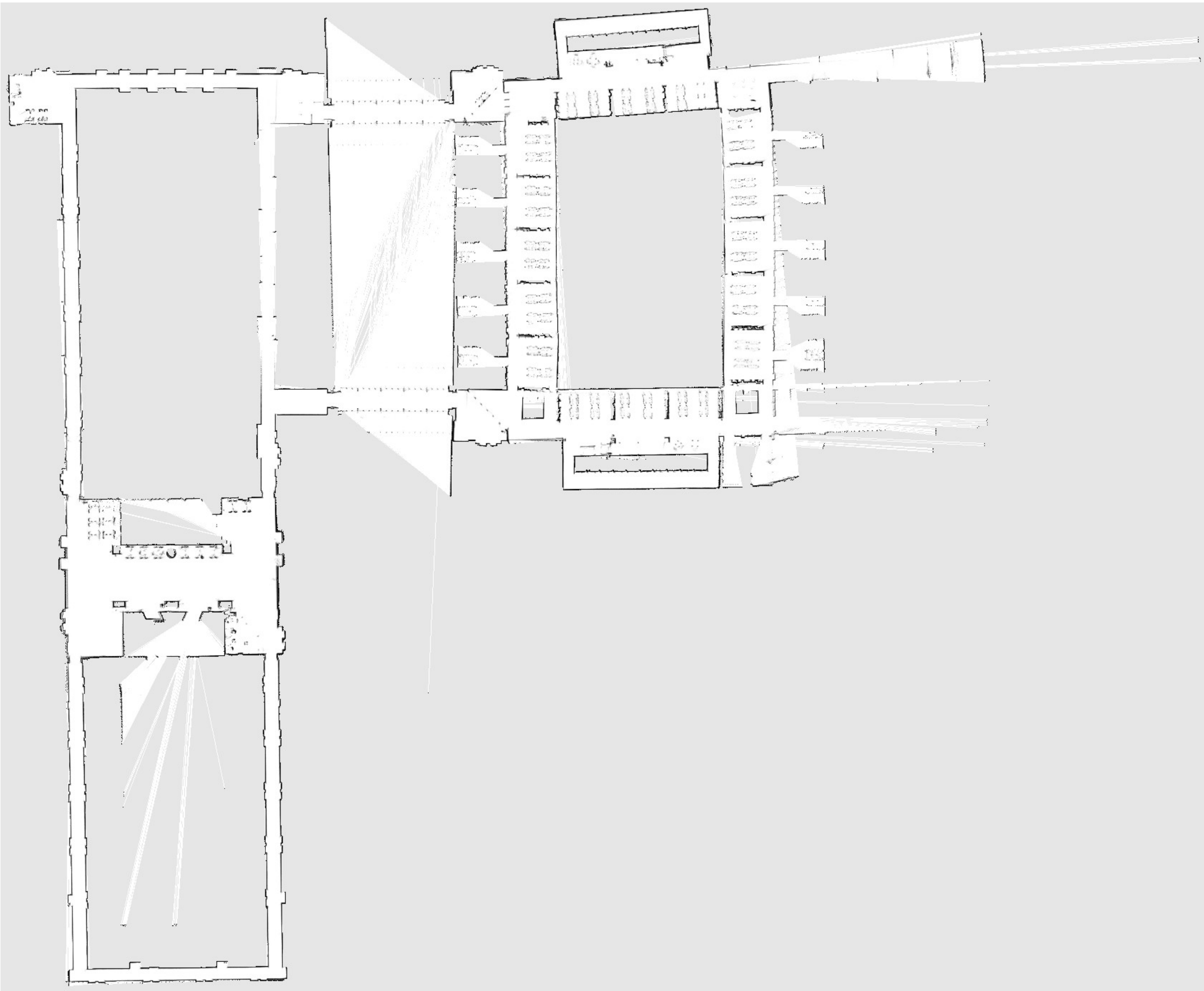
Validation of SICK laser overlap using scan matching on I*ndoor / Static_Lamps/Bicocca_2009-02-25b dataset*

3) The synchronization of the laser data is verified by selecting several portions of the trajectory with high angular velocity. The angular velocities obtained by the laser odometry and the IMU are compared by cross-correlation. The delay of the laser data with respect to the IMU corresponds to the maximum of the cross-correlation, as shown in the figure. The delay of SICK laser throughout the dataset is smaller than 50ms, and do not pose any problem for SLAM.



Validation of the SICK laser synchronization by cross-correlation of the angular velocities obtained from laser odometry and IMU

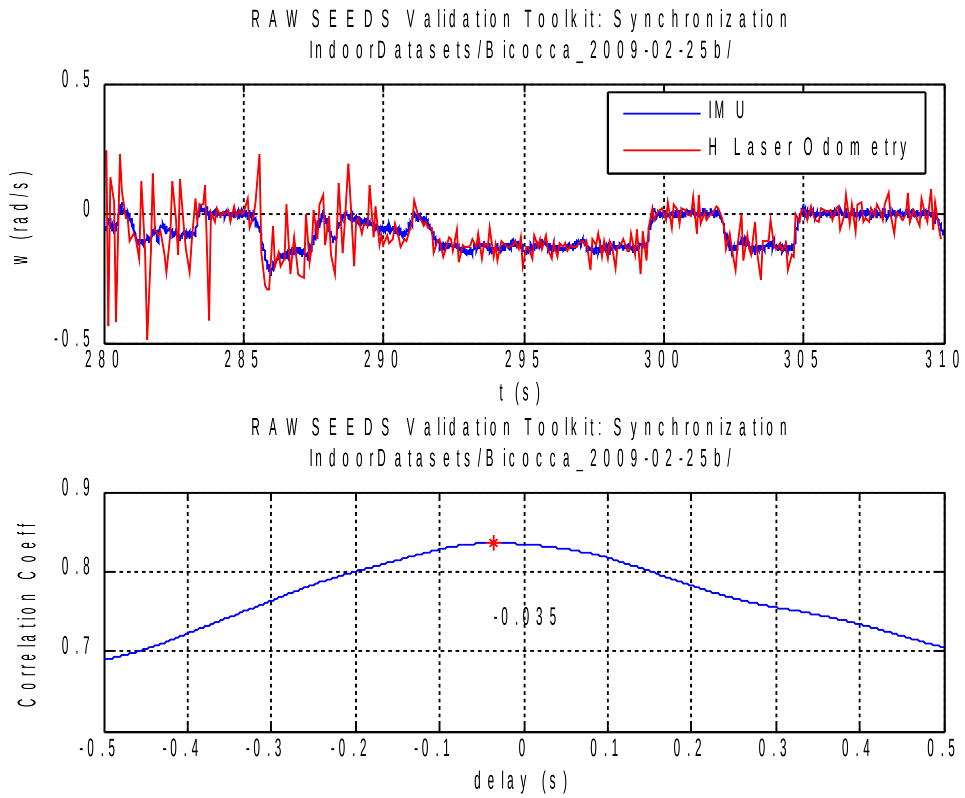
4) Data density and quality are validated by running ALUR software throughout the trajectory and building maps using graph-based SLAM. An inspection is carried out on the graph constraints that have been poorly optimized by the technique. A high error indicates a configuration of the graph in which observations are contradictory. This facilitated the manual matching procedure by identifying the parts of the dataset which are likely to be erroneous. The identified parts have all been manually inspected and the individual transitions computed based on the odometry as well as the laser range finder data have been checked for consistency.



Graph-based SLAM using SICK laser in session Indoor/Static_Lamps/ Bicocca_2009-02-25b

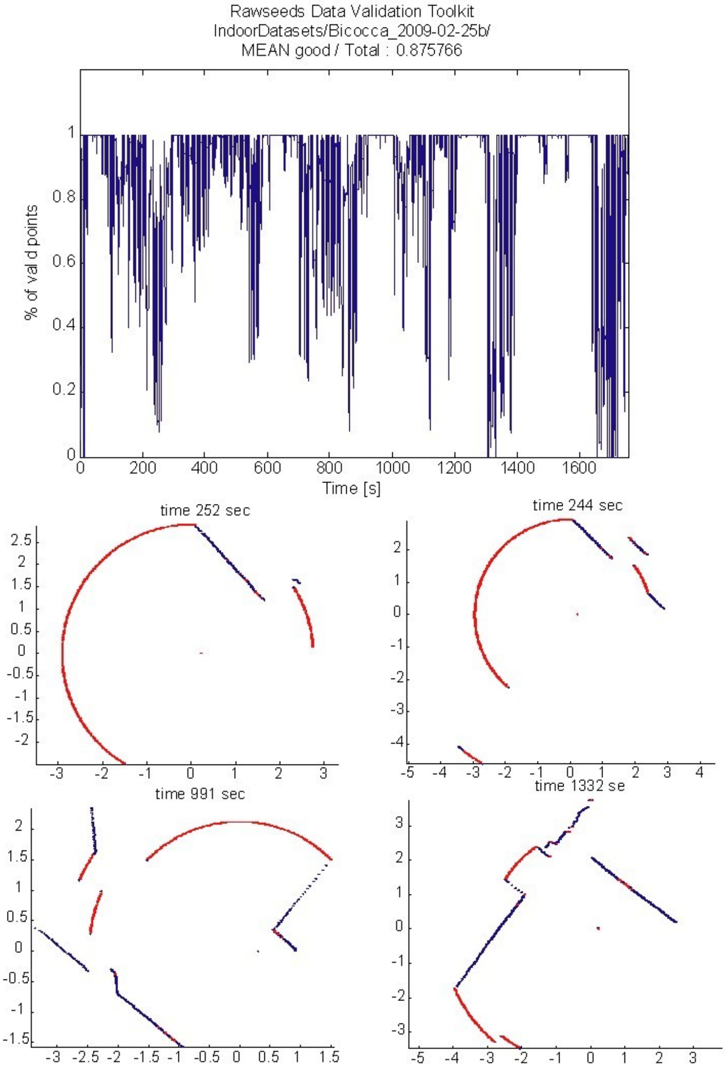
4.1.5. Hokuyo Laser

1) Data is verified to be in compliance with the file specification and timestamped.
2) Data overlap is verified by performing scan-matching between successive scans. The matchings are used to compute the robot motion (laser odometry). Given the short range of the Hokuyo sensor, laser based odometry was only successful in some parts of the trajectory.
3) The synchronization of the laser data is verified by selecting several portions of the trajectory with high angular velocity. The angular velocities obtained by the laser odometry and the IMU are compared by cross-correlation. The delay of the laser data with respect to the odometry corresponds to the maximum of the cross-correlation, as shown in the figure. Only one of the trajectory intervals could be evaluated with a corresponding delay around 40ms. In the remaining intervals cross correlation could not be computed and thus the mean delay and its standard deviation is not inferred.



Validation of the Hokuyo laser synchronization by cross-correlation of the angular velocities obtained from laser odometry and IMU

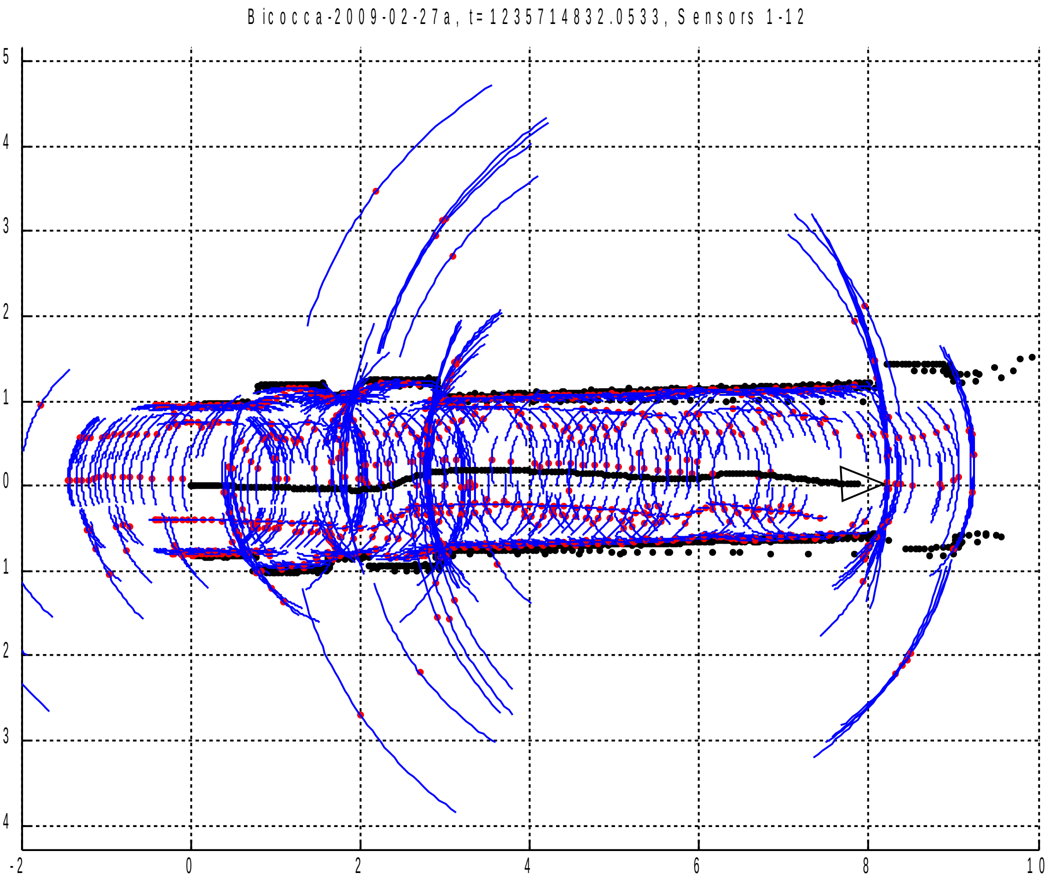
4) The main limitation of this sensor is its short range (4 meters). Data density and quality are validated by detecting the number of valid returns in each scan throughout the trajectory. As it can be seen in the following figures, in some portions of the indoor trajectory, the number of valid points is enough for SLAM, but there are several areas where the rooms are bigger and the percentage of valid returns is below 30%. In those areas, the usefulness of the Hokuyo laser data for SLAM or localization is limited. Since the Hokuyo is not mounted parallel to the ground, some observations report the floor ahead of the robot. It looks like the Hokuyo is shaking with the robot. The provided data should be sufficient for obstacle avoidance.



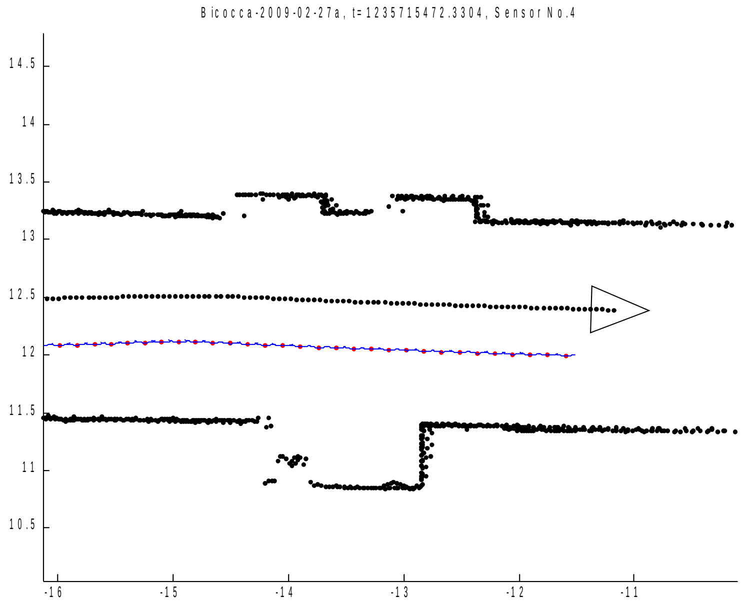
Valid (blue) and invalid (red) points from the Hokuyo laser throughout the dataset

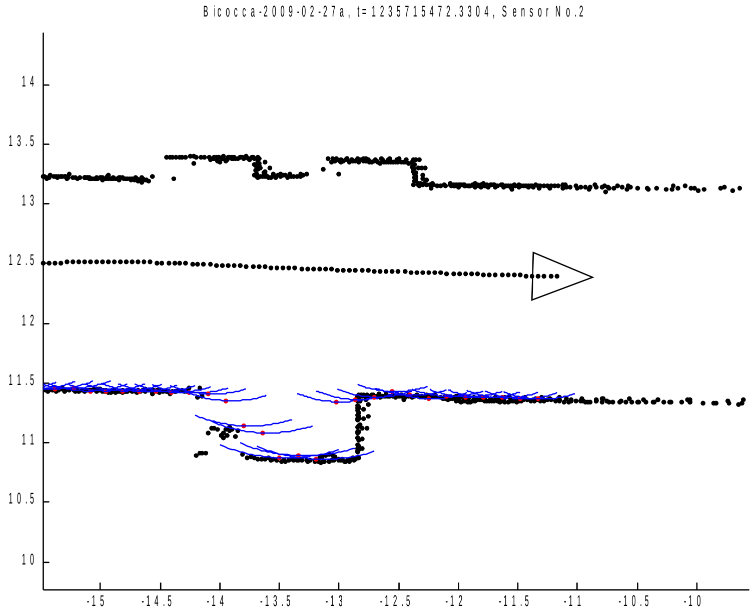
4.1.6. Sonar Belt

The file format and nominal frequency of acquisition is verified. No critical data gaps were detected in the static datasets. To validate data quality and timestamps synchronization, we have plotted the sonar returns obtained in selected parts of the robot trajectory and inspected them manually. The following figure shows an example. As it is typical with sonar sensors [Tardós et al., IJRR 2002], part of the returns come from the walls in the environment, but there is also a significant number of spurious returns.



The following figure shows an example of a sensor giving good returns and a sensor giving spurious returns, probably due to sensor cross-talk, in the same trajectory portion.



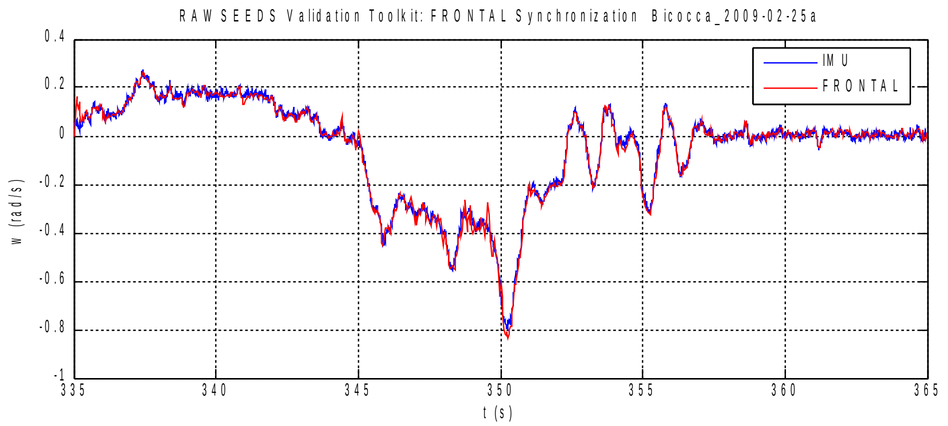


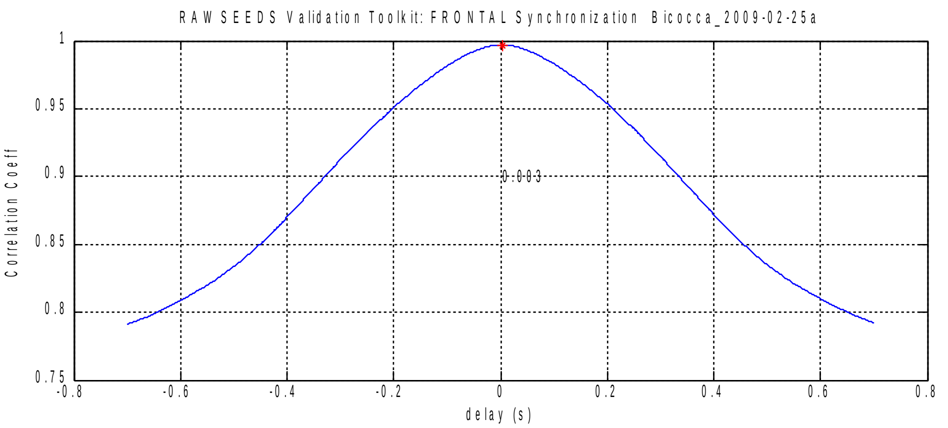
4.1.7. Monocular Vision

1) Data is verified to be in compliance with the file specification and timestamped File format: all image files are readable.

2) Timing: see table in section 4.1.1. During the timing validations, we did not find data gaps in indoor static sessions.

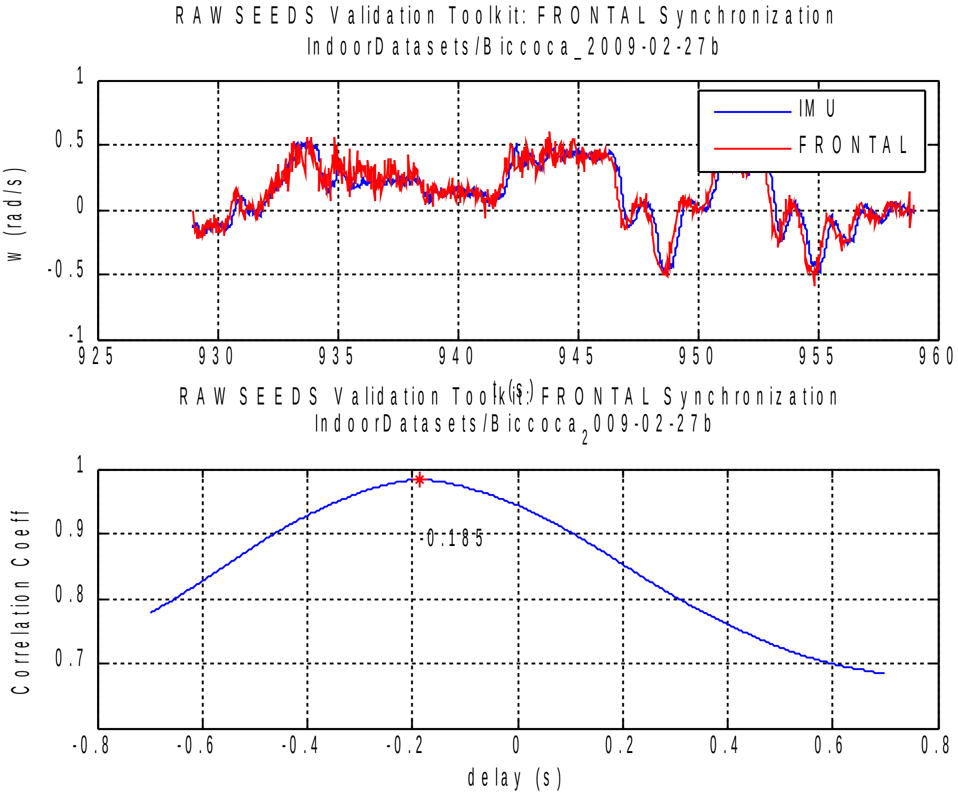
3) The synchronization of the vision data is verified by selecting several portions of the trajectory with high angular velocity. The angular velocities obtained by pure visual SLAM and IMU are compared by cross-correlation, as shown in the figure. In two of the datasets, the monocular vision is perfectly synchronized, with delays of around 5ms.





Validation of monocular vision synchronization

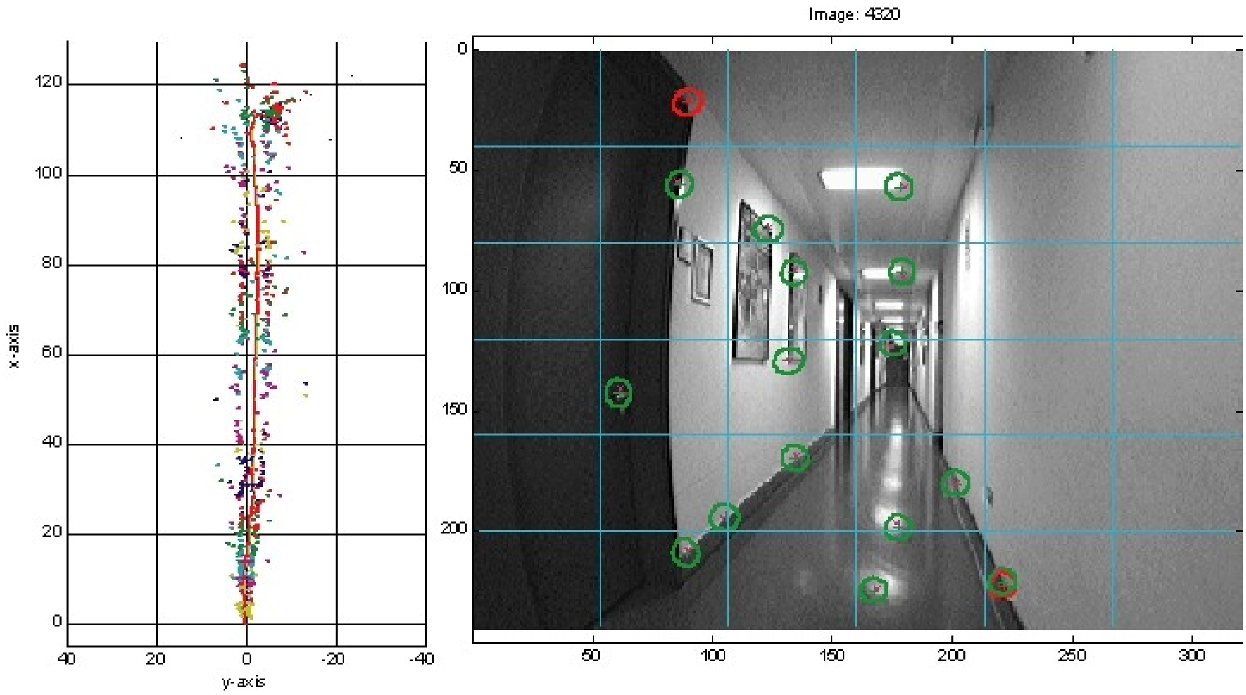
4) In the indoor dataset Bicocca_2009-02-27b, the timestamps of monocular and trinocular streams have periodic gaps of 1 second, but no frames were lost. This seems to be caused by an error in the ptpd clock synchronization daemon, that introduced jumps in the clock of the computer in charge of acquiring monocular and trinocular streams. The timestamps have been manually corrected, and the synchronization with IMU has been verified by correlation, as shown in the figure:



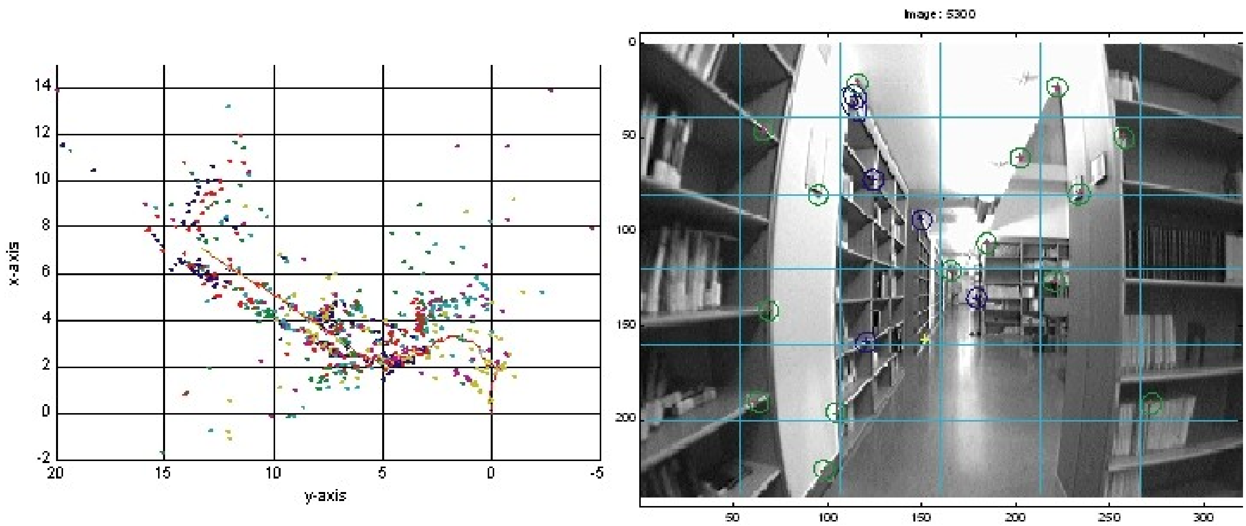
Validation of monocular vision synchronization after correction.

After correcting the timestamp jumps, monocular has been found to run ahead of time with respect to IMU by 183,4ms (with 20,8ms standard deviation). The constant part of the delay probably corresponds to a fixed offset in the clock of the computers involved. The suggested corrective action is to subtract the mean delay from the monocular timestamps. The variable part, with standard deviation around 20ms, can be taken into account in the SLAM algorithms by increasing the odometry uncertainty.

5) Data overlap: It has been verified that the sequence can be processed by standard inverse depth + JCBB monocular SLAM. The next figure shows an example after processing a typical indoor scenario

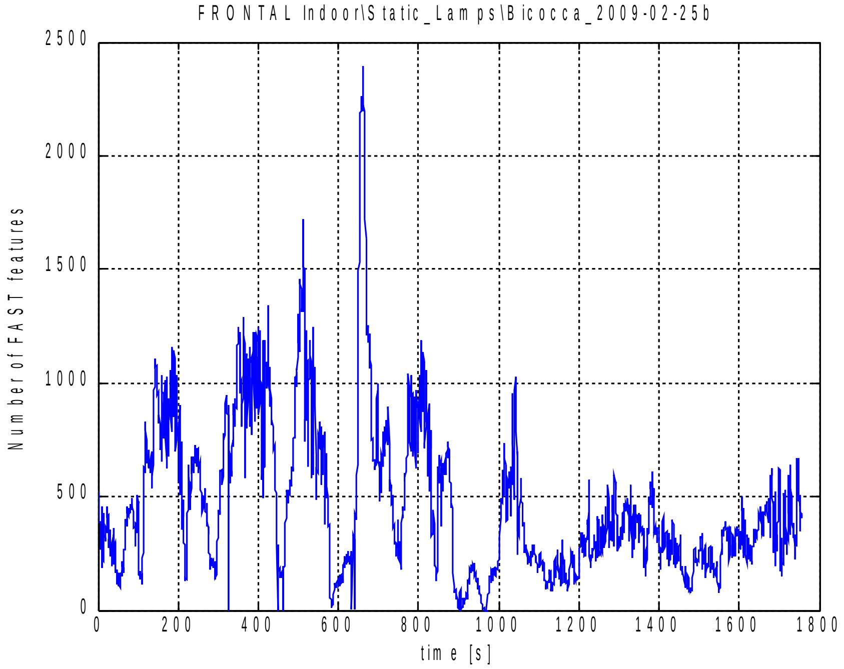


Map and camera trajectory obtained after running visual SLAM on Indoor / Static_Lamps/ Bicocca_2009-02-27b, from frame 1000 to frame4320.

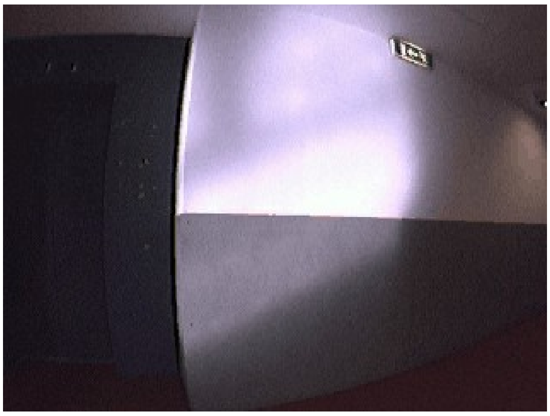


Map and camera trajectory obtained after running visual SLAM on Indoor / Static_Lamps/ Bicocca_2009-02-25b, from frame 3500 to frame 5300.

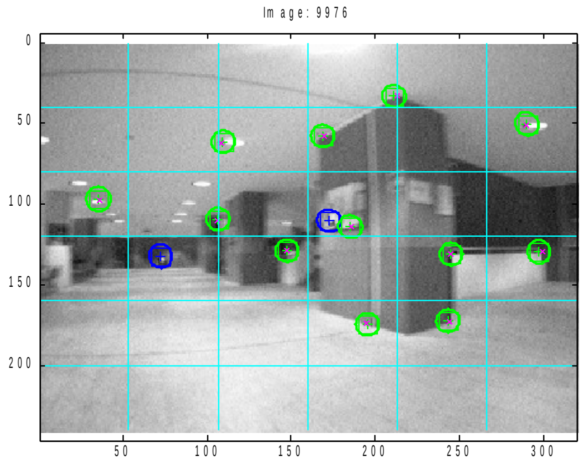
6) Data density and quality: the next figure shows the number of FAST features extracted in the same session. In general, feature density is considered good enough for feature-based monocular SLAM.



We have found that some parts of the dataset, mainly in the corridors, have low feature density, making them challenging for pure visual SLAM. In old datasets it was found that in quick turns the images appear blurred. The suggested corrective actions described in Deliverable 3.1 has been considered for the new datasets, and now only very few blurred images appear in the datasets.



Example of images with poor texture in Biccoca_2009-02-25b



Old Datasets: Example of blurred image and Harris corners obtained.

New datasets contain very few blurred images.
Examples extracted from Biccoca_2009_02_25b dataset.

Dark images are a latent problem in new indoor datasets (See next figure). This can be seen also when analyzing the number of FAST features along the sequence: minima in the plot corresponds mostly to dark frames.

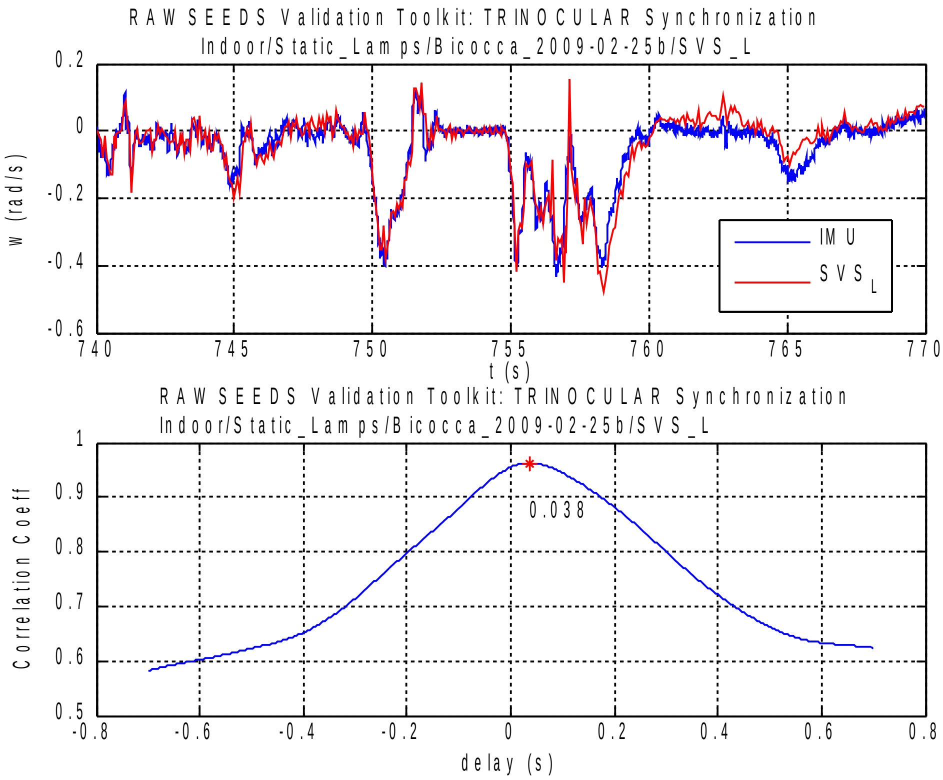
Example of dark image in sequence Biccoca_2009_02_25b.

All these image defects are common in realistic visual experiments and constitute challenging problems. We note that the probabilistic approaches commonly used for SLAM can deal successfully with blurring issues and some low texture scenarios.

7) Camera calibration is a critical issue for a visual SLAM dataset. The calibration sequences and the calibration results provided with the dataset have been manually inspected to verify their quality levels. Our main conclusion is that the calibration process has been improved and provides a good quality. The calibration images were properly acquired and the precision of the calibration obtained is better than the past sequences used in previous calibrations. The values are close to the usual standards for this type of cameras. More details and suggestions about how to perform correct calibration are described in section 5.

4.1.8. Trinocular Vision

1) Data is verified to be in compliance with the file specification and timestamped File format: all image files are readable.
2) Timing: see table in section 4.1.1. Trinocular camera also present stable timing characteristics with none gap. We also inspected the images with timestamps along the sequence. The results do not show evidence of lost frames.
3) The synchronization of the vision data with IMU is verified by comparing the angular velocities obtained running visual SLAM on the datasets. Most of the datasets register delays around 50ms with respect to IMU (see figure below). We notice that the stereo camera used has a narrow field of view and a slower frequency compared to monocular cameras. This might be one of the reason for which the estimated angular velocities are rather worse. In any case, we find it valid to estimate the delays.



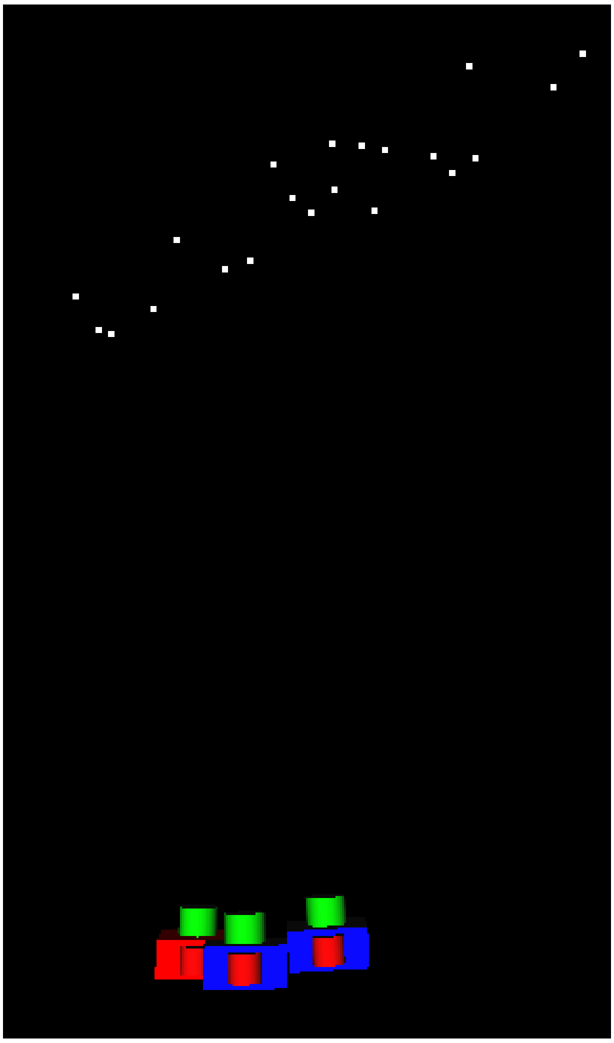
Validation of TRINOCULAR synchronization by cross-correlation with IMU of the angular velocities obtained from SLAM

4) Calibration: In comparison to past datasets, the new datasets provide calibration for the external parameters (the cameras relative position and

orientation). The calibration images provided have been found of good quality to perform the extrinsic calibration. More details about this important issue are given in section 5.3.

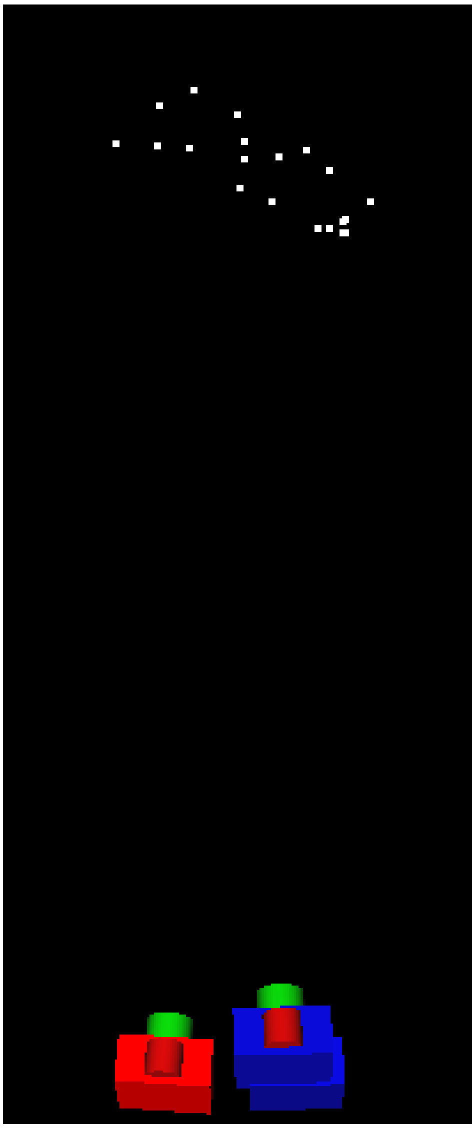
5) Data quality: In order to validate the position of the three cameras, a 3D reconstruction is performed on trinocular frame 6386 of the dataset Indoor\Static_Lamps\Bicocca_2008-02-25b. We did not find incoherences.

L: 1235603761.776759 *T: 123560376 1.776668* *R: 1235603761.776839*



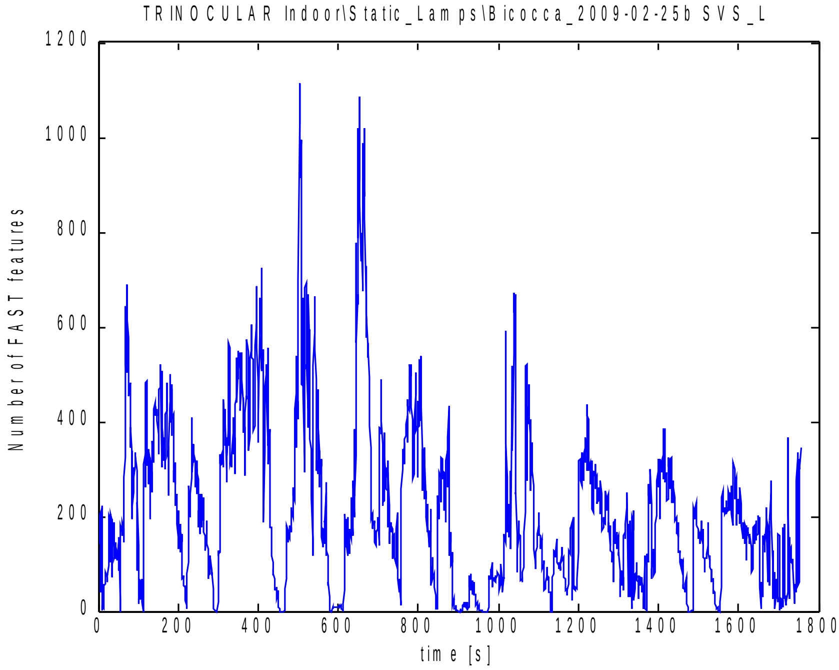
3D reconstruction of frame 6386 in Indoor\Static_Lamps\Bicocca_2008-02-25b. The SVS L image corresponds to the red camera.

L:1235762927.931062 *T:1235762927.932067* *R: 1235762927.931062*



3D reconstruction of frame 20438 in Indoor\Static_Lamps\Bicocca_2008-02-27b. The SVS L image corresponds to the red camera.

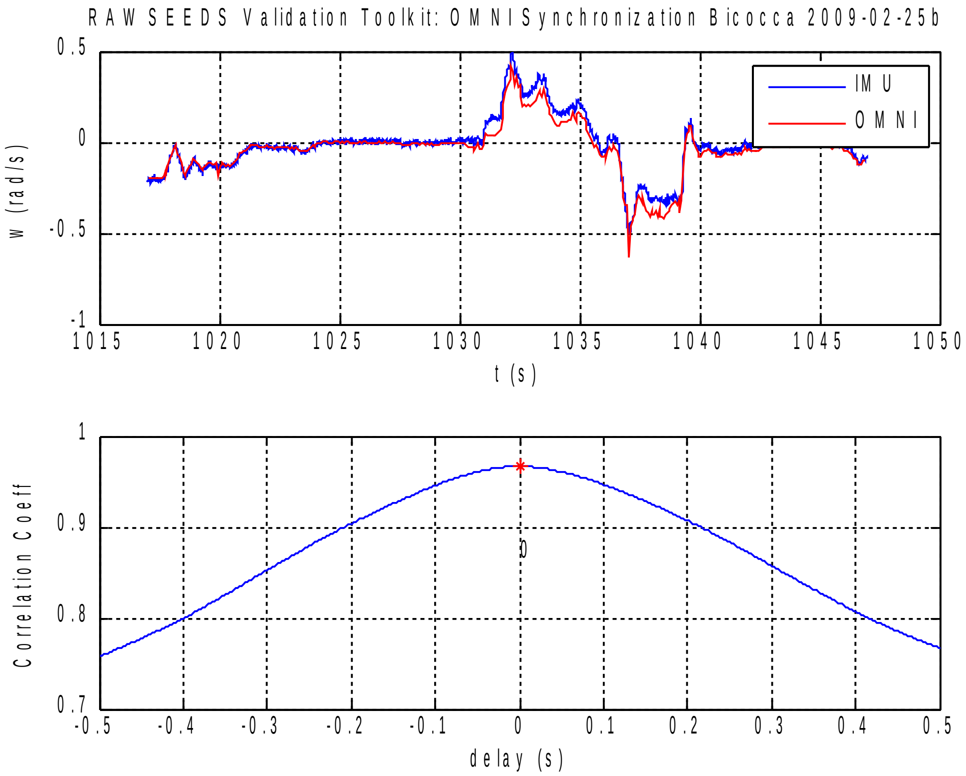
6) Data density: Detection of point features together Monocular SLAM have been run on sequences to validate the density of features. The following figure shows the number of features points detected per frame.



The minimum values in the figure are mainly due to low textured frames and dark images as it has been corroborated by visual inspection. This, however, does not invalidate the use of the datasets for visual SLAM applications.

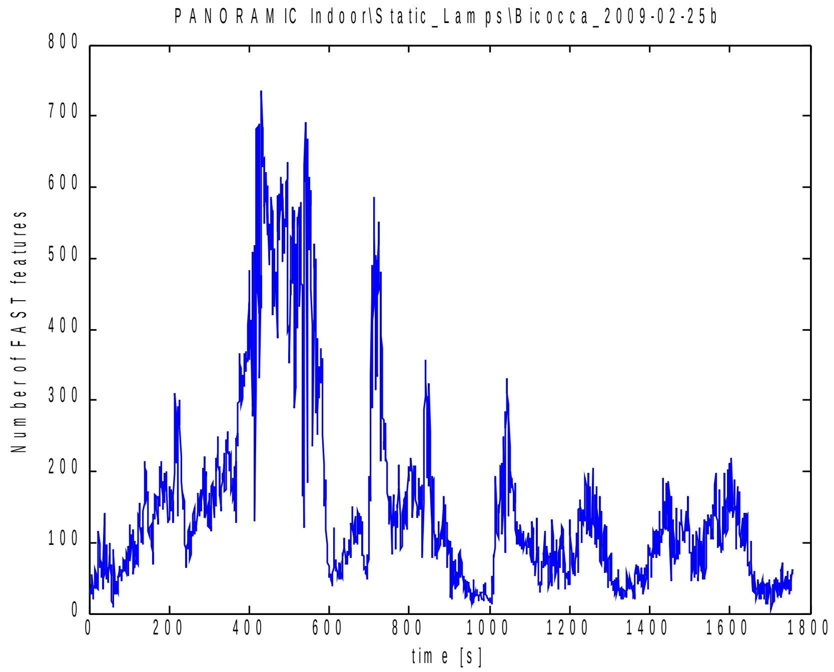
4.1.9. Panoramic Vision

1) Data is verified to be in compliance with the file specification and timestamped File format: all image files are readable.
2) Timing: see table in section 4.1.1. We did not find critical data gaps when evaluating the delta time in static Indoor datasets.
3) The synchronization is verified by matching SURF points between pair of images [A.C. Murillo et al, ICRA 2007]. The result allowed us to compute the relative orientation of the camera in each instant of time. This information has been enough to obtain angular velocities and thus, determine the correlation with IMU angular velocities.



Validation of the Panoramic synchronization by cross-correlation with IMU of the angular velocities obtained from SURF Matchcing

4) Data density and quality are validated by running SURF feature extractor throughout the image sequences. We also run SLAM software along the sequence to check the density of FAST features.



We did not detect any defect such as black frames, missing frames, or images with excessive blur due to camera motion.

5) Calibration: the intrinsic parameters are provided for this deliverable. We validate the central point value for the camera obtaining 0,31% of error in Y-coordinate and 0,0009% in X-coordinate. We conclude that these parameters are of good quality and usable for any visual localization algorithm.

4.2. Validation of Indoor-Dynamic sessions

In these datasets there is not severe data loss. It is only present for Hokuyo laser and it is not recommended its use for SLAM. In the following, we first present the main time characteristics of the dataset, and then present the most important details of the validations performed for each sensor stream. Only the sensors that present some novelties with respect to Inddoor-static sessions are described, e.g. the Hokuyo laser is not mentioned here. This means that considerations similar to the ones exposed in the previous session also apply here.

4.2.1. Basic time properties

The following tables summarize the main timing characteristics of the data streams obtained from the different sensors (F: mean acquisition frequency, T: mean period, Tmax: maximum time interval between two consecutive acquisitions, Delay: mean delay with respect to IMU time base, std Delay: standard deviation of the delay). Cells highlighted in yellow represent data loss or synchronization issues, cells marked with '--' could not be computed.

Indoor / Dynamic_Lamps / Bicocca_2009-02-26b										
	IMU	Odometry	Sick R	Sick F	Hokuyo R	Hokuyo F	Frontal	Trinocular	Panoramic	Sonar
F (Hz)	127,96	47,62	76,92	76,92	10,09	10,06	29,95	15	14,97	12,5
T (ms)	7,8	20,99	13,00	13,00	99,02	99,35	33,37	66,65	66,78	79,97
Tmax (ms)	7,8	29,05	21,06	23,04	171,16	172,06	34,92	68,05	127,96	91,02
Delay (ms)	--	-152,17	-45,70	-49,76	--	--	7,0	-63,66	-3,4	--
std Delay (ms)	--	65,38	7,23	6,75	--	--	4,3	20,33	9,4	--

Indoor / Dynamic_Daylight / Bicocca_2009-02-25a										
	IMU	Odometry	Sick R	Sick F	Hokuyo R	Hokuyo F	Frontal	Trinocular	Panoramic	Sonar
F (Hz)	127,96	47,62	76,92	76,92	10,09	10,06	29,95	15	14,97	12,5
T (ms)	7,8	20,99	13,00	13,00	99,01	99,34	33,37	66,65	66,78	79,97
Tmax (ms)	7,8	27,01	23,92	22,59	105,78	105,79	66,65	68,36	108,52	104,13
Delay (ms)	--	-135,38	-46,76	-44,92	--	--	-0,4	-58,5	-6,3	--
std Delay (ms)	--	31,34	5,59	6,02	--	--	4,4	10,94	10,7	--

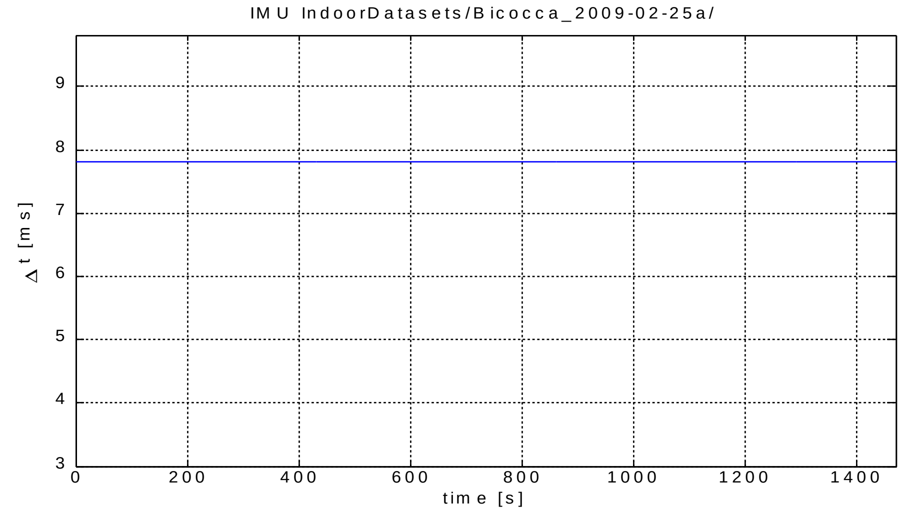
Indoor / Dynamic_Daylight / Bicocca_2009-02-26a										
	IMU	Odometry	Sick R	Sick F	Hokuyo R	Hokuyo F	Frontal	Trinocular	Panoramic	Sonar
F (Hz)	127,96	47,61	76,92	76,92	10,09	10,06	29,95	15	14,97	12,5
T (ms)	7,8	21,00	13,00	13,00	99,02	99,31	33,37	66,65	66,78	79,97
Tmax (ms)	7,8	30,53	19,60	39,99	171,08	171,04	63,27	67,68	98,58	109,98
Delay (ms)	--	-151,25	-43,41	-43,16	--	--	1,6	-85,25	-6,8	--
std Delay (ms)	--	48,51	7,57	8,40	--	--	4,0	40,34	5	--

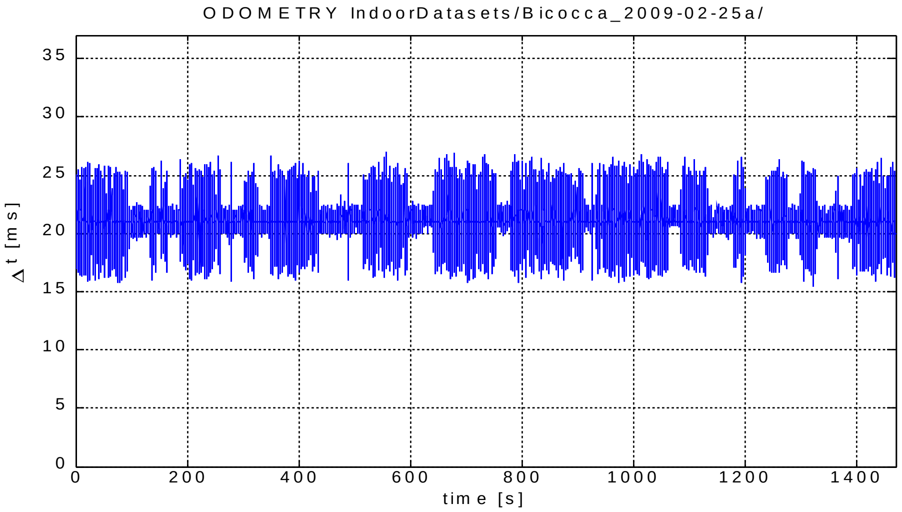
The delays are similar to those in indoor static sessions. With respect to time periods, when for a sensor stream Tmax is bigger than 2*T, most probably some data have been lost. This can be seen more clearly in the following figures that plot the time separation between every pair of consecutive acquisitions.

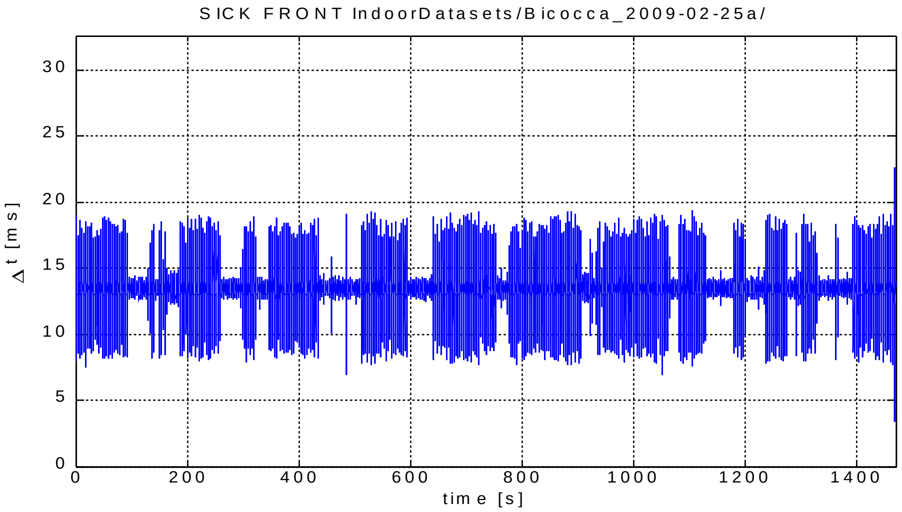
The conclusions for this dataset are:

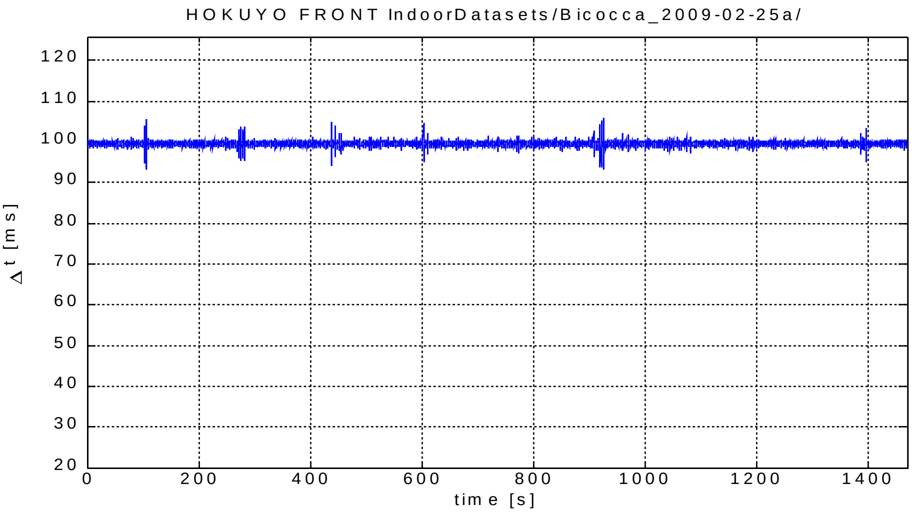
1) FRONTAL camera presents data gaps of 66 ms (2*T). It means that at least 1 frame per data gap is lost. This amount of lost frames is admissible and will not affect tasks such as monocular SLAM.

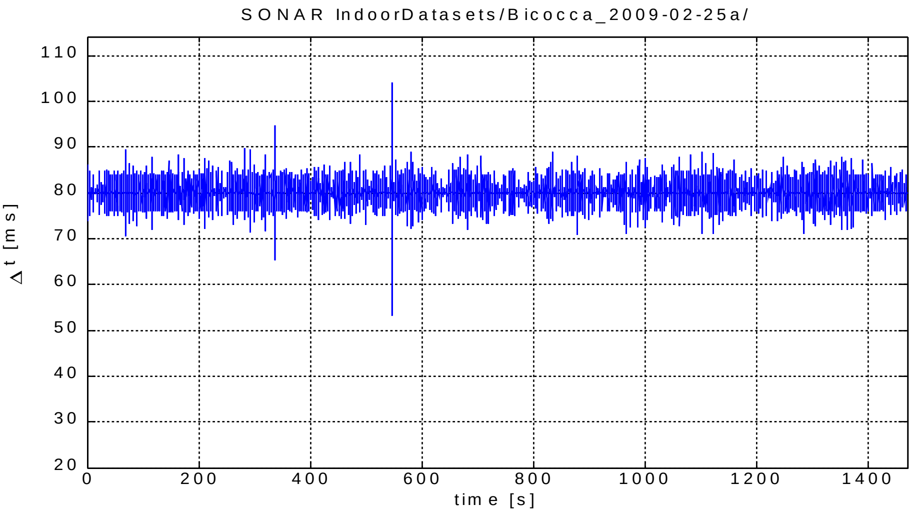
2) Most of the sensor data is correct, with minor period oscillations.

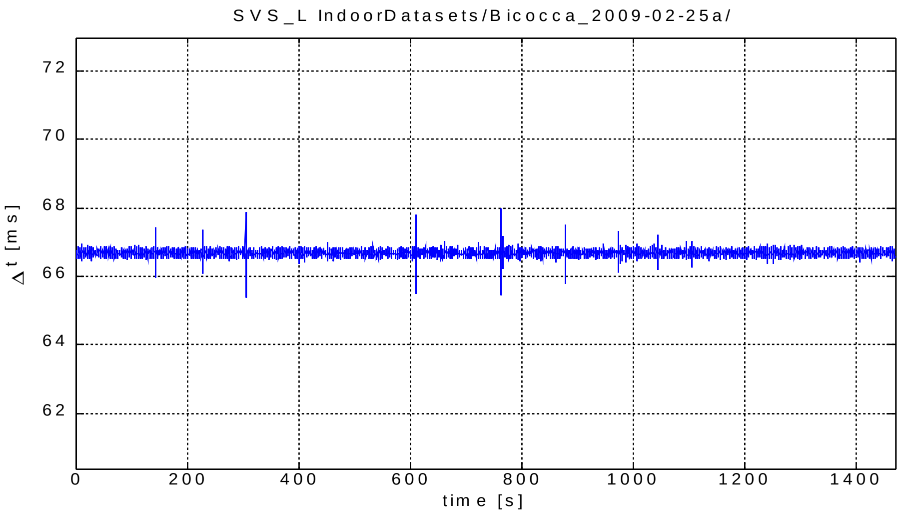


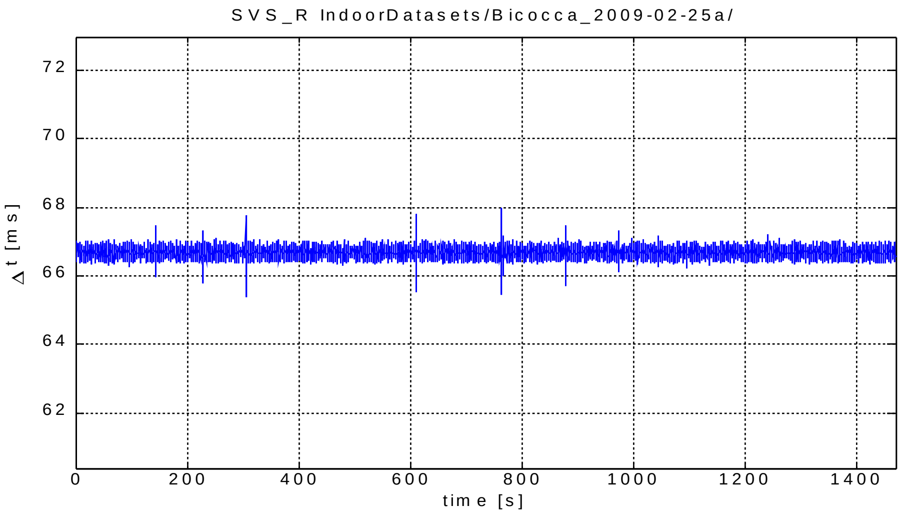


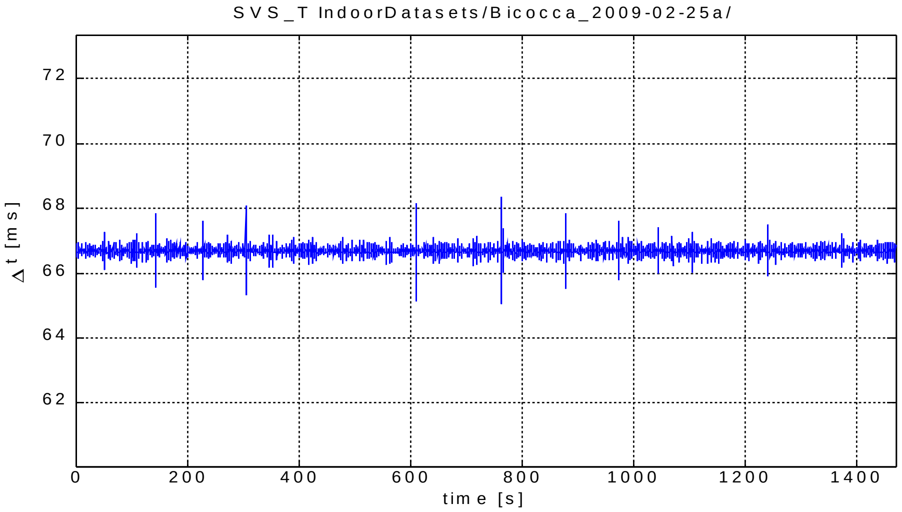


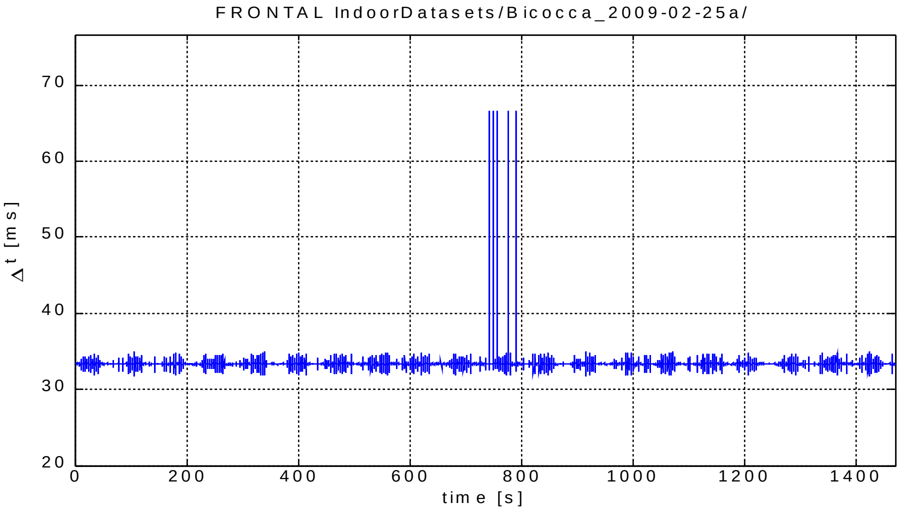

HOKUYO FRONT IndoorDatasets/Bicocca_2009-02-25a/
Δt [ms]
time [s]

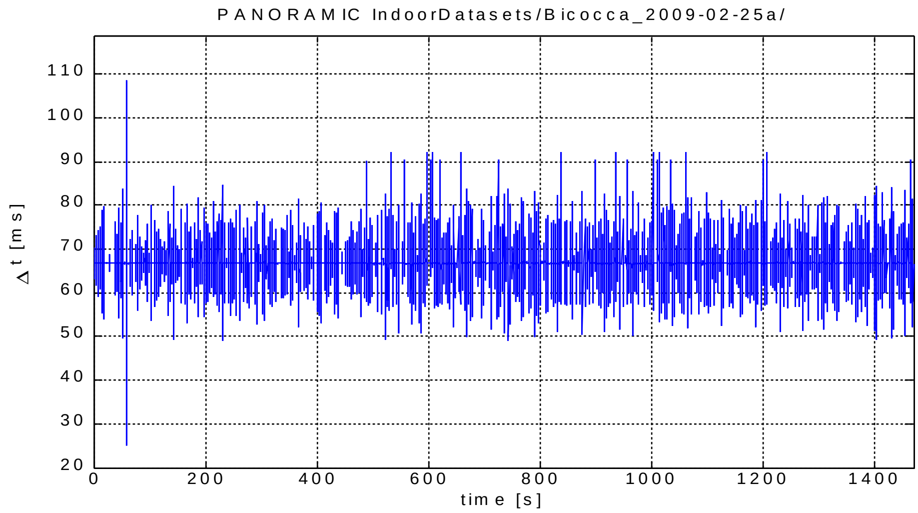

SONAR IndoorDatasets/Bicocca_2009-02-25a/
Δt [ms]
time [s]


SVS_L IndoorDatasets/Bicocca_2009-02-25a/
Δt [ms]
time [s]


SVS_R IndoorDatasets/Bicocca_2009-02-25a/
72
70
68
66
64
62
Δt [ms]
0
200
400
600
800
1000
1200
1400
time [s]

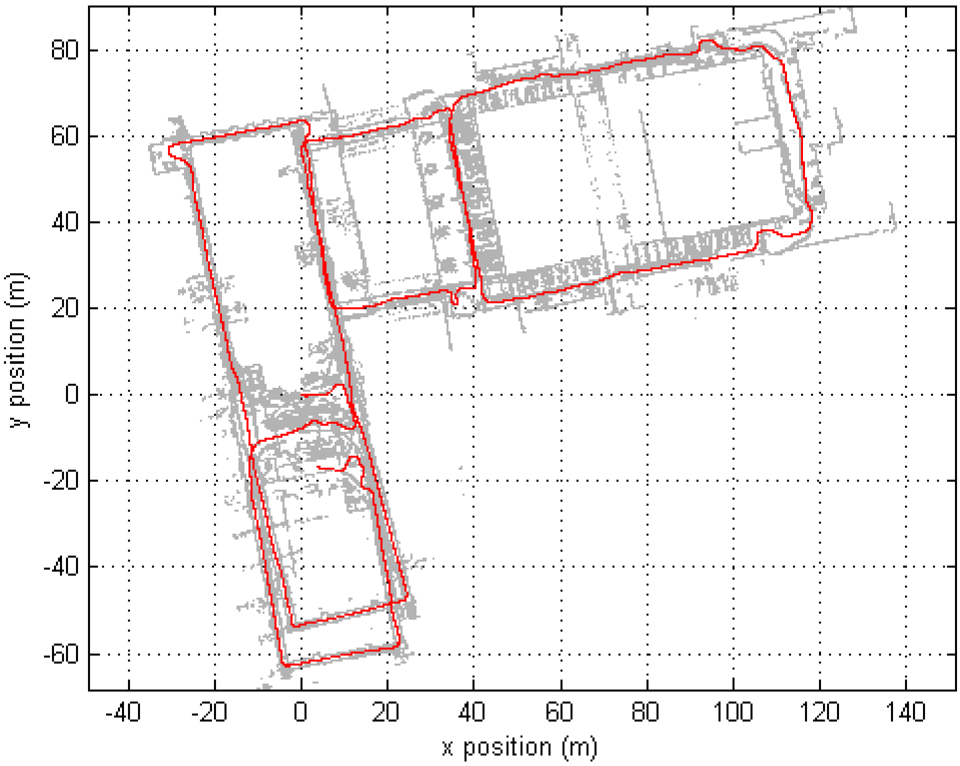

SVS_T IndoorDatasets/Bicocca_2009-02-25a/
72
70
68
66
64
62
Δt [ms]
0
200
400
600
800
1000
1200
1400
time [s]


FRONTAL IndoorDatasets/Bicocca_2009-02-25a/
70
60
50
40
30
20
Δt [ms]
0
200
400
600
800
1000
1200
1400
time [s]


PANORAMIC IndoorDatasets/Bicocca_2009-02-25a/
Δt [ms]
time [s]
110
100
90
80
70
60
50
40
30
20
0
200
400
600
800
1000
1200
1400

4.2.2. SICK Laser

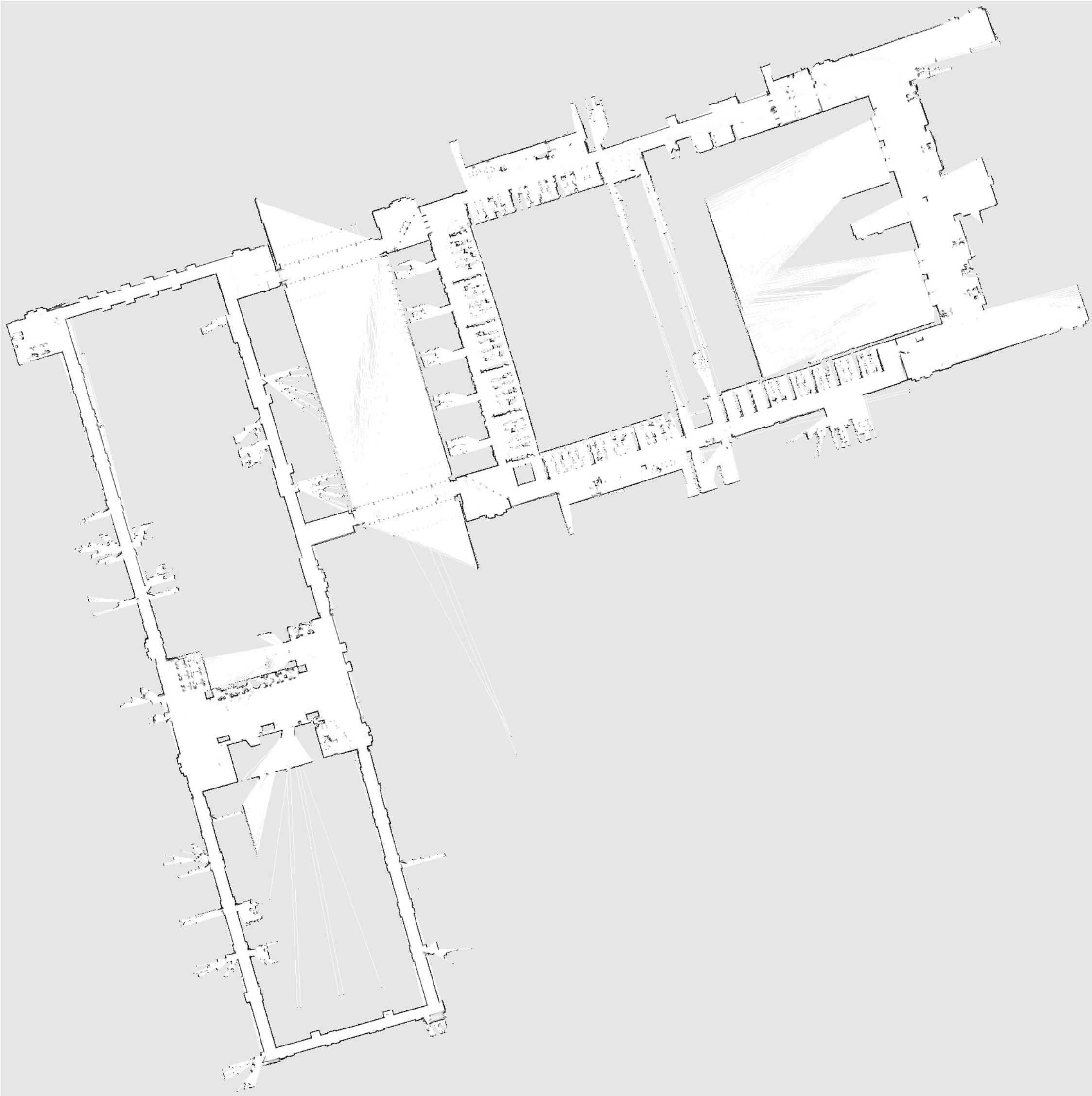
1) File format is correct and fulfill the specifications.
2) Timing: the nominal frecuency is validated. There are not data loss.
3) Data density and quality are validated by running laser scan matching software developed in UNIZAR to obtain the missing odometry data:



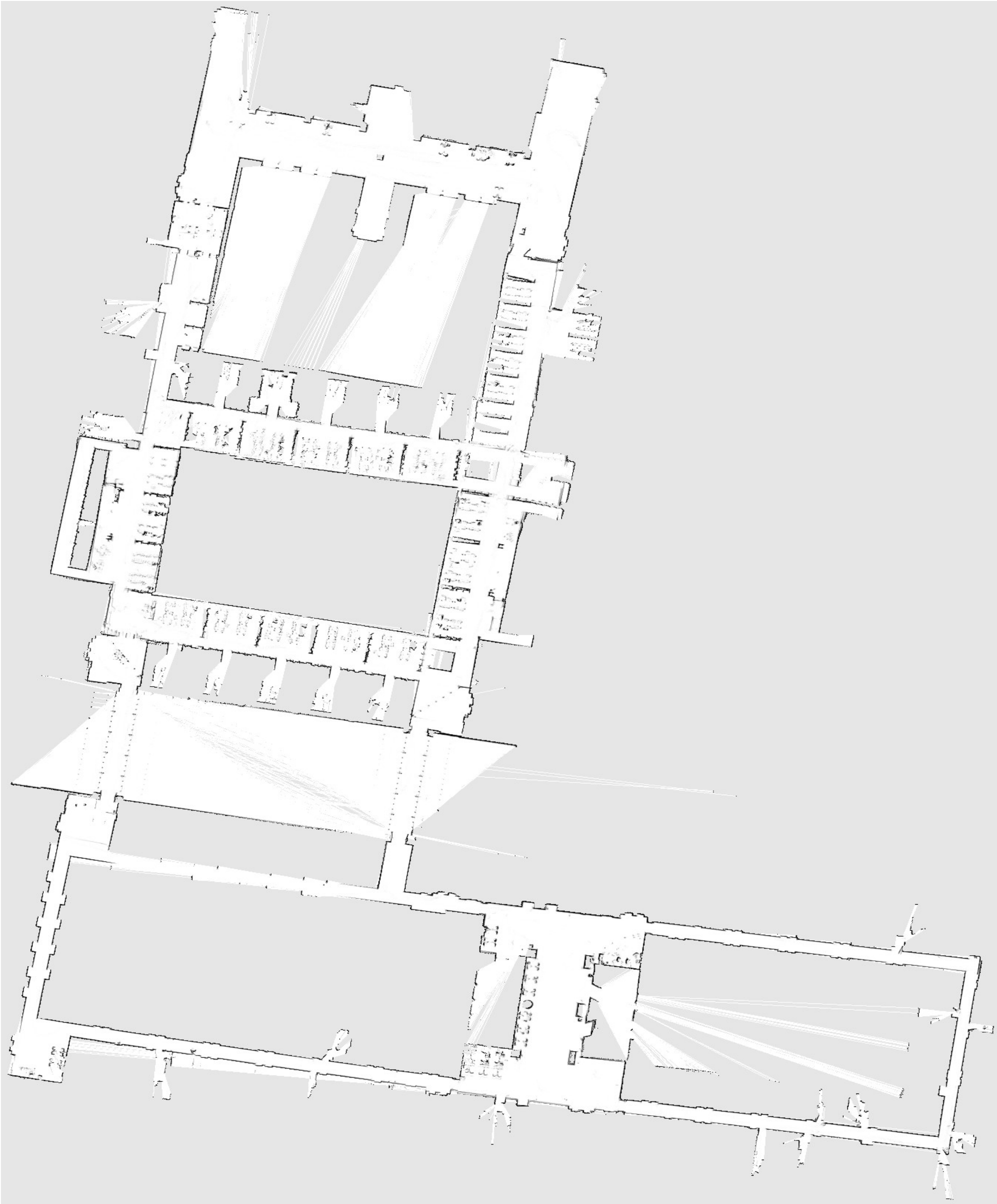
Scan Matching on Indoor/Bicocca_Dynamic_Daylight/Bicocca_2009-02-25a/ dataset. This method improve odometry but do not perform Map correction.

Although map correction is not carried out, the results obtained are sufficient to initialize a 2D SLAM with any robust algorithm.

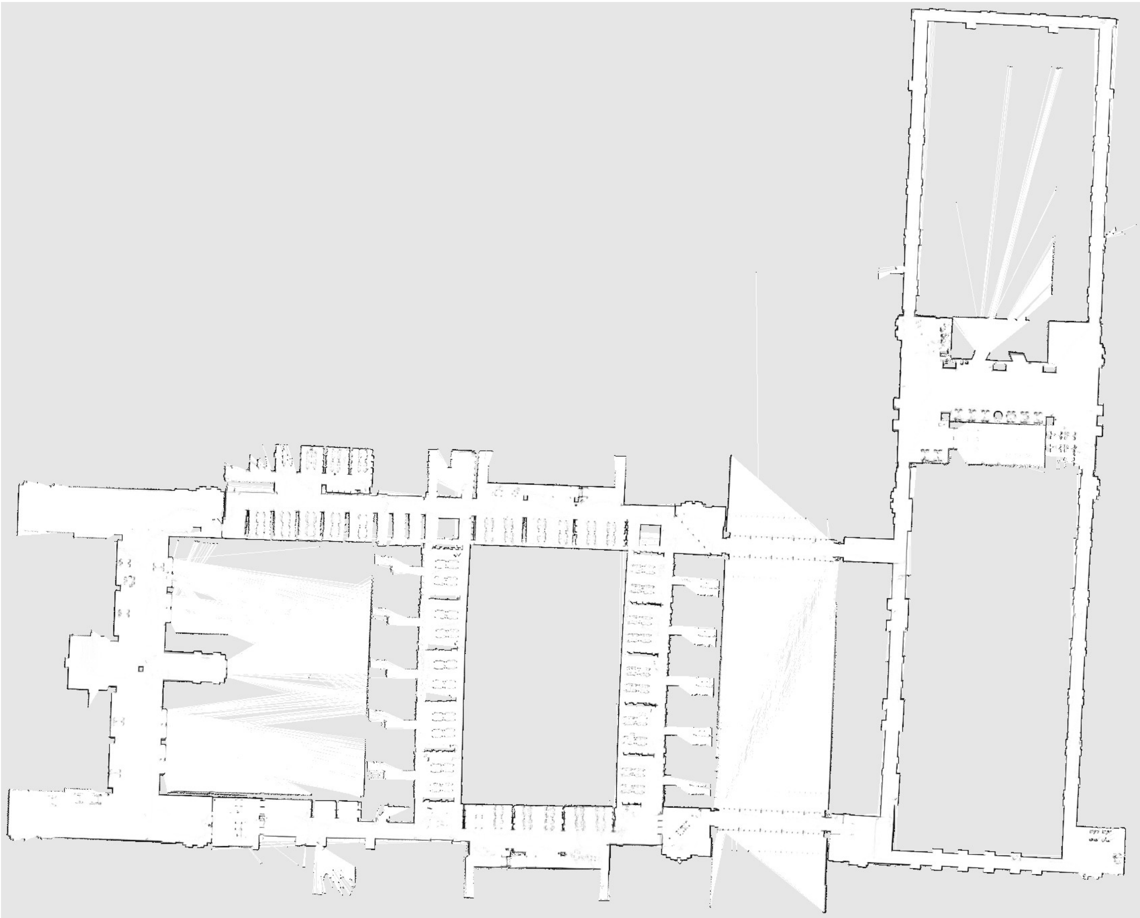
4) Data Overlap: ALURF software has been run to validate the requirements of the dynamic datasets for SLAM tasks.



Map obtained from Bicocca_2008_02_25a using Graph SLAM algorithm.



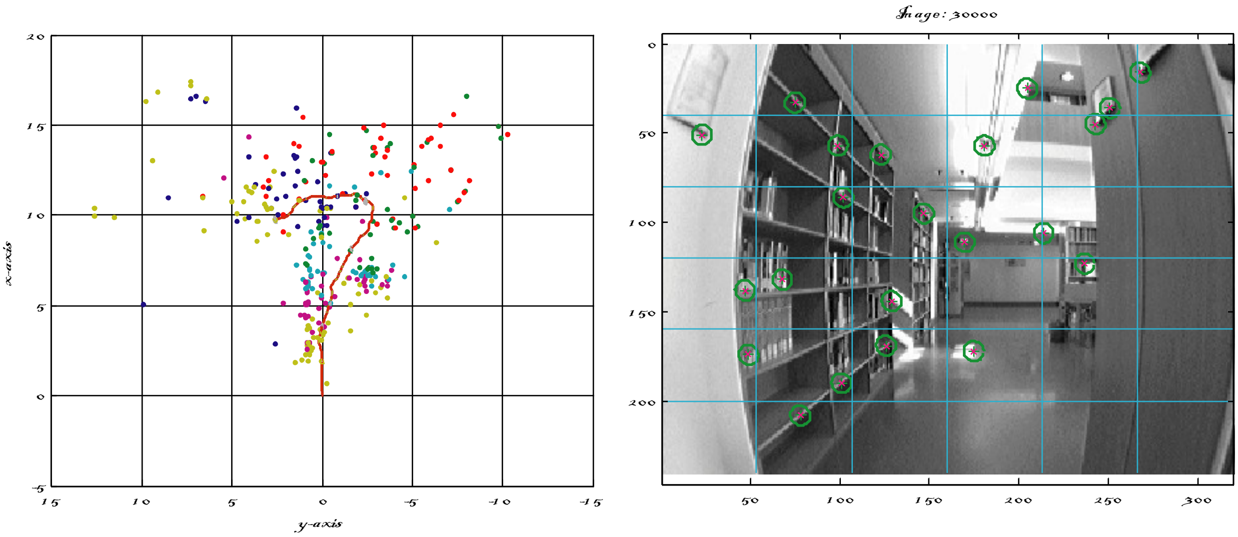
Map obtained from Bicocca_2008_02_26a using Graph SLAM algorithm.



Map obtained from Bicocca_2008_02_26b using Graph SLAM algorithm.

4.2.3. Monocular Vision

1) Data is verified to be in compliance with the file specification and timestamped File format: all image files are readable.
2) Timing: see table in section 4.2.1.

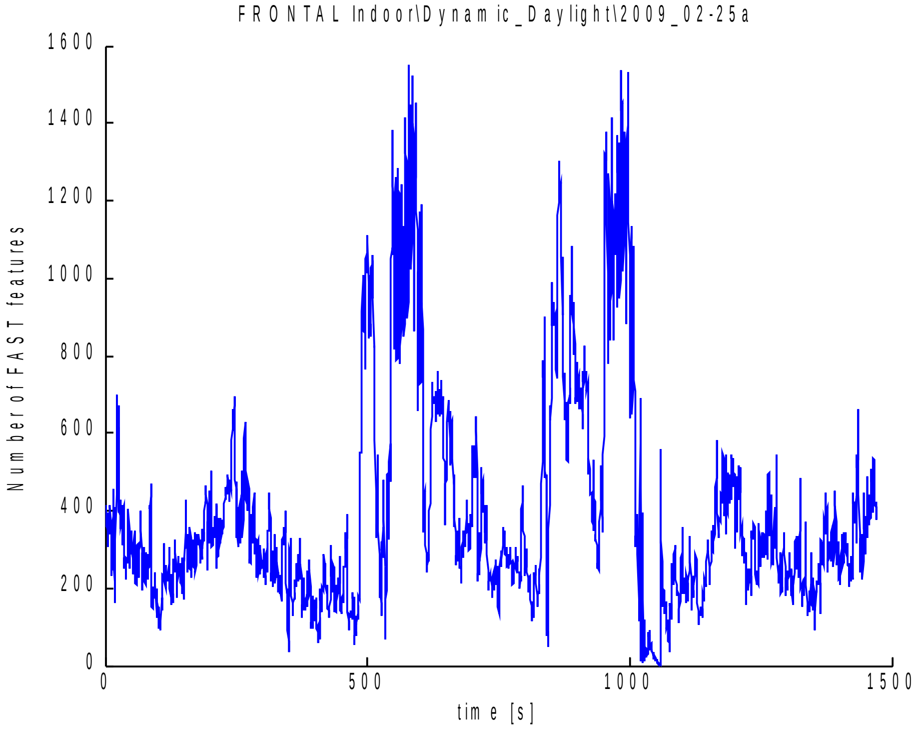


Map results obtained from Indoor /Bicocca_Dynamic_Daylight/Bicocca_2009-02-25a from frame 30000 to frame 33500

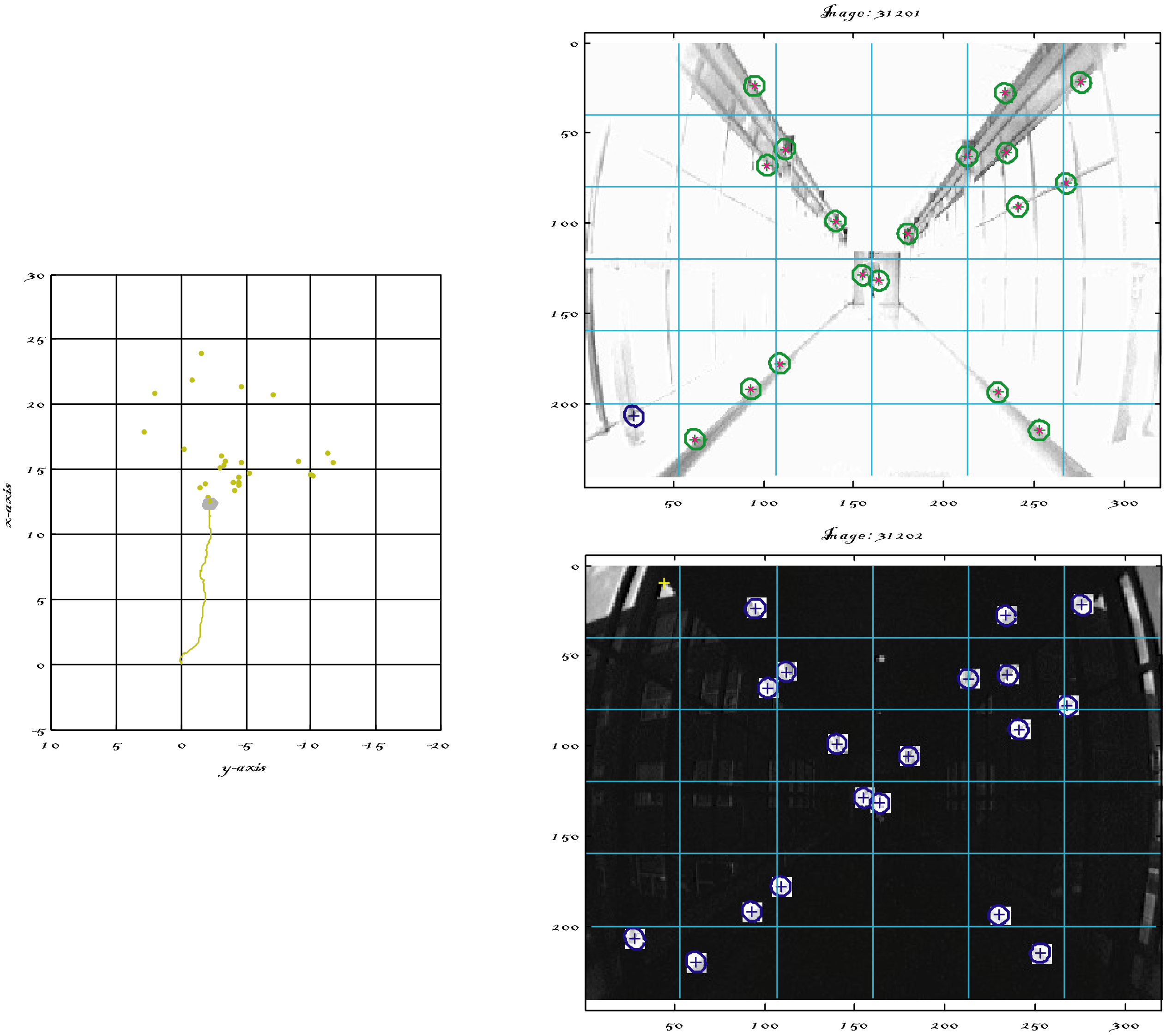
3) Data overlap: It has been verified that the sequence can be processed by standard inverse depth + JCBB monocular SLAM. The figure shows an example after processing a typical scenario in indoor dynamic session; corresponding to a trajectory about 30 meters long.

   Dark frames are still found in dynamic datasets, but their effect on the monocular SLAM is negligible. For example, in the above processed sequence, a dark frame was encountered and managed without problems by the SLAM algorithm.

4) Data density: The next figure shows the number of FAST features extracted. The density of features can be guarantee to run visual SLAM algorithms.



Low density frames correspond either to the reported "dark" frames, or to low textured images. The figure above is an example of the set of dark images that we found from frame 30800 (time instant 1023s) to frame 31760 (time instant 1059). This set represent a corridor scene for which we executed visual SLAM with success:



Monocular SLAM along a corridor subsequence. One of two images corresponds to a dark frame. Nonetheless the tracking is performed without problems. The map result and the estimated trajectory are still admissible solutions.

5) Calibration images used in this session fulfill the guidelines proposed by Bouguet. See section 5.3 for more details.

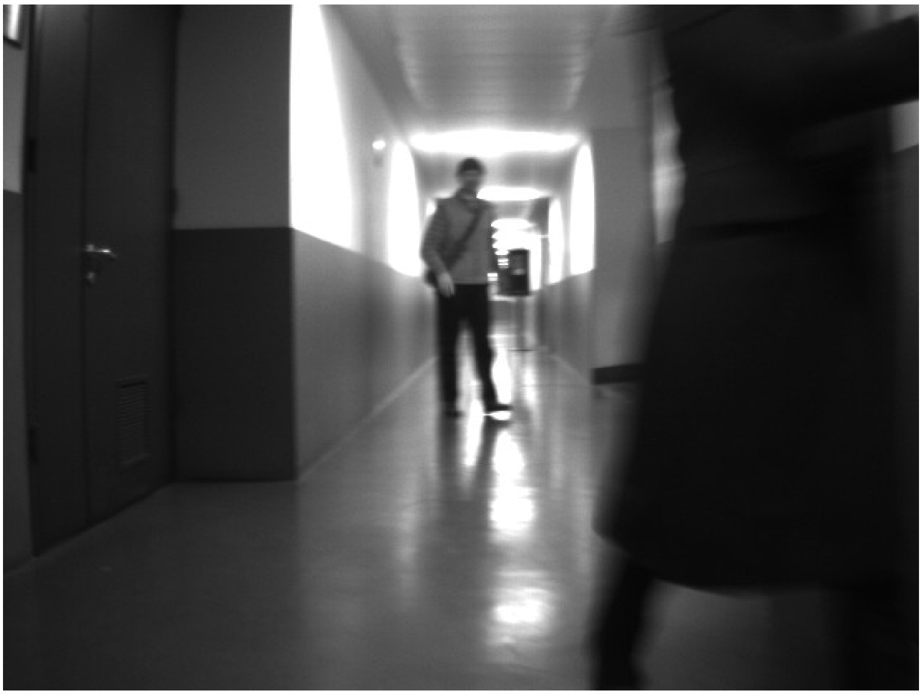
4.2.4. Trinocular Vision

1)Data is verified to be in compliance with the file specification and timestamped File format: all image files are readable.

2)Timing: see table in section 4.2.1. Trinocular delta times do not present data gaps. We run visual SLAM software developed in UNIZAR to evaluate the synchronization of trinocular camera with IMU. The results shows that none of the indoor dynamic datasets provides delays higher than 40ms.

3)Data density and quality is evaluated by running visual SLAM the parts of the sequence. Indoor dynamic datasets are exposed to poor light conditions making difficult the features extraction process. Also, the low texture scenarios still appear. This, however, correspond to realistic environment problems and does not restrict the validation of the datasets. Although important efforts have been done to improve the quality of the images, attention should be paid to blurred images, especially when the robot turns.

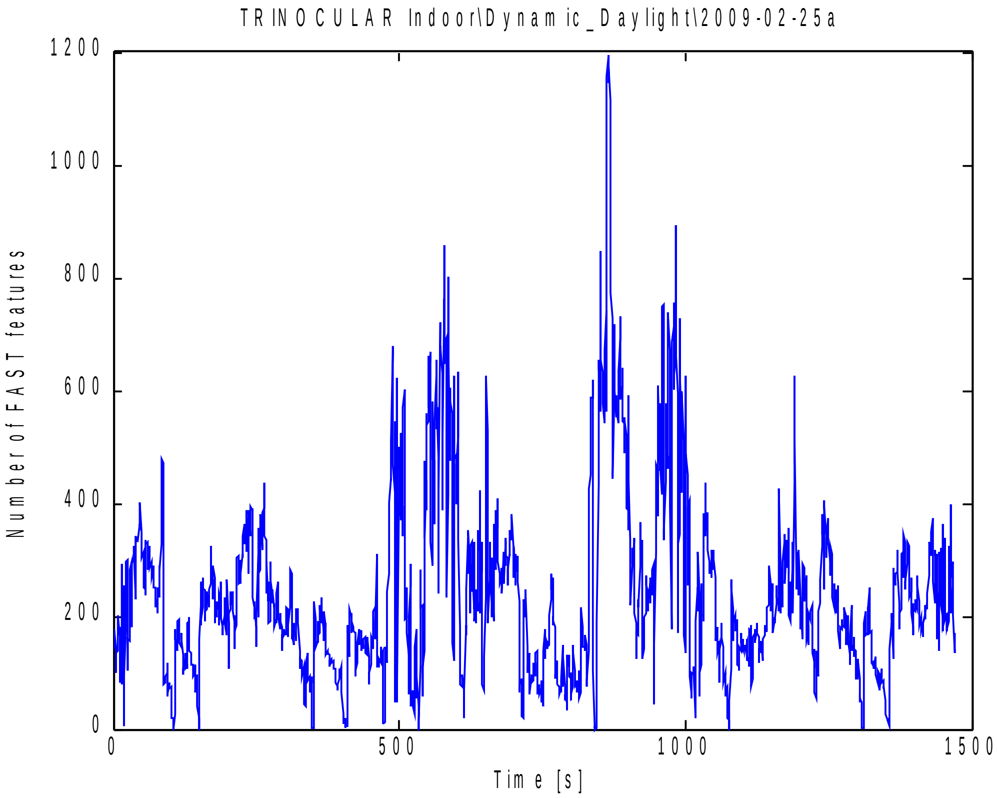
image 4250



Example of a blurred image extrated from the interval 4240-4260 in Indoor\Dynamic_Daylight\Bicocca_2009-02-26a dataset

In order to evaluate the density of the data, we analyzed the number of FAST features obtained in each step when running our visual SLAM algorithm.

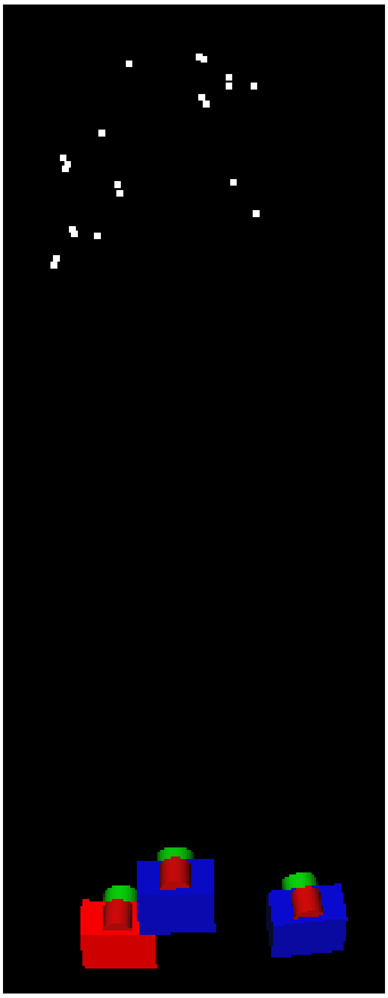
The behavior of the plot is very similar to that obtained for FRONTAL camera and do not impose any constraint to carry out SLAM.



4) Calibration is the same that for indoor static datasets and do no imposed problems.

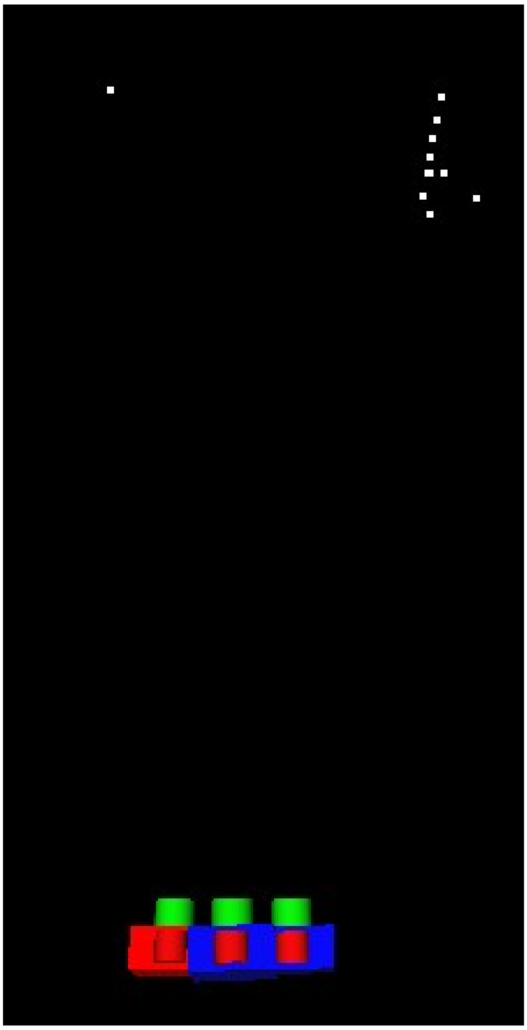
The position of the three cameras is also corroborated by performing 3D reconstruction. The results are shown in following figures without discrepancies:

L: 1235563000.330458 *T: 1235563000.330173* *R: 1235563000.330313*



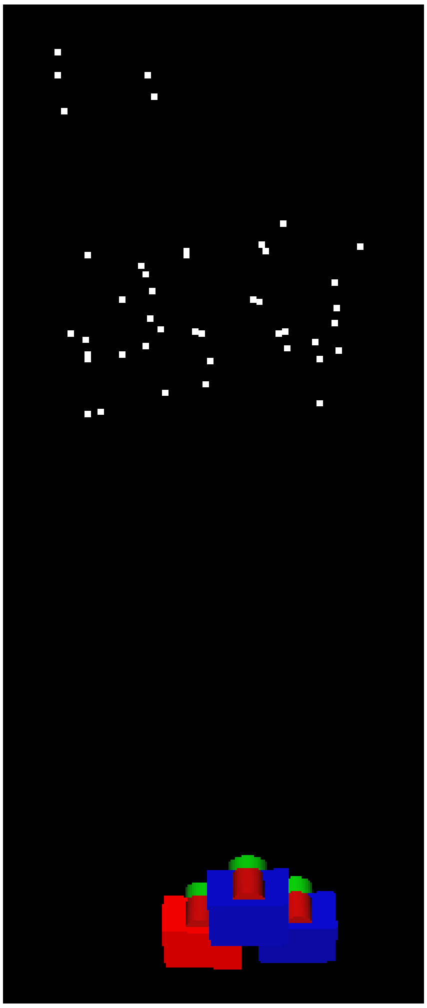
3D reconstruction on Biccoca_2009_02_25a frame *19860*. The SVS L image corresponds to the red camera.

L: 1235647061.176057 T: 1235647061.175928 R: 1235647061.176179



3D reconstruction on Biccoca_2009_02_26a frame 153. The SVS L image corresponds to the red camera.

L: 1235673841.975043 T: 1235673841.974988 R: 1235673841.975091

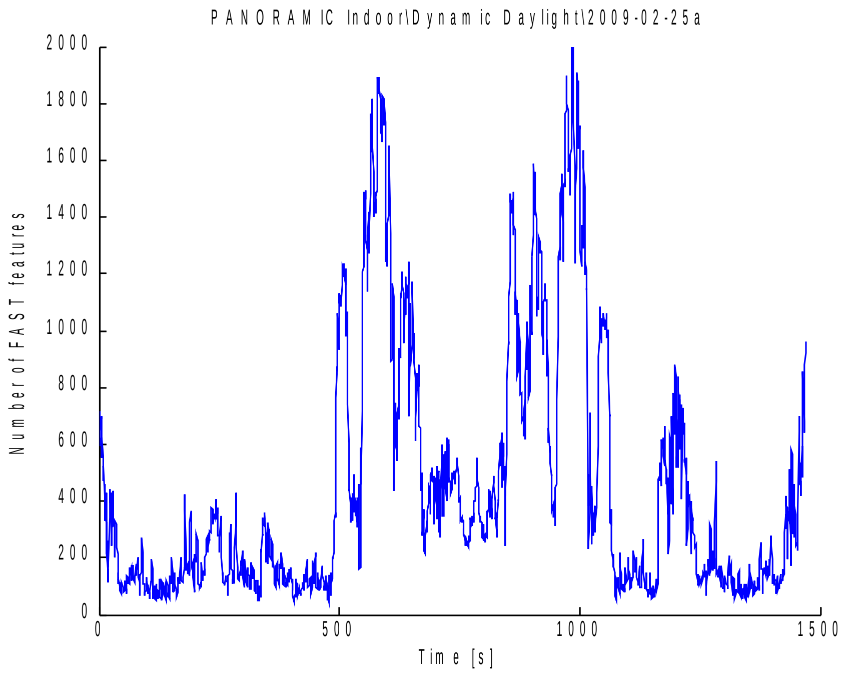


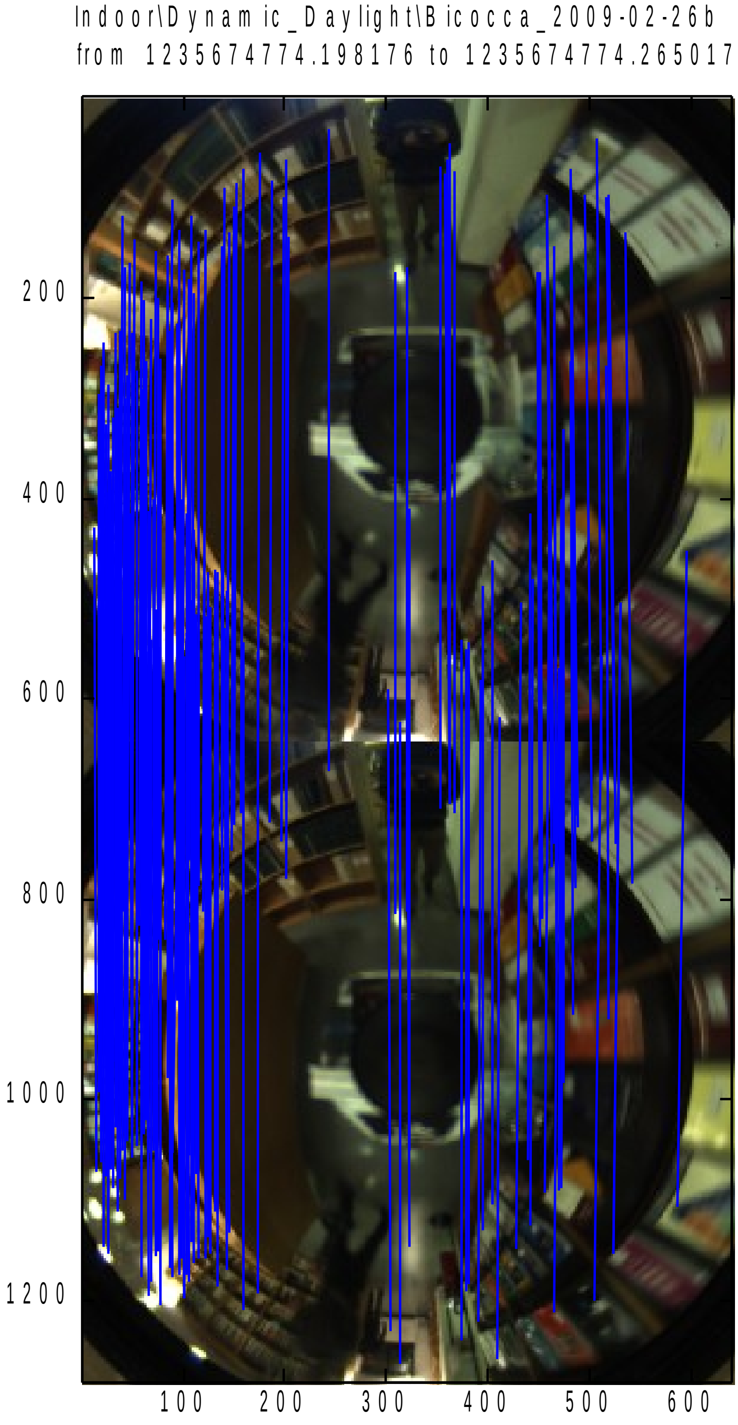
3D reconstruction on Biccoca_2009_02_26b frame 6508. The SVS L image corresponds to the red camera.

4.2.5. Panoramic Vision

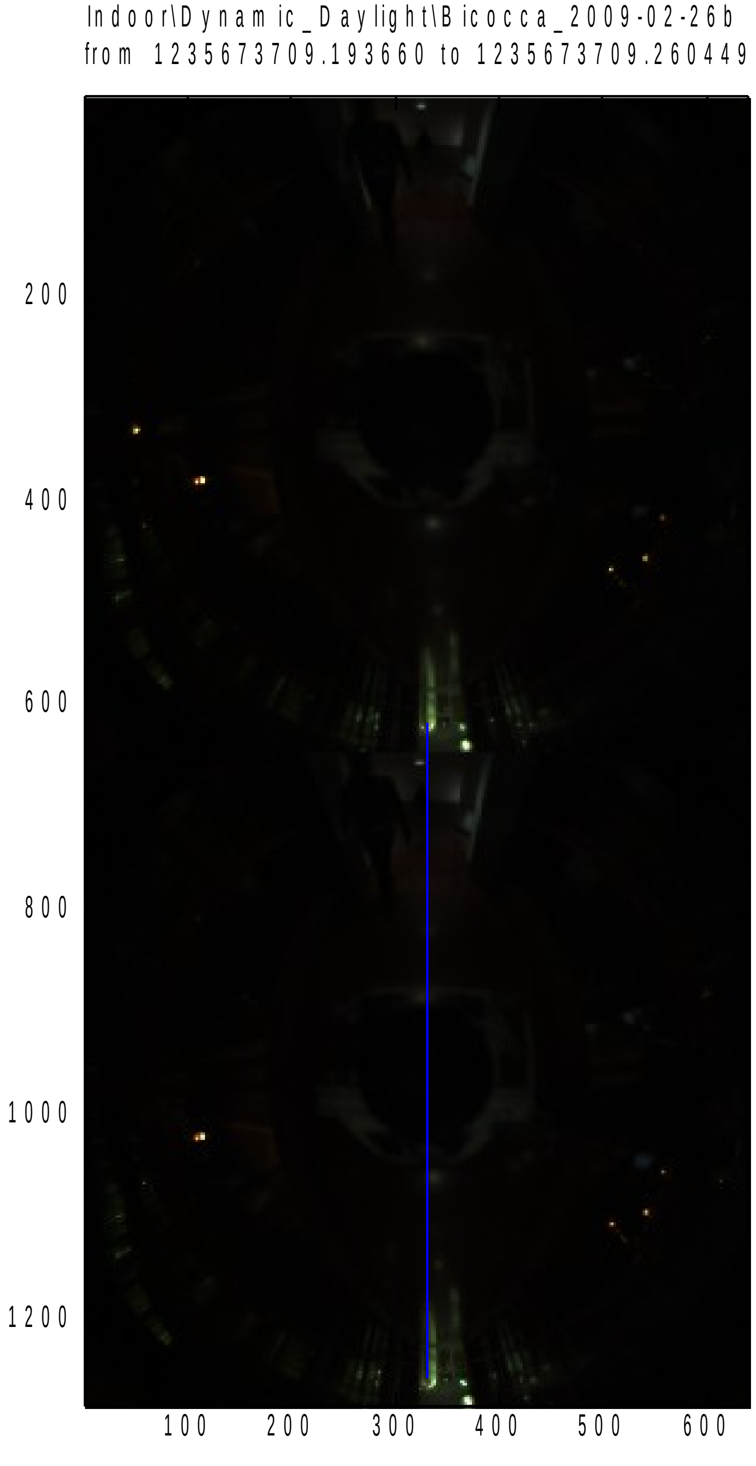
1) Data is verified to be in compliance with the file specification and timestamped File format: all image files are readable.
2) Timing: see table in section 4.2.1. nominal camera frequency has been validated without presenting data gaps. As for Indoor Static sessions, we extract SURF features in order to provide a matching solution and then compute angular velocities. Also, the inspection of the sequence demonstrated that there are not lost images.
3) Data density and quality: Next figure shows a normal result after running SURF features detector and the matching process. The number of FAST features are also extracted. The density of features can be guarantee to run visual SLAM algorithms.

   Defects such as black or missing frames, or images with excessive blur due to camera motion are not detected. However, indoor datasets taken under daylight conditions produce a low number of matches and sometimes wrong matches (see next figures). The portion of the image sequence with this defect can corrupt the solution provided for any feature based visual SLAM algorithm. Nonetheless this is common in realistic environments where it is considered a challenging problem.





Example of a successful Matching



Example of low illuminated panoramic images and the matches obtained into the sequence interval 21361—24855. There is only one match.

4.3. Validation of Mixed-Static Sessions

In the following, we first present the main time characteristics of the dataset, and then present the most important details of the validations performed for each sensor stream.

4.3.1. Basic time properties

The following tables summarize the main timing characteristics of the data streams obtained from the different sensors (F: mean acquisition frequency, T: mean period, Tmax: maximum time interval between two consecutive acquisitions, Delay: mean delay with respect to IMU time base, std Delay: standard deviation of the delay). Cells highlighted in yellow represent data loss or synchronization issues, cells marked with '--' could not be computed.

Mixed / Bovisa_2008-09-01_Static										
	IMU	Odometry	Sick R	Sick F	Hokuyo R	Hokuyo F	EYE	Trinocular	Panoramic	GPS
F (Hz)	127,97	47,62	76,85	76,83	10,09	10,07	30,0	15	15	5
T (ms)	7,8	20,99	13,01	13,01	99,02	99,29	33,4	66,65	66,68	199,92
Tmax (ms)	7,8	45,04	33,49	39,99	173,54	8831,21	133,3	133,3	109,97	316,84
Delay (ms)	--	-130,53	-45,12	-49,76	--	--	-40,5	28	-29,6	--
std Delay (ms)	--	28,66	5,73	14,05	--	--	8,7	9,2	13,2	--

Mixed /Bovisa_2008-10-11a_Static										
	IMU	Odometry	Sick R	Sick F	Hokuyo 1	Hokuyo F	Frontal	Trinocular	Panoramic	GPS
F (Hz)	127,97	47,62	76,83	76,83	10,2	12,5	29,9	15	15	5
T (ms)	7,8	20,99	13,01	13,01	98,5	80,0	33,4	66,65	66,68	199,92
Tmax (ms)	7,8	31,36	24,01	24,06	13375,6	19957,1	67,9	133,42	3541,33	371,94
Delay (ms)	--	-92,84	-49,05	-53,89	--	--	-10,9	23,1	-26,4	--
std Delay (ms)	--	49,00	7,25	10,56	--	--	8,8	25,3	14,1	--

The odometry still runs ahead of time with respect to IMU, but the offset is smaller than in the indoor datasets. The rest of delays are similar. With respect to the periods, when for a sensor stream Tmax is bigger than 2*T, most probably some data has been lost. This can be seen more clearly in the following figures that plot the time separation between every pair of consecutive acquisitions. Only visual inspection of image sequences is carried out to corroborate if data loss occurs.

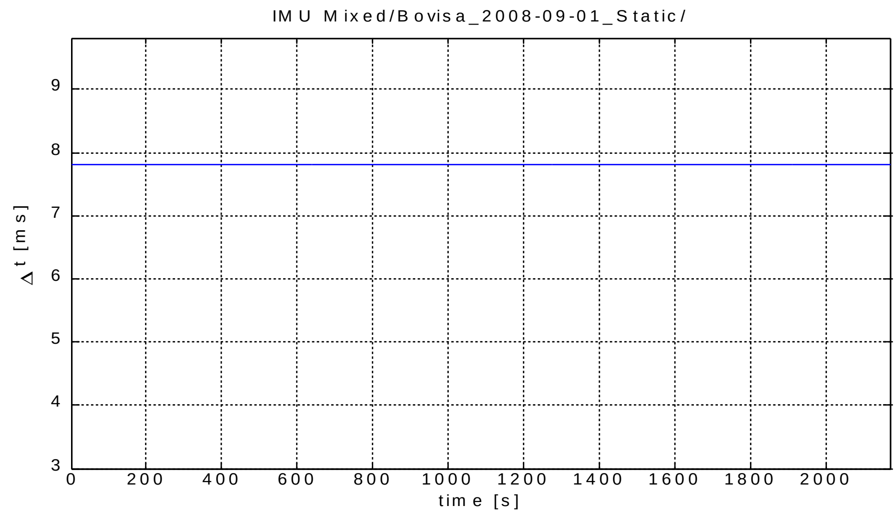
We would like to notice that dataset Mixed\Bovisa_2008-09-01_Static was previously validated in the preliminary version of this document (Deliverable 3.1), as session 20080901 . Nonetheless, we inspected for dataset changes finding that only IMU timestamps were corrected with correct interpolation.

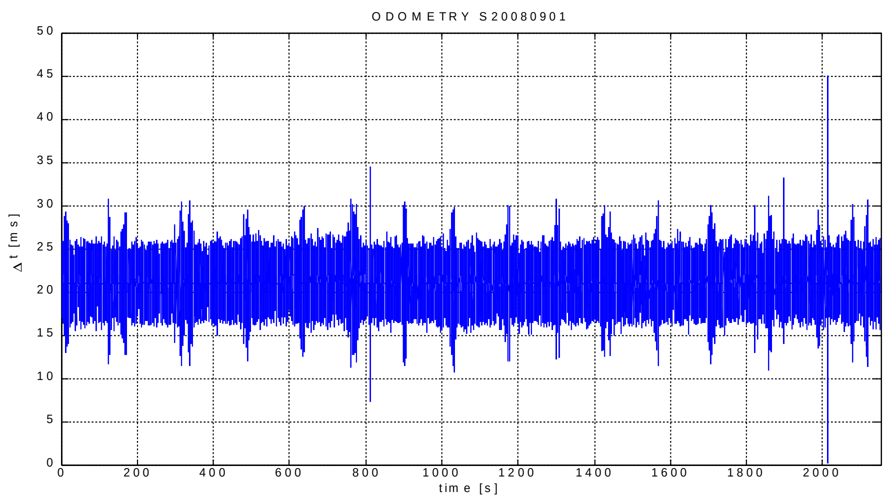
The conclusions for these datasets are:

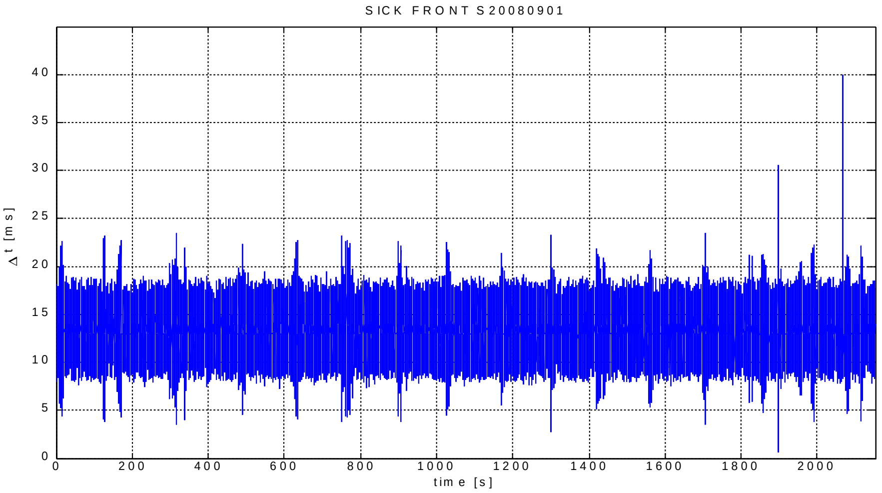
1) IMU do not present data loss, and can be used for SLAM algorithms.

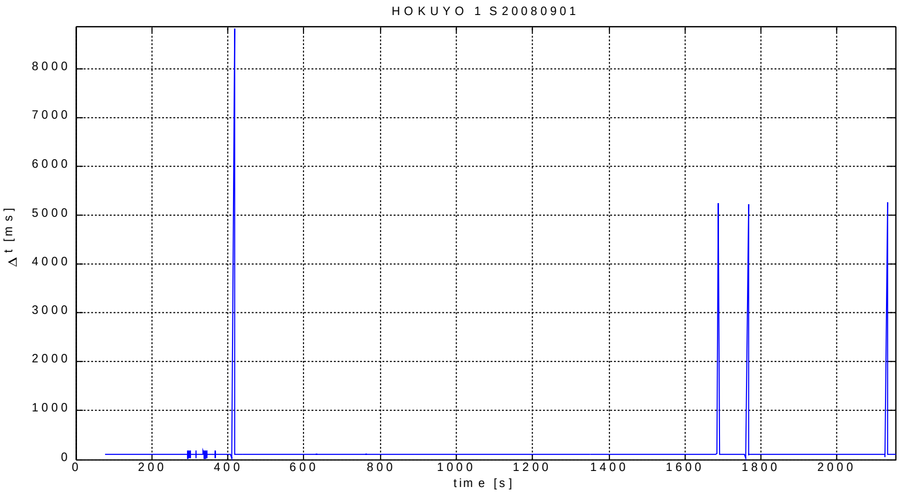
2) Odometry, Sick laser, and GPS are correct, with some period oscillations.
3) Hokuyo front laser presents data gaps of several seconds, but they are not problematic.
4) Monocular vision presents some frames lost in Bovisa_2008-09-01_Static, as it can be seen in the figures below. About 1 out of every 15 images is lost, and two or even three consecutive lost frames are frequent. Dataset Bovisa_2008-09-11a_Static also presents some isolated frames lost. As it can be seen in the test presented in section 4.3.5, these gaps are not critical to perform visual SLAM.
5) PANORAMIC vision present an important data gap of 3.5s, that is further analyzed in section 4.3.7

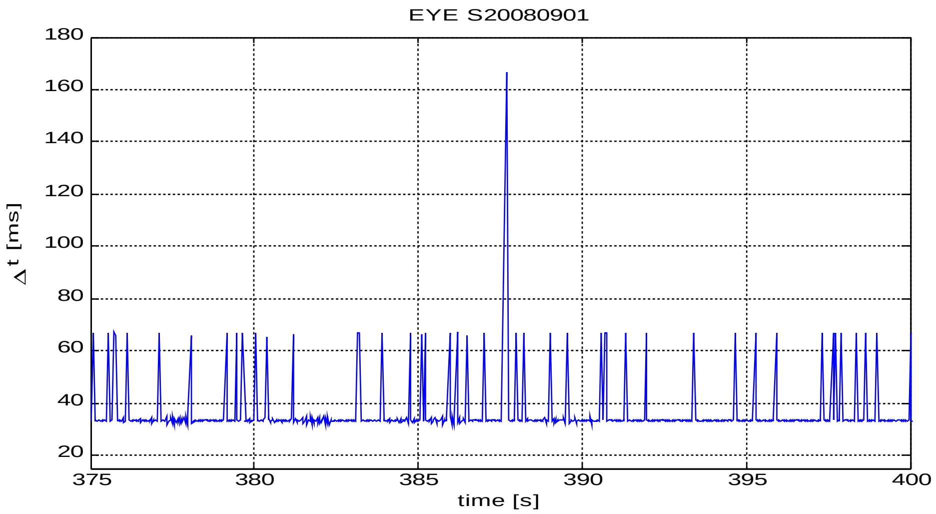
Timing figures for dataset Mixed\Bovisa_2008-09-01_Static (session 2008-09-01):

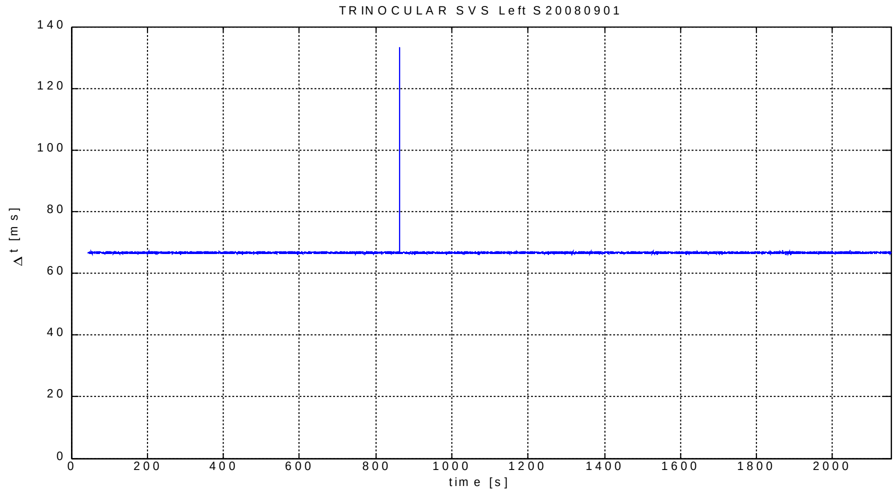


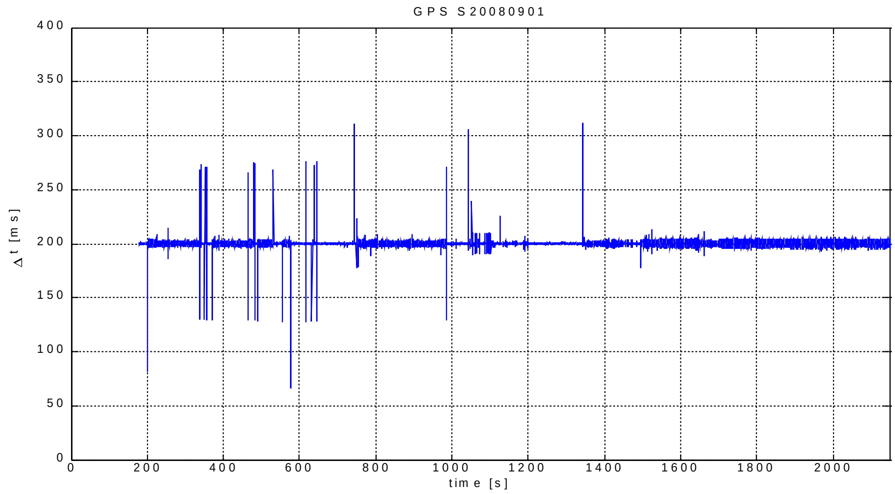



SICK FRONT S20080901
Δt [ms]
time [s]

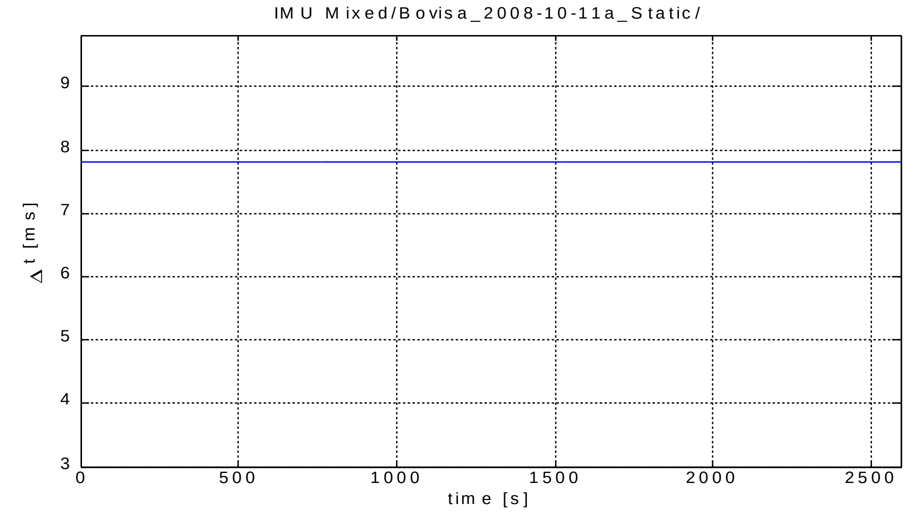

HOKUYO 1 S20080901
Δt [ms]
time [s]

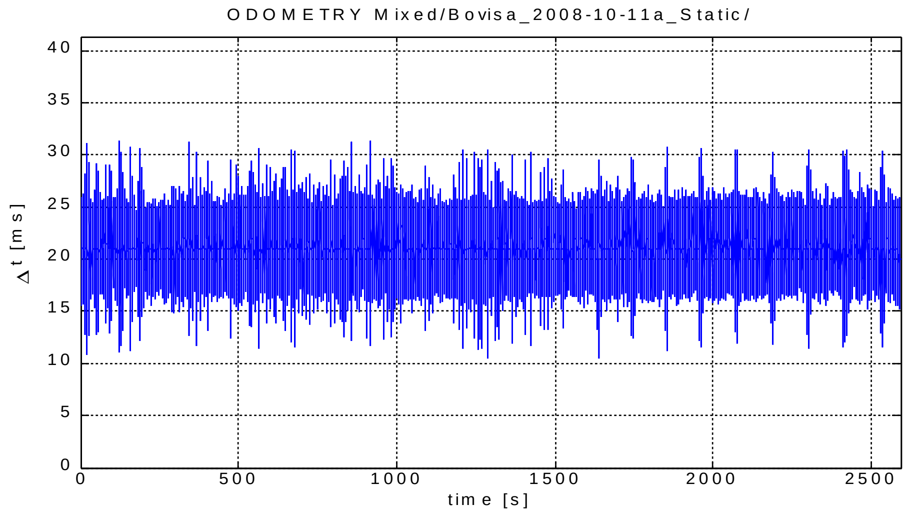

EYE S20080901
Δt [ms]
time [s]

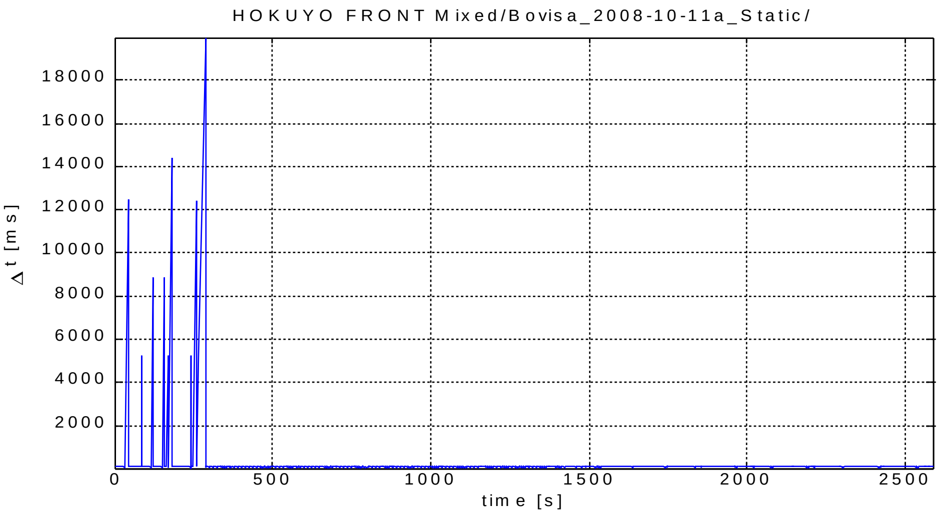

TRINOCULAR SVS Left S20080901
140
120
100
80
60
40
20
0
Δt [ms]
0
200
400
600
800
1000
1200
1400
1600
1800
2000
time [s]

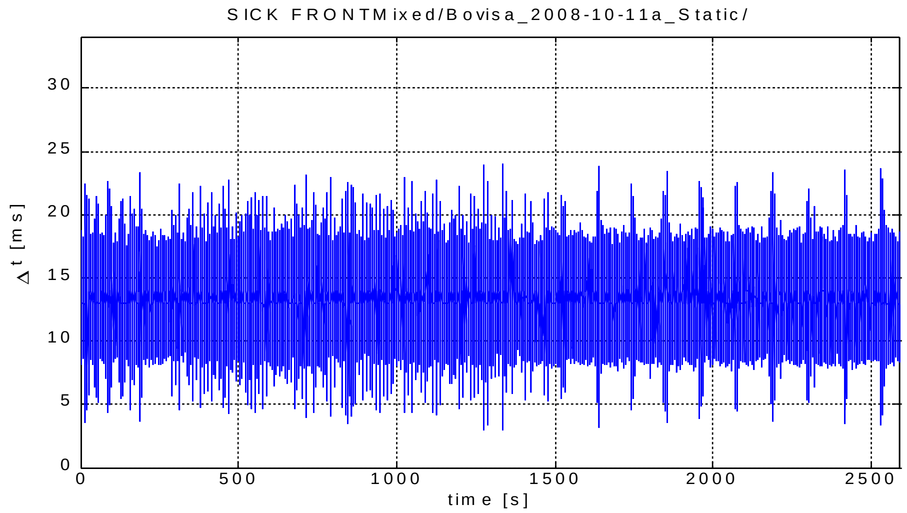

GPS S20080901
400
350
300
250
200
150
100
50
0
Δt [ms]
0
200
400
600
800
1000
1200
1400
1600
1800
2000
time [s]

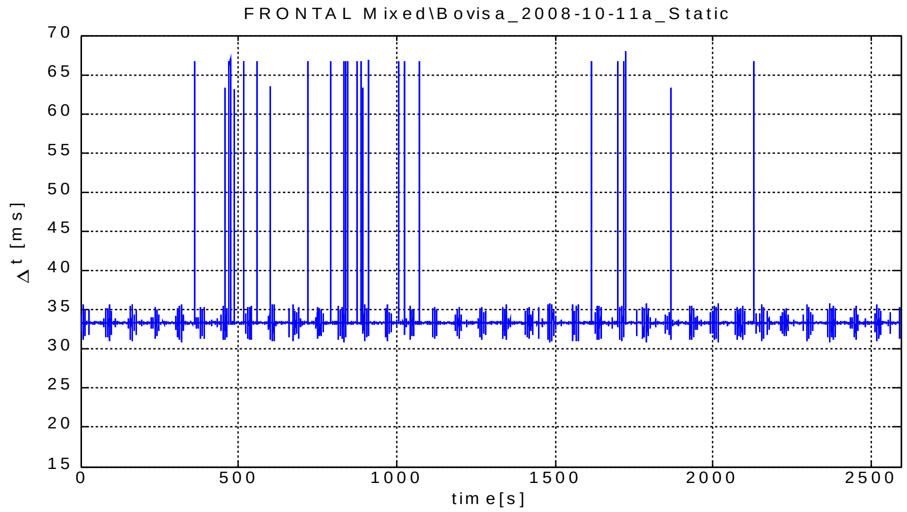
Timing Figures for dataset \Mixed\Bovisa_2008-10-11a_Static:

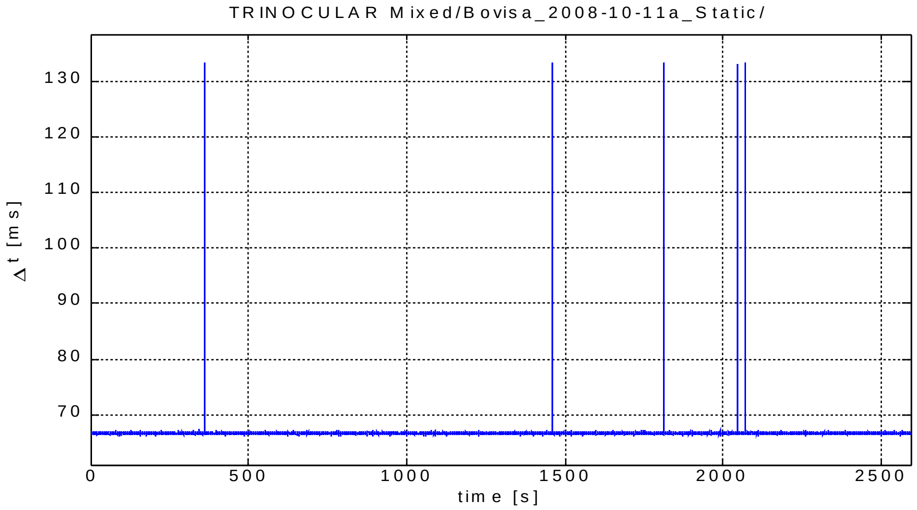


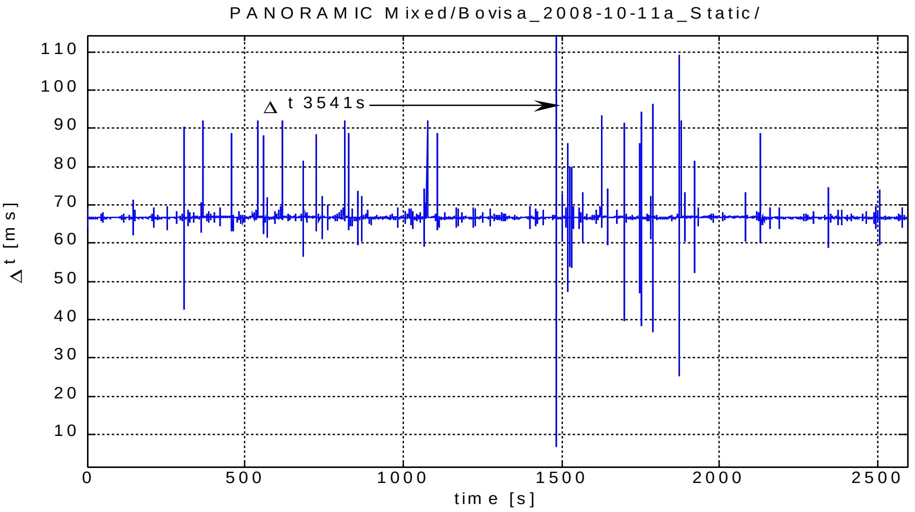


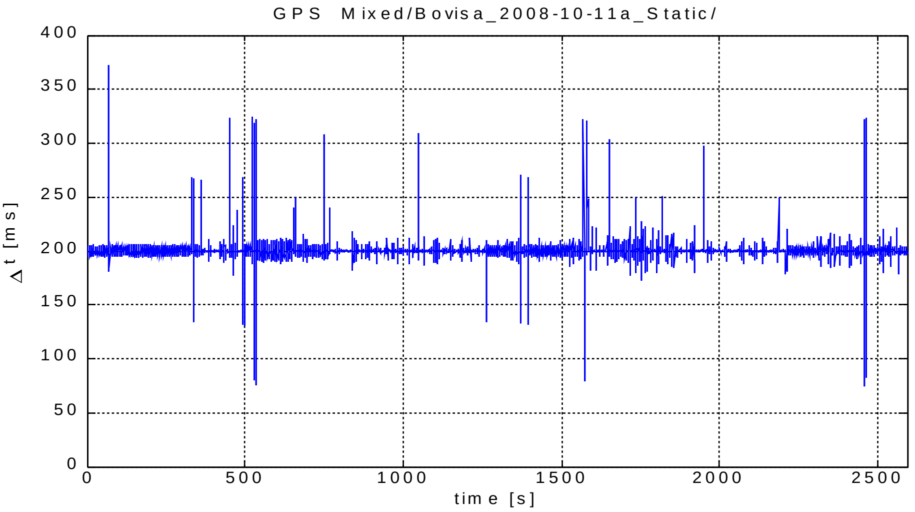



SICK FRONTMixed/Bovisa_2008-10-11a_Static/
Δt [ms]
time [s]


FRONTAL Mixed\Bovisa_2008-10-11a_Static
Δt [ms]
time[s]

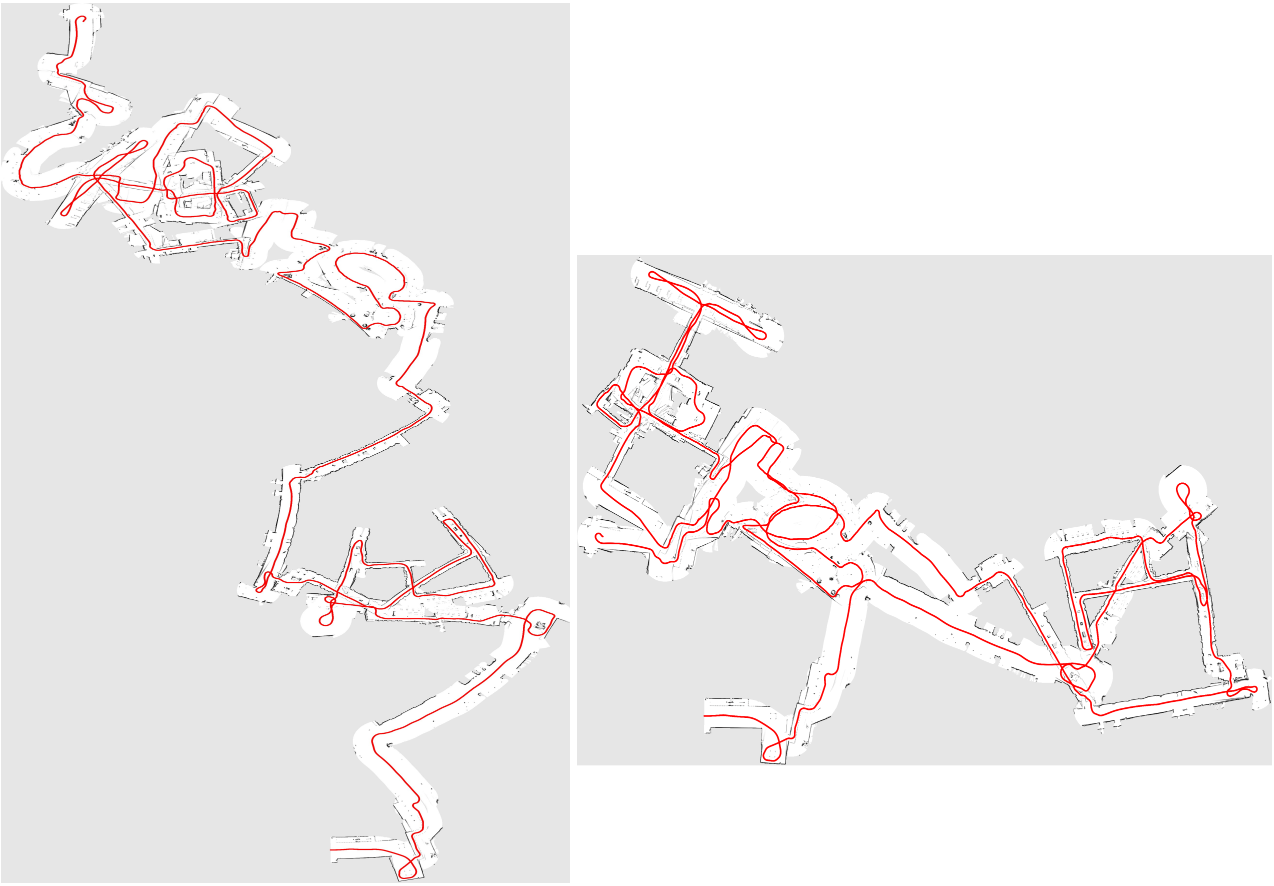

TRINOCULAR Mixed/Bovisa_2008-10-11a_Static/
Δt [ms]
time [s]


PANORAMIC Mixed/Bovisa_2008-10-11a_Static/
Δt 3541s
Δt [ms]
time [s]
0
500
1000
1500
2000
2500
10
20
30
40
50
60
70
80
90
100
110


GPS Mixed/Bovisa_2008-10-11a_Static/
Δt [ms]
time [s]
0
500
1000
1500
2000
2500
0
50
100
150
200
250
300
350
400

4.3.2. Odometry

1) Data is verified to be in compliance with the file specification and timestamped.
2) Data quality: odometry presents a significant bias towards the left hand side. This is a common problem in may mobile robots, typically caused by the center of gravity of the robot not being on the geometrical center of the robot: one wheel tire supports more weight and get compressed resulting in a smaller wheel radius. Being a systematic effect it can be corrected by an appropriate calibration technique, such as the one developed by ALUFR that is described in section 6.1. An example of the bias and the correction obtained by calibration is shown in the following figure.

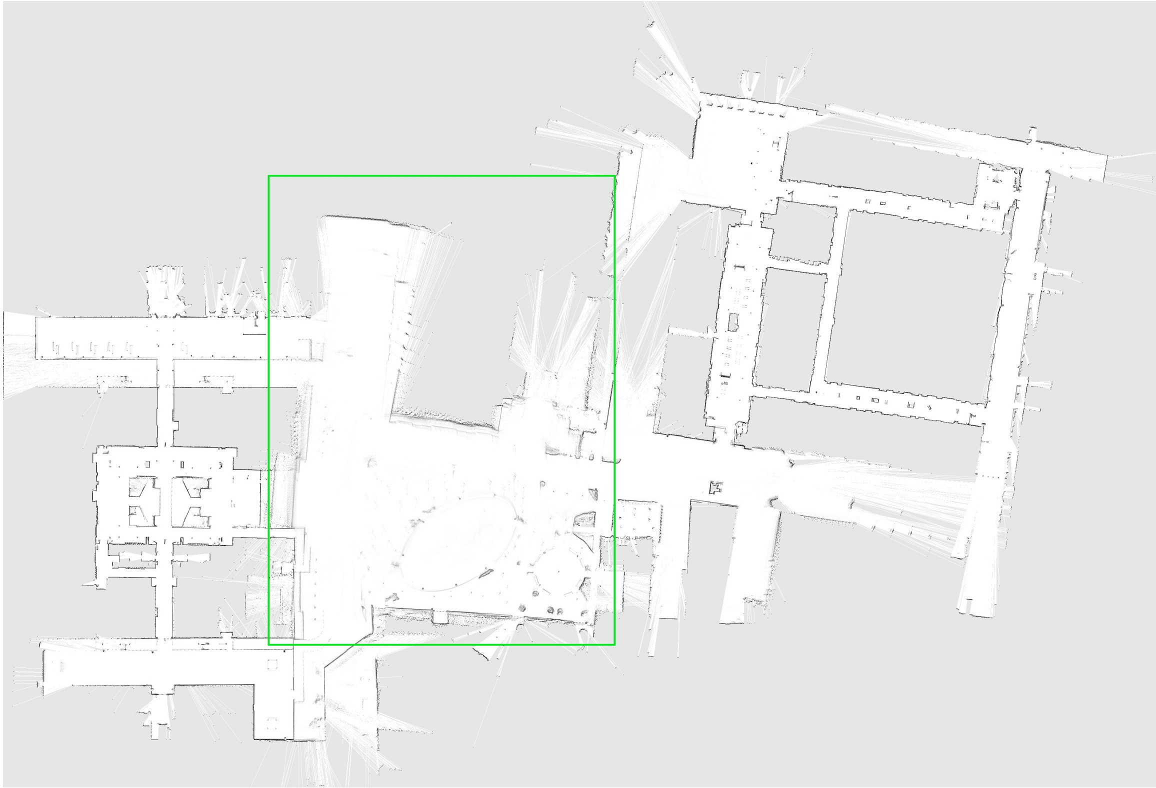


Mixed/Bovisa 2008-10-11a Static: Map obtained using the laser scans and the robot odometry, before and after odometry calibration.

4.3.3. SICK Laser

1) Data density and quality are validated by running the laser graph-based SLAM software from ALUFR (Grisetti et al 2007, Grisetti et al 2008). The maps obtained are quite good, although there are some misalignments in the outdoor parts of the trajectories, marked in green in the figures. Improving these results will probably require the fusion of information coming from of other sensor streams in the datasets.

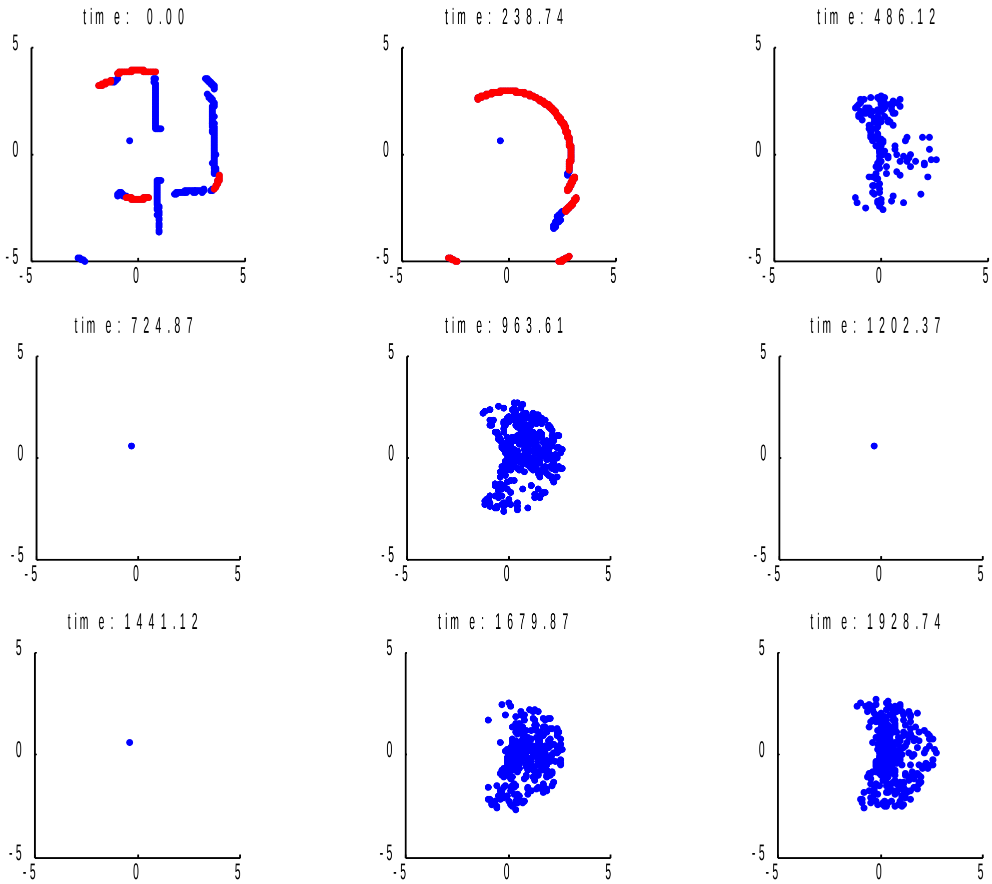
Graph-based SLAM on dataset Mixed /Bovisa_2008_09_01_static (Session20080901)



Resulting Graph SLAM map of Mixed / Bovisa 2008-10-11a Static.

4.3.4. Hokuyo Laser

1) Apart from its short range (4 meters), according to the manufacturer, the Hokuyo laser is designed for indoor use only, and its maximum operating ambient light is 10.000lux (a typical overcast day gives 10.000-25.000lux and bright sunlight gives 120.000lux). As it can be seen in the following figure, in most parts of the trajectory the sensor does not return any valid point, making the Hokuyo laser useless in the outdoor parts of datasets taken in daylight.

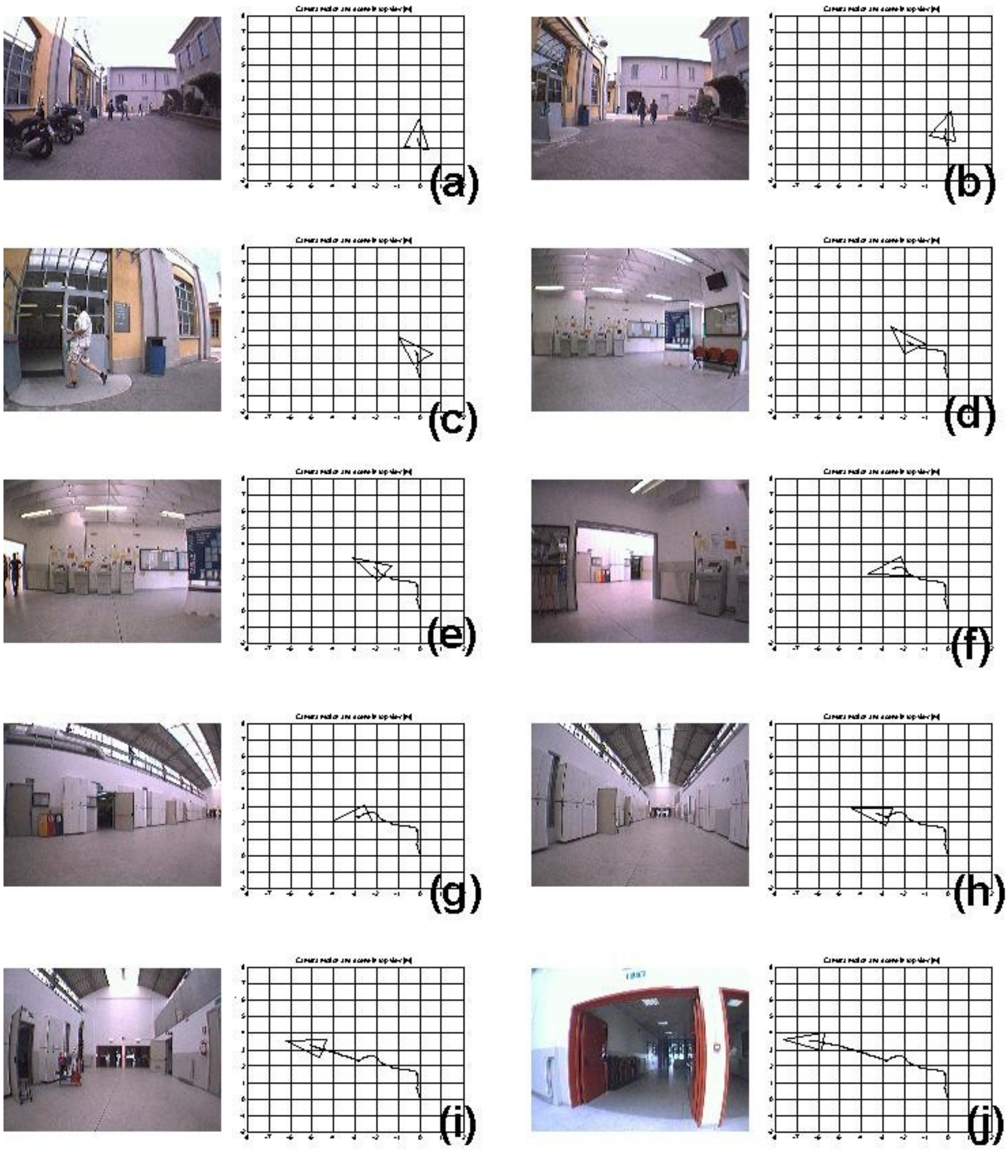


Points from the Hokuyo laser throughout the dataset Mixed\Bivosa_2008_09_01

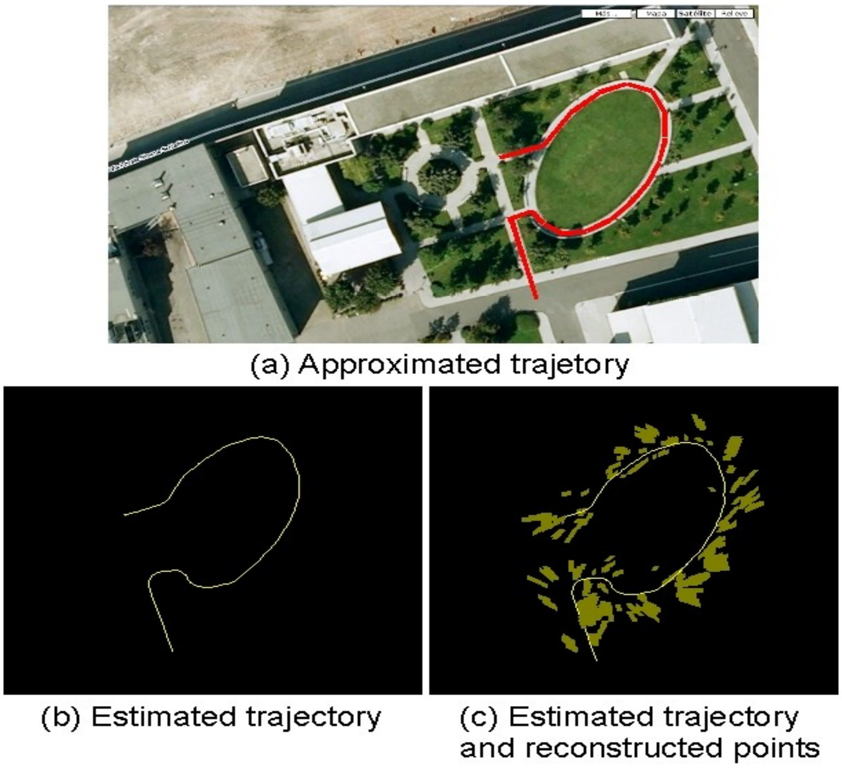
4.3.5. Monocular Vision

1) File format: All image files are readable.
2) Timing: see table in section 4.3.1.
3) Data overlap:

   It has been verified that the sequence can be processed by standard inverse depth + JCBB monocular SLAM. The next figure shows an example after processing 4157 images, from image 16000 to 20156 in Session Mixed\Bovisa_2008_09_01.

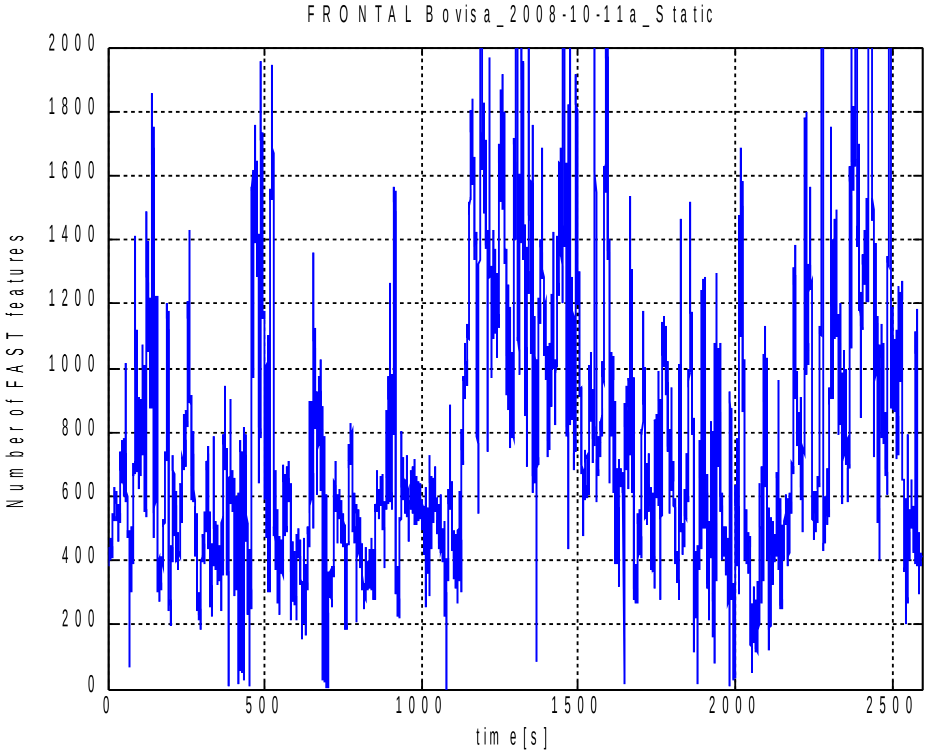


Map obtained from Bovisa_20080_10_11a_static on the indoor part.



Map obtained from Bovisa_20080_10_11a_static on the outdoor part.

4) Data density and quality: the next figure shows the number of FAST features extracted from sequence Bovisa_20080_10_11a_static. No dark frames have been detected in this sequence.



As it is expected, feature density is high as it corresponds to outdoors sequence. Low density frames are in this sequence due to poor lighting conditions because the sun is in front of the camera.

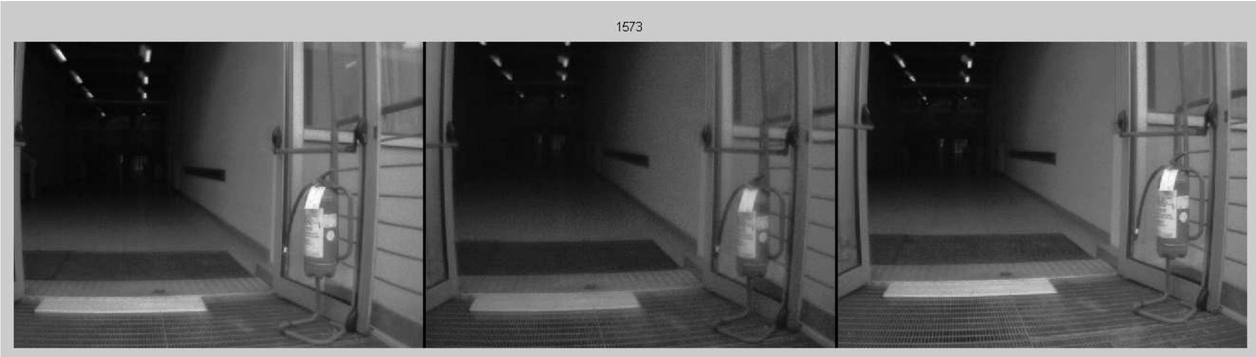
5) Calibration has been improved following the Bouguet's calibration toolbox guidelines: the calibration target is not always parallel and it appears a bit bigger in the images. As a result, the calibration accuracy information offered by the Matlab toolbox reports smaller calibration errors. For example, error in focal length is reduced from 3,2% in old datasets to 0,20% in mixed sessions. The calibration results are described in section 5.3.

4.3.6. Trinocular Vision

1) File format: All image files are readable.
2) Timing: see table in section 4.3.1. We found a critical gap when evaluating the sensor period along the sequence (3,5sec). This correspond to 53 lost frames. However, as it is shown in the following figure, is is still possible to find good matchings between the images before and after the gap and the dataset is considered valid. The gap must be documented in the datasets to warn the users that this dataset has a greater degree of difficulty.
3) Calibration: The dataset does provide calibration for the external parameters (the cameras relative position and orientation). The calibration images provided have been found of good quality to perform the extrinsic calibration. In this case, the calibration pattern used is bigger, making the calibration obtained to be precise enough (see section 5.3).
4) Data quality: The position of the three cameras is computed carrying out 3D reconstruction from one frame. For all datasets we found incoherences in the position of the left camera. Left camera position does not correspond to the left image. This is only a minor mistake that can be corrected by renaming the left and right images correctly. The following figures exemplify the latent mistake.

L: 1220288275.243586 T: 1220288275.243502 R: 1220288275.243547

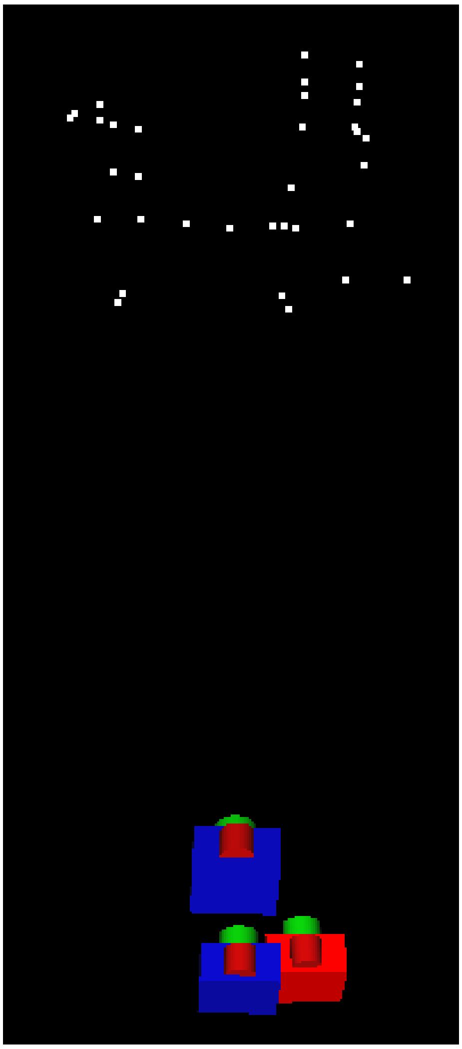
3D reconstruction from frame 10607 in Biccoca_2008_09_01 Dataset. The SVS L image corresponds to the red camera.



L: 1223309685.884441 T: 1223309685.884545 R: 1223309685.884653

3D reconstruction from frame 1573 in Biccoca_2008_10_06 Dataset. The SVS L image corresponds to the red camera.

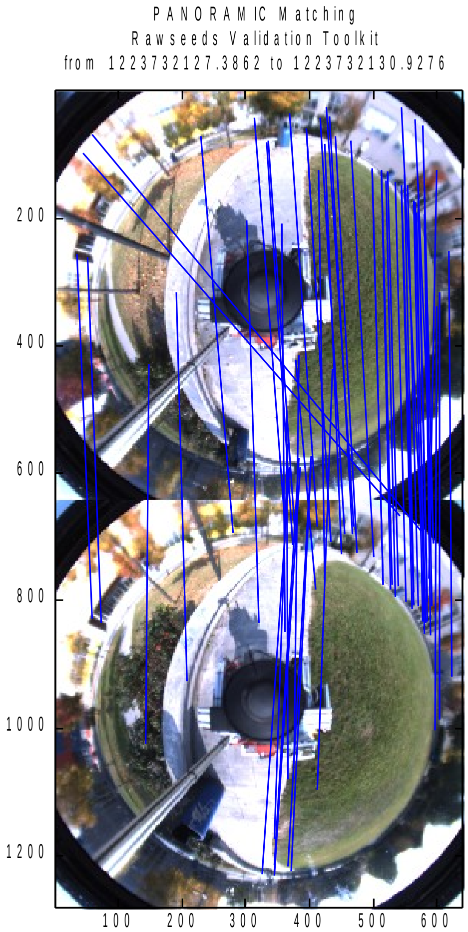
L: 1223731002.113374 T: 1223731002.113488 R: 1223731002.113253



3D reconstruction from frame 5386 in Biccoca_2008_10_06 Dataset. The SVS L image corresponds to the red camera.

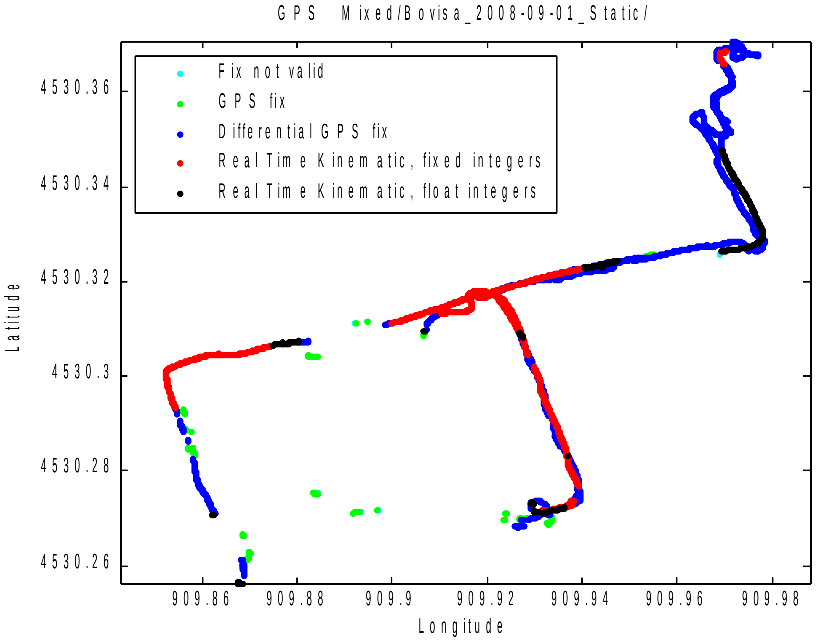
4.3.7. Panoramic Vision

1. File format: All image files are readable.
2. We found a critical gap when evaluating the sensor period along the sequence (3,5s). This correspond to 53 lost frames. However, as it is shown in the following figure, is is still possible to find good matchings between the images before and after the gap and the dataset is considered valid. The gap must be documented in the datasets to warn the users that this dataset has a greater degree of difficulty.

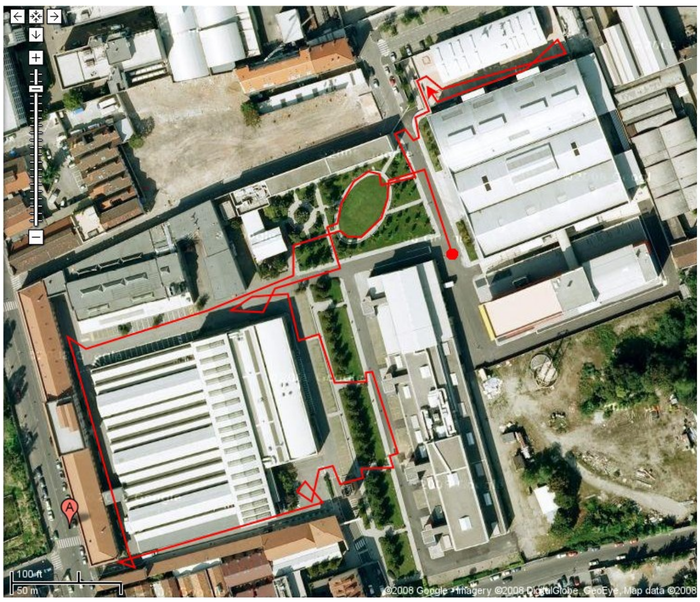


4.3.8. GPS

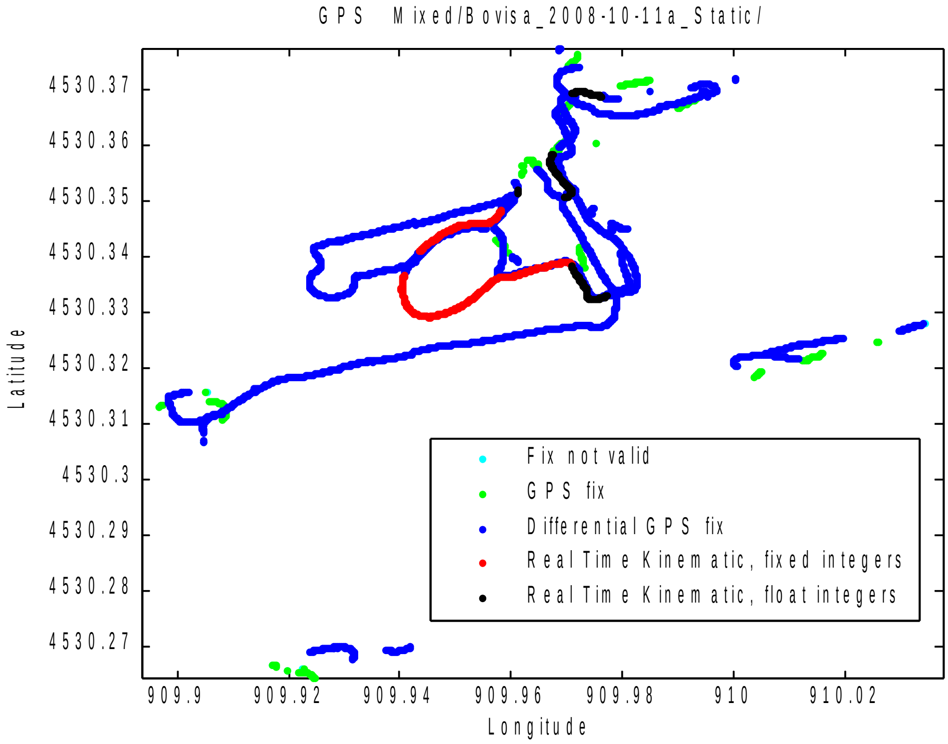
1. Data density and quality are validated by plotting the robot positions obtained from GPS. We verify that they cover sufficiently the outdoor parts of the trajectory.



GPS raw data



Planed Trajectory on google earth



GPS raw data

Planed Trajectory on google earth

4.4. Validation of Mixed-Dynamic Session

In the following, we first present the main time characteristics of the dataset, and then present the most important details of the validations performed for each sensor stream.

4.4.1. Basic time properties

The following tables summarize the main timing characteristics of the data streams obtained from the different sensors (F: mean acquisition frequency, T: mean period, Tmax: maximum time interval between two consecutive acquisitions, Delay: mean delay with respect to IMU time base, std Delay: standard deviation of the delay). Cells highlighted in yellow represent data loss or synchronization issues, cells marked with '--' could not be computed.

Mixed /Bovisa_2008-10-06_Dynamic										
	IMU	Odometry	Sick R	Sick F	Hokuyo R	Hokuyo F	Frontal	Trinocular	Panoramic	GPS
F (Hz)	127,97	47,62	76,84	76,84	10,09	10,05	29,9	15	15	5
T (ms)	7,8	20,99	13,01	13,01	99,05	99,47	33,4	66,65	66,68	199,92
Tmax (ms)	7,8	32,49	24,36	23,78	171,05	171,34	66,7	133,55	108,16	356,29
Delay (ms)	--	-84,57	-45,84	-46,00	--	--	-3,6	29	-20,2	--
std Delay (ms)	--	63,25	5,30	4,20	--	--	9,5	11,5	14,3	--

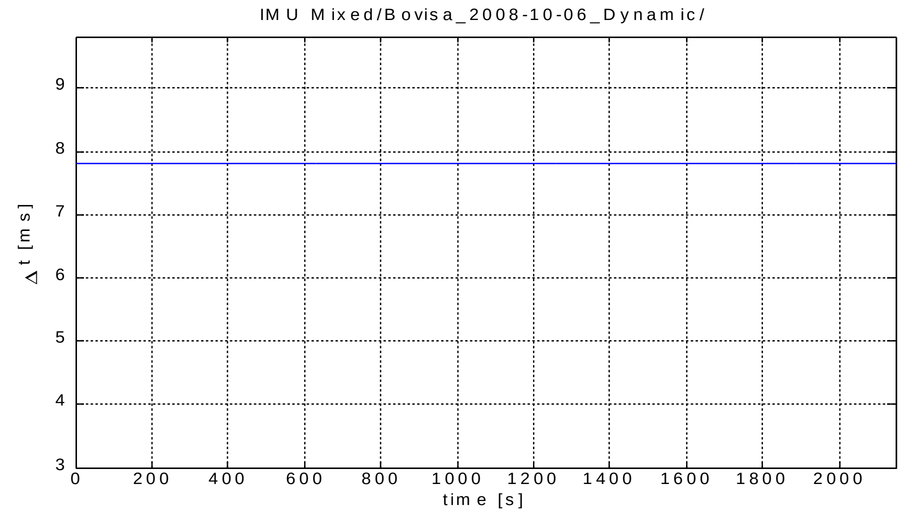
The delays are similar to previous sessions. With respect to time periods, if for a sensor stream Tmax is bigger than 2*T, most probably some data acquisitions have been lost. This can be seen more clearly in the following figures that plot the time separation between every pair of consecutive acquisitions.

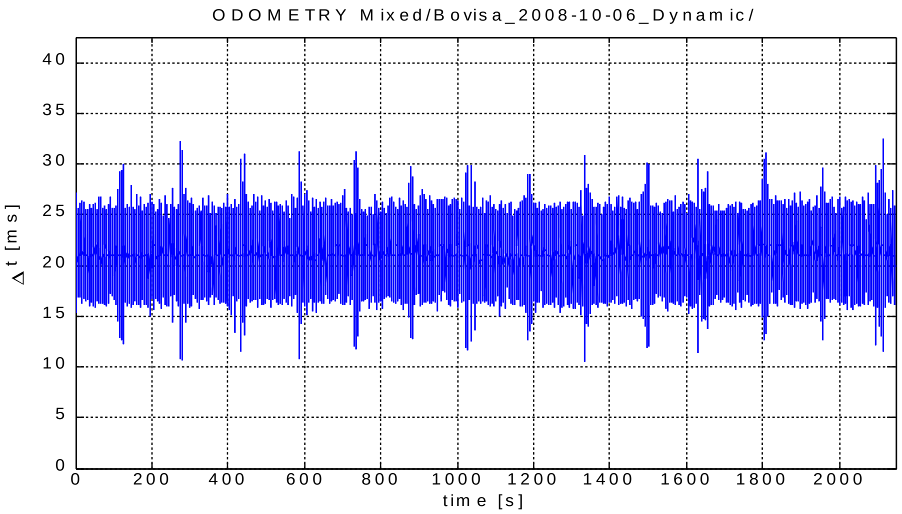
The conclusions for this dataset are:

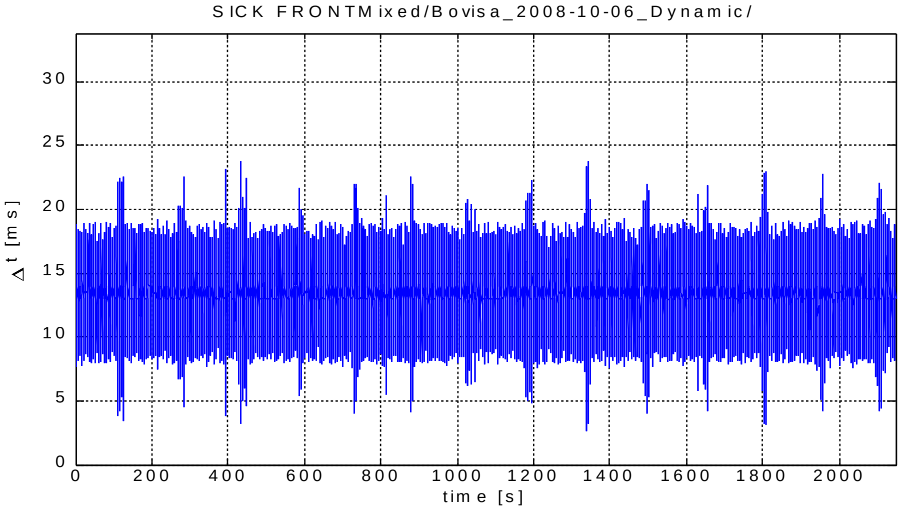
1) HOKUYO present some sporadic data loss, that will not affect SLAM algorithms.

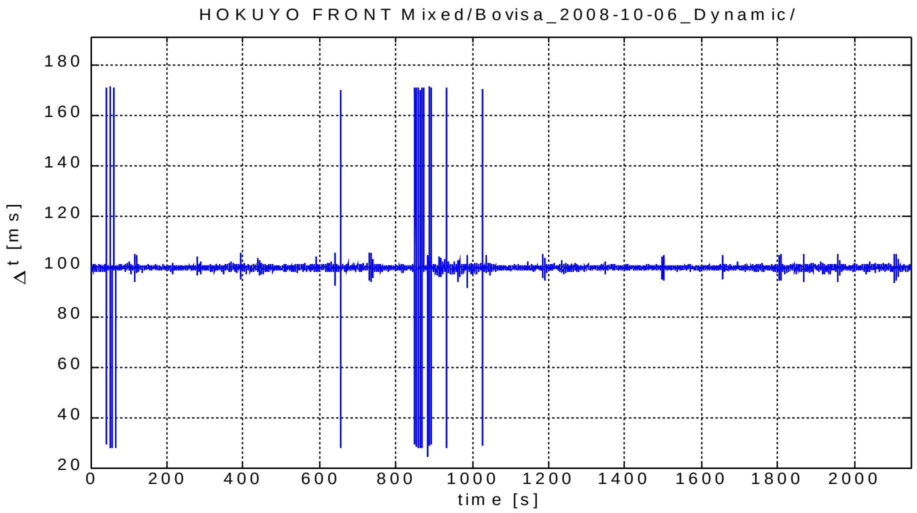
2) Odometry is correct, with minor period oscillations.

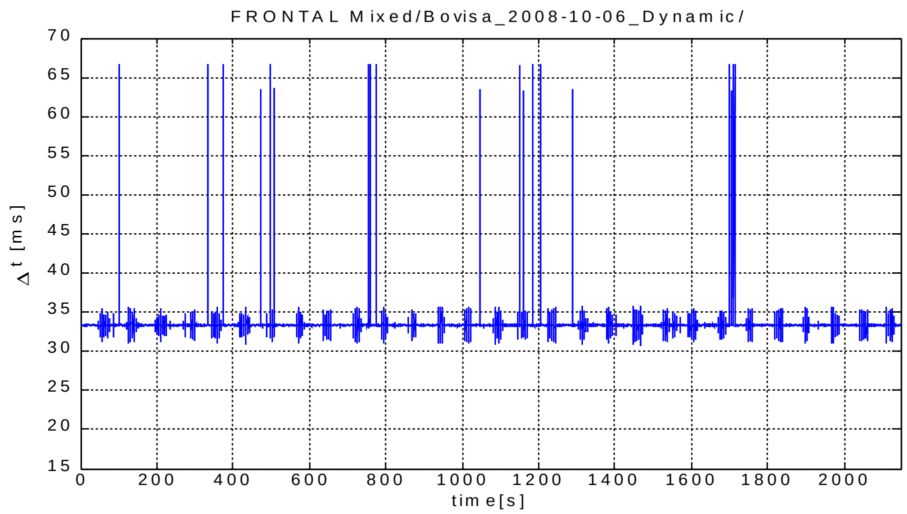
3) Monocular and Trinocular cameras present a sporadic frecuency gaps.

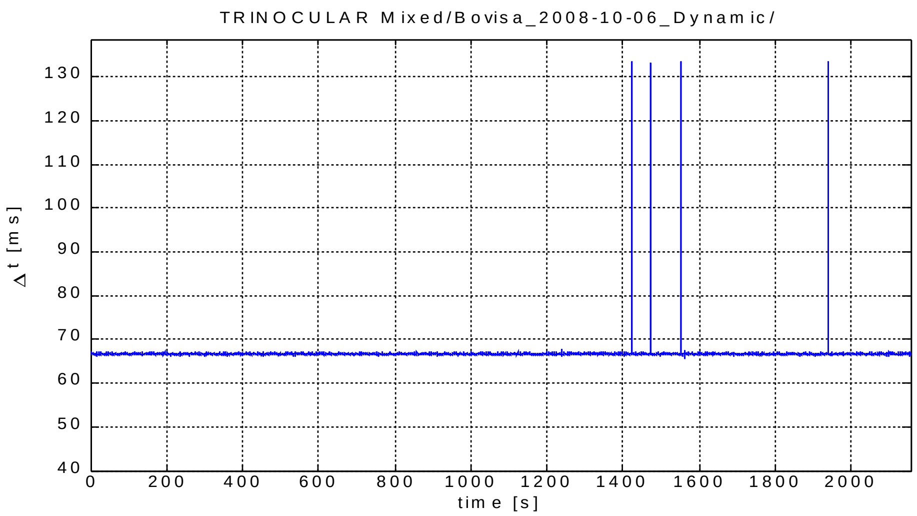

IMU Mixed/Bovisa_2008-10-06_Dynamic/
Δt [ms]
time [s]

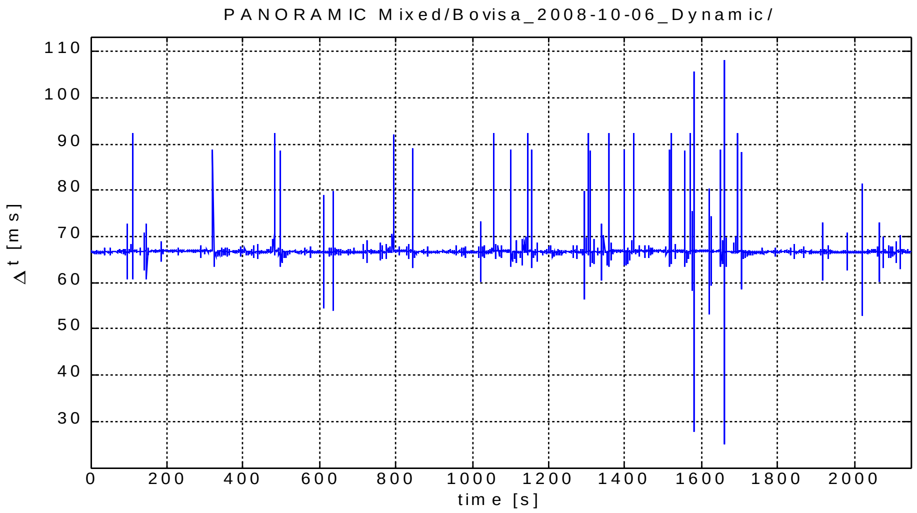

ODOMETRY Mixed/Bovisa_2008-10-06_Dynamic/
Δt [ms]
time [s]

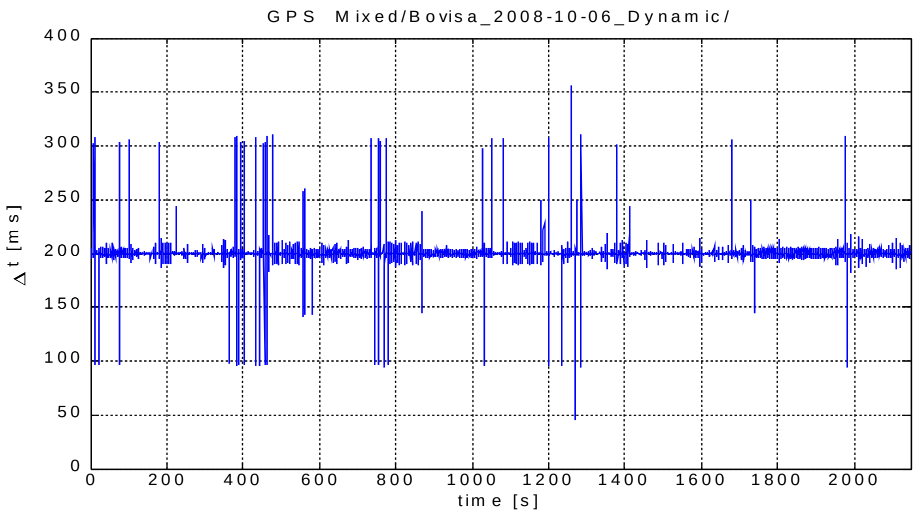

SICK FRONTMixed/Bovisa_2008-10-06_Dynamic/
Δt [ms]
time [s]


HOKUYO FRONT Mixed/Bovisa_2008-10-06_Dynamic/
Δt [ms]
time [s]


FRONTAL Mixed/Bovisa_2008-10-06_Dynamic/
Δt [ms]
time[s]

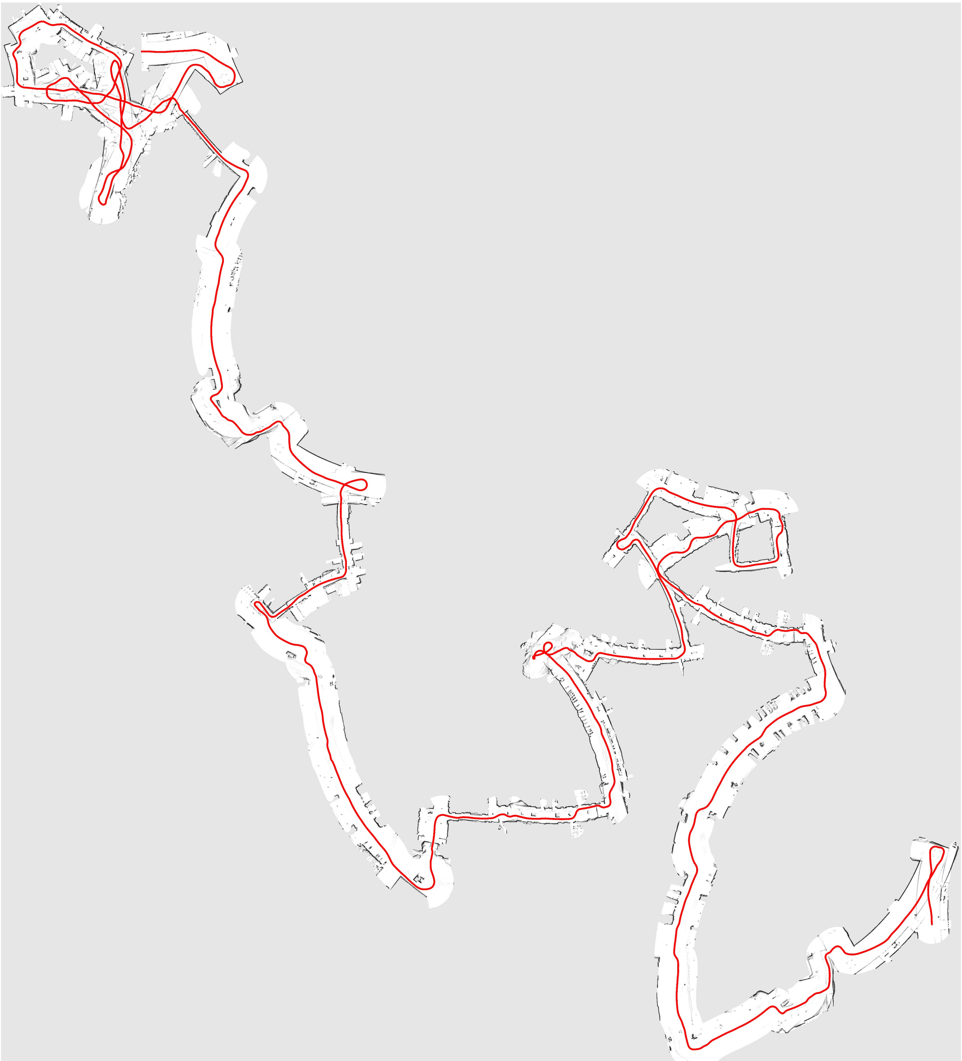

TRINOCULAR Mixed/Bovisa_2008-10-06_Dynamic/
Δt [ms]
time [s]


PANORAMIC Mixed/Bovisa_2008-10-06_Dynamic/
Δt [ms]
time [s]


GPS Mixed/Bovisa_2008-10-06_Dynamic/
Δt [ms]
time [s]

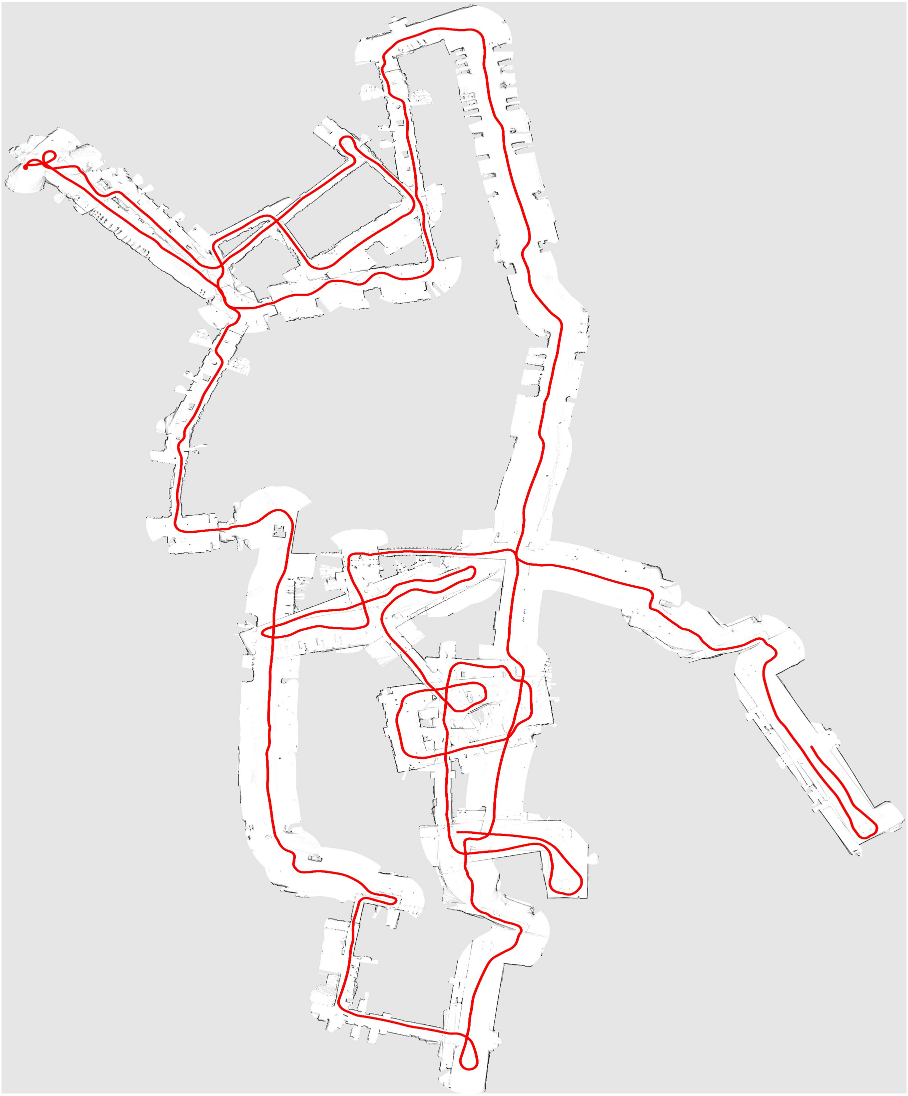
4.4.2. Odometry

1) Data is verified to be in compliance with the file specification and timestamped.
2) Data quality is evaluated by plotting the odometry information to reveal mapping inconsistencies. The corresponding parts of the trajectory are depicted in following figures.



Bovisa 2008-10-06 Dynamic: Map based on raw odometry and integrated laser scans.

The problem is partially corrected using calibration on the raw odometry readings. The results show an improved odometry along the traversed trajectory (see next figure).



Bovisa 2008-10-06 Dynamic: Map based on improved odometry

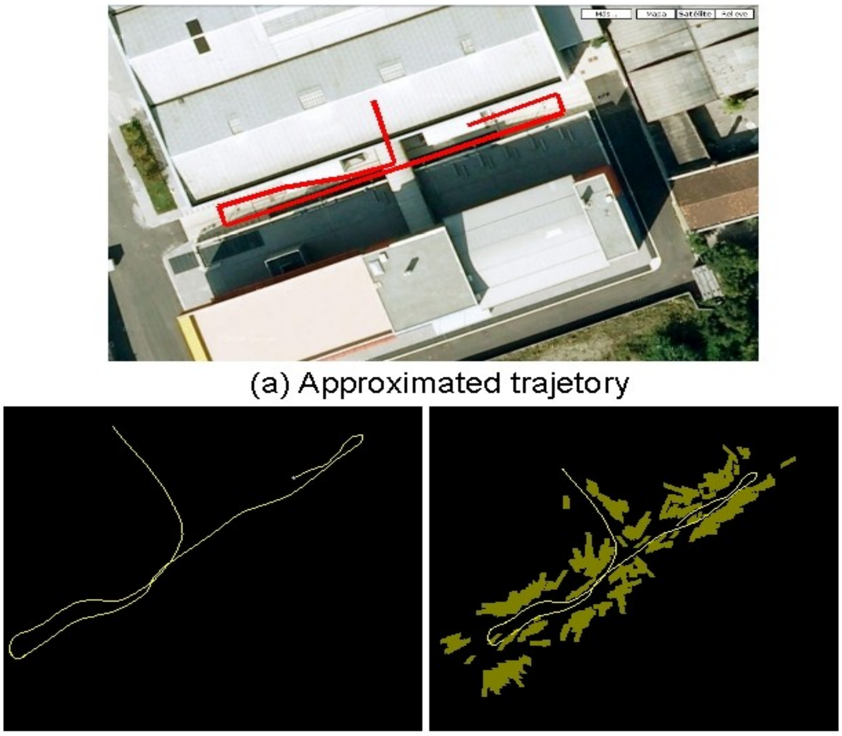
4.4.3. SICK Laser

1) Data density and quality are validated by running the laser SLAM software from ALUFR (Grisetti et al 2007, Grisetti et al 2008). Using each session alone, the dataset presents insufficient overlap for loop closure:

Resulting GraphSLAM map on Mixed/Bovisa 2008-10-06 Dynamic. The trajectory of this data set leads to a better map of the park.

4.4.4. Monocular Vision

1) File format: All image files are readable.
2) Timing: See table in section 4.4.1.
3) Data overlap: It has been verified that the sequence can be processed by standard inverse depth + JCBB monocular SLAM. Next figure shows an example.



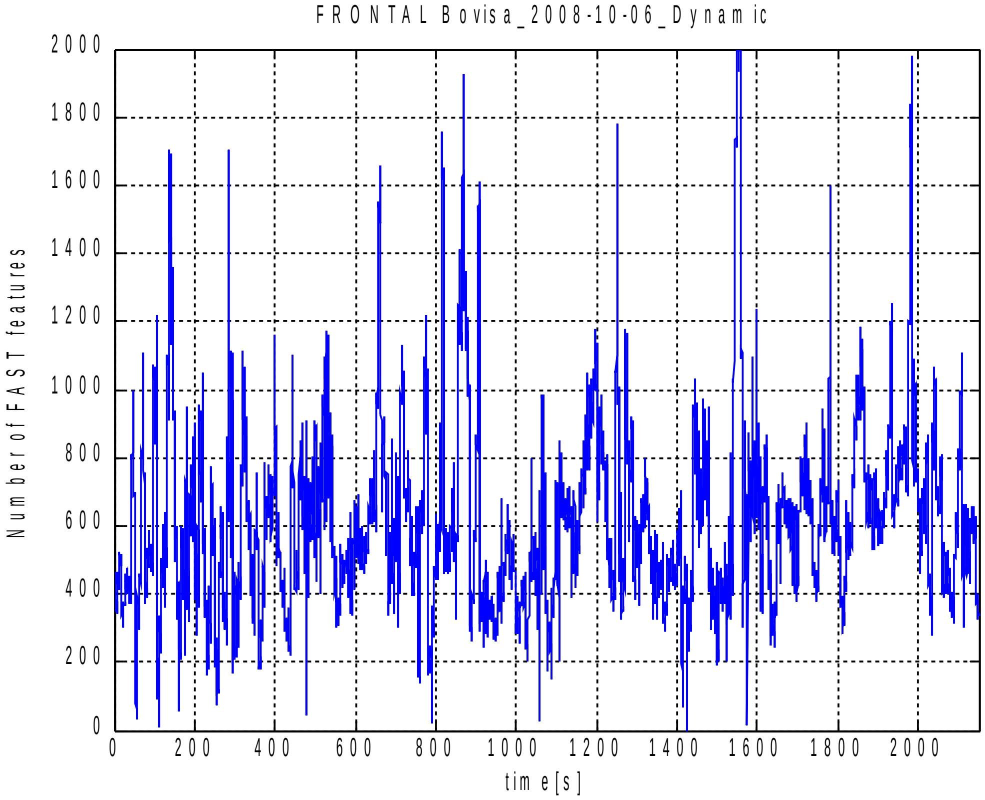
(a) Approximated trajetory

(b) Estimated trajectory

(c) Estimated trajectory and reconstructed points

Map obtained from Mixed\Bovisa_2008_10_06_dynamic

4) Data density: Next figure shows the number of FAST features extracted for the dynamic dataset.

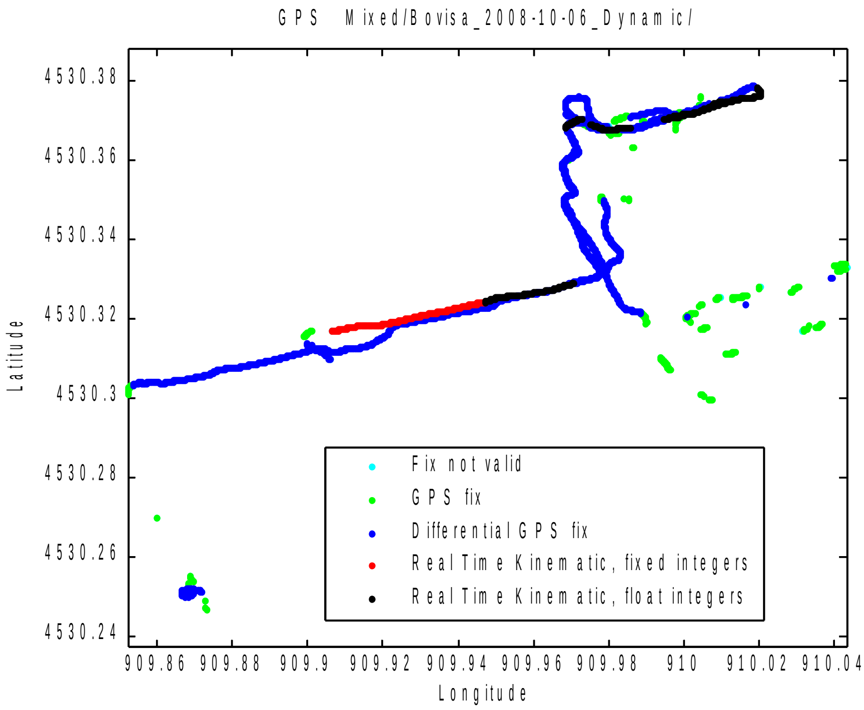


There are some low density frames, corresponding to low textured areas.

5) Calibration images has been also improved with a focal length error of 0,20%. For more details, go to section 5.3.

4.4.5. GPS

1) Data density and quality are validated by plotting the robot positions obtained from GPS and verifying that they cover sufficiently the outdoor parts of the trajectory.



GPS raw data

Planed trajectory on google maps

4.5. Validation of Outdoor-Static Sessions

4.5.1. Basic time properties

The following tables summarize the main timing characteristics of the data streams obtained from the different sensors (F: mean acquisition frequency, T: mean period, Tmax: maximum time interval between two consecutive acquisitions, Delay: mean delay with respect to IMU time base, std Delay: standard deviation of the delay). Cells highlighted in yellow represent data loss or synchronization issues, cells marked with '--' could not be computed.

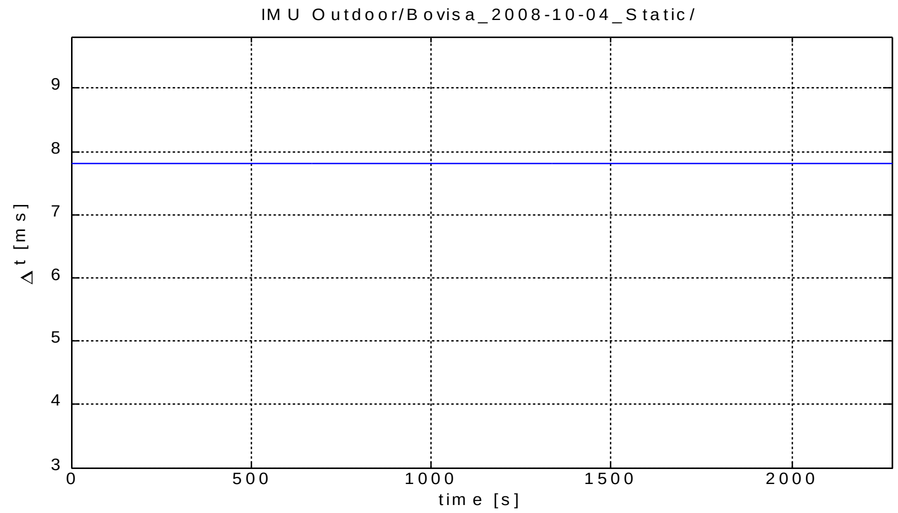
Outdoor/Bovisa_2008-10-04_Static										
	IMU	Odometry	Sick R	Sick F	Hokuyo R	Hokuyo F	Frontal	Trinocular	Panoramic	GPS
F (Hz)	127,97	47,62	76,84	76,84	12,5	12,5	30,0	15	15	5
T (ms)	7,8	20,99	13,01	13,01	80,0	80,0	33,3	66,65	66,68	199,93
Tmax (ms)	7,8	37,11	34,58	26,05	17974,0	20583,2	66,7	133,6	94,83	303,91
Delay (ms)	--	-90,38	-48,87	-50,1	--	--	-12,0	-44,2	-35,6	
std Delay (ms)	--	56,99	5,34	5,1	--	--	7,9	9,2	5,5	

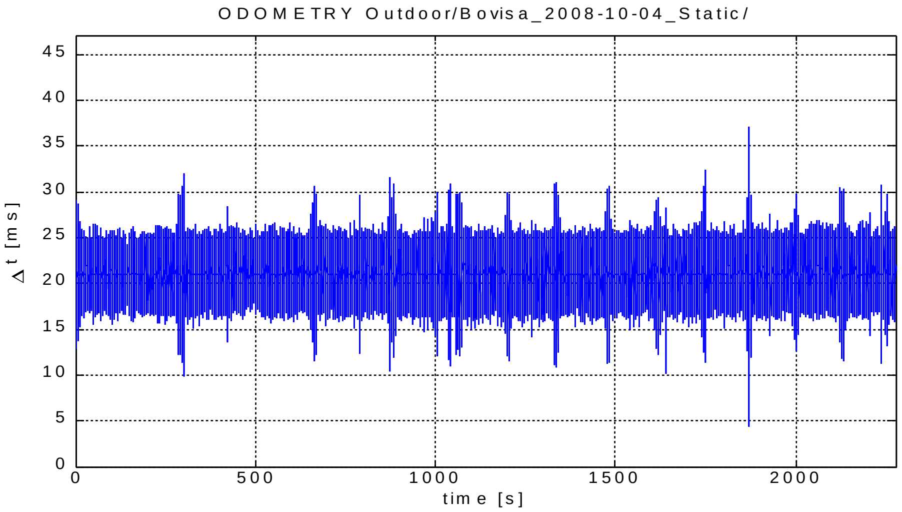
Outdoor/Bovisa_2008-10-11b_Static										
	IMU	Odometry	Sick R	Sick F	Hokuyo R	Hokuyo F	Frontal	Trinocular	Panoramic	GPS
F (Hz)	127,97	47,62	76,84	76,83	10,1	10,05	29,8	15	15	5
T (ms)	7,8	20,99	13,01	13,01	99,0	99,41	33,6	66,65	66,68	199,92
Tmax (ms)	7,8	31,27	24,13	23,75	171,1	185,43	68,4	12800	108,31	331,82
Delay (ms)	--	-96,58	-49,50	-50,22	--	--	-7,0	-40	-28,5	
std Delay (ms)	--	41,51	5,05	4,34	--	--	7,5	7,3	6,6	

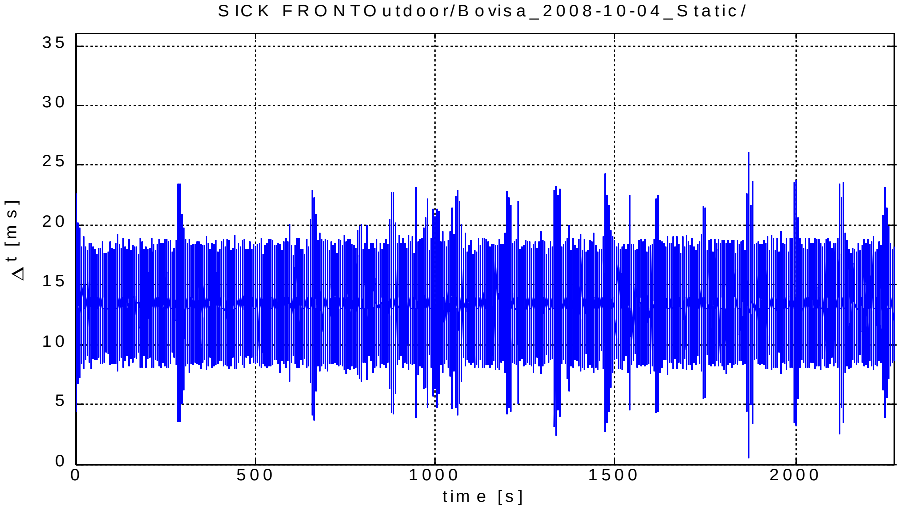
We conclude that the main problems of this datasets are those related to:

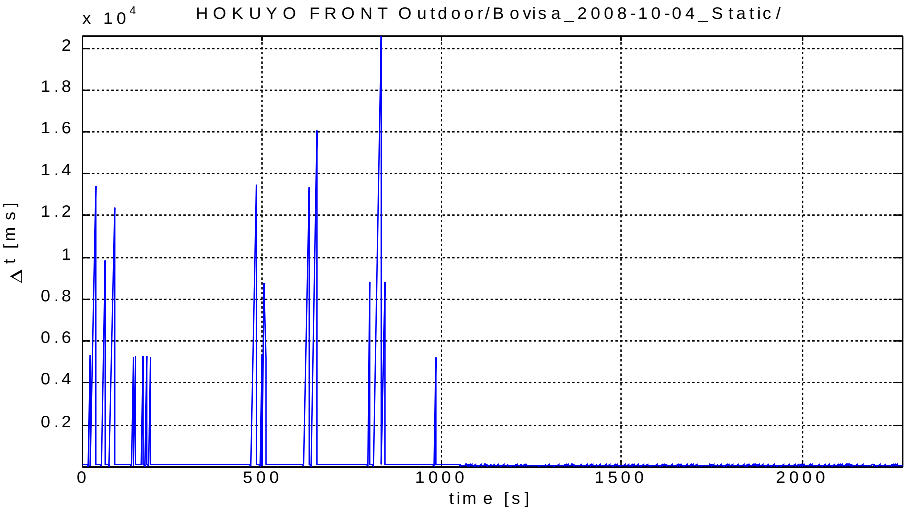
1. The odometry calibration
2. Data loss in HOKUYO and cameras.
3. Some sporadic data loss in FRONTAL and TRINOCULAR cameras, up to one frame for dataset Bovisa_2008-10-04_Static and 192 frames for the top camera of Bovisa_2008-10-11b_Static.
4. Some oscillations for PANORAMIC and GPS.

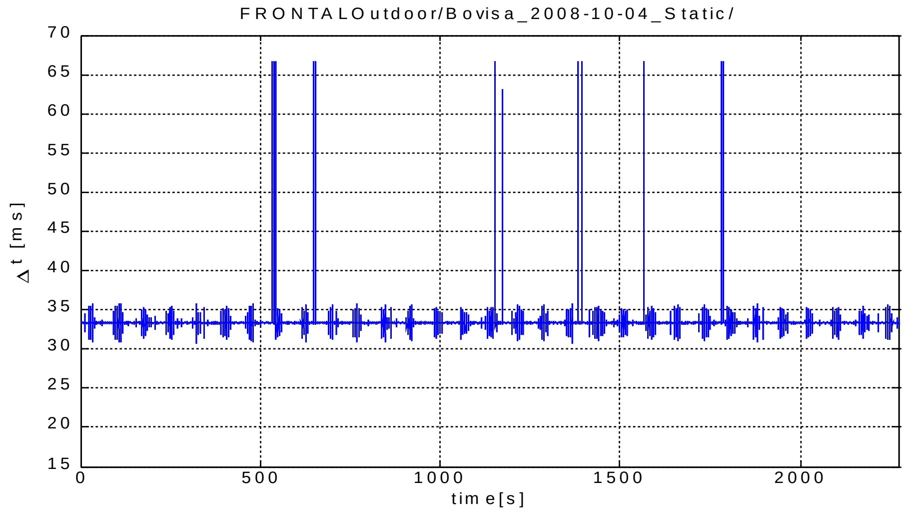
The following images shows the timing results.

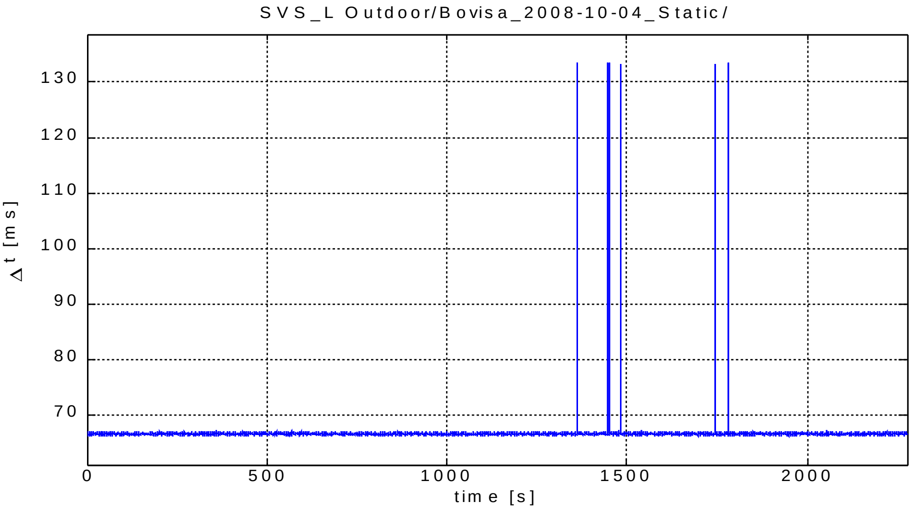

IMU Outdoor/Bovisa_2008-10-04_Static/
Δt [ms]
time [s]

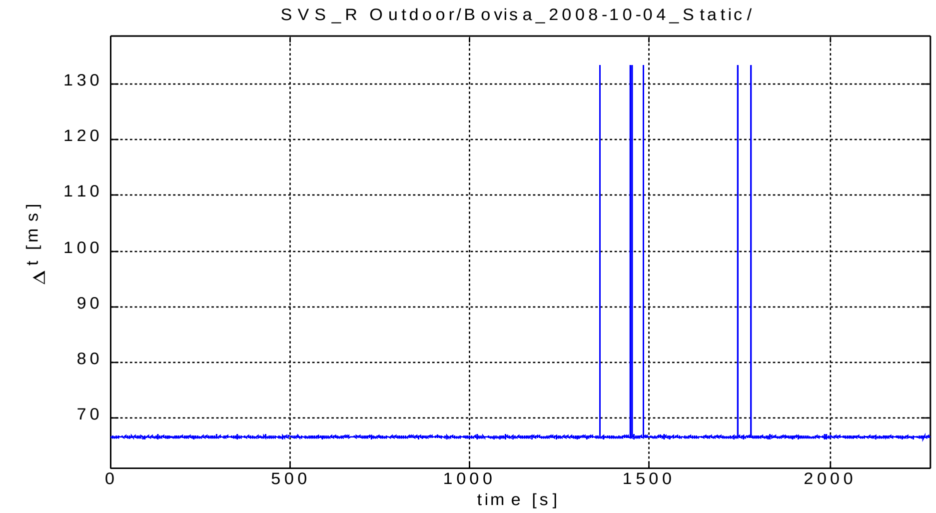

ODOMETRY Outdoor/Bovisa_2008-10-04_Static/
Δt [ms]
time [s]

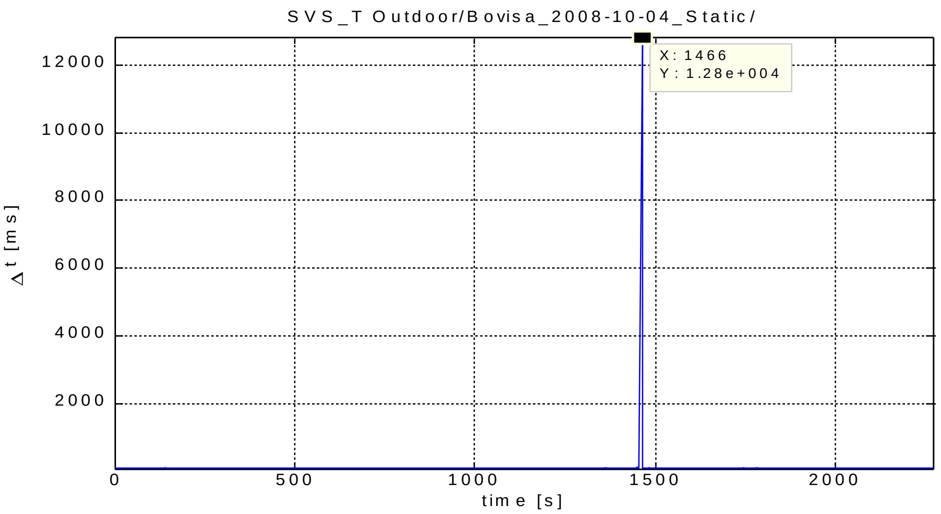

SICK FRONTOutdoor/Bovisa_2008-10-04_Static/
Δt [ms]
time [s]

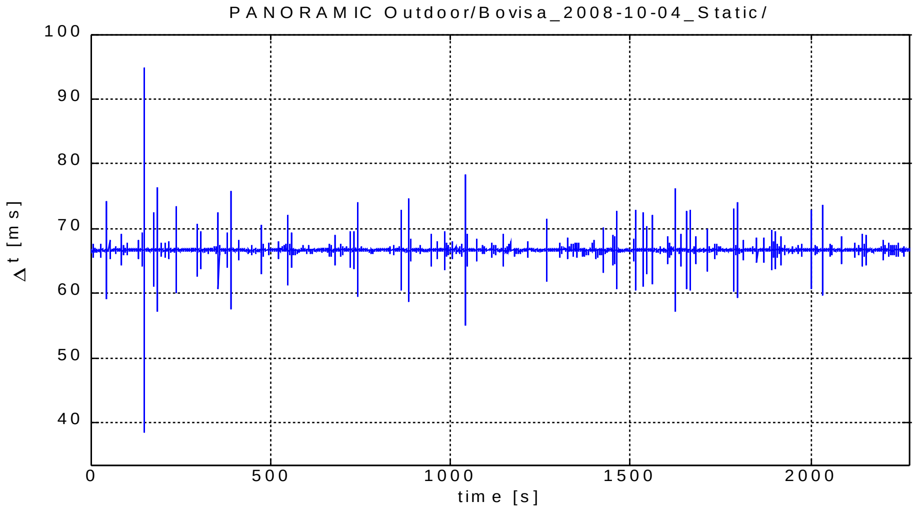

HOKUYO FRONT Outdoor/Bovisa_2008-10-04_Static/
x 10^4
Δt [ms]
time [s]

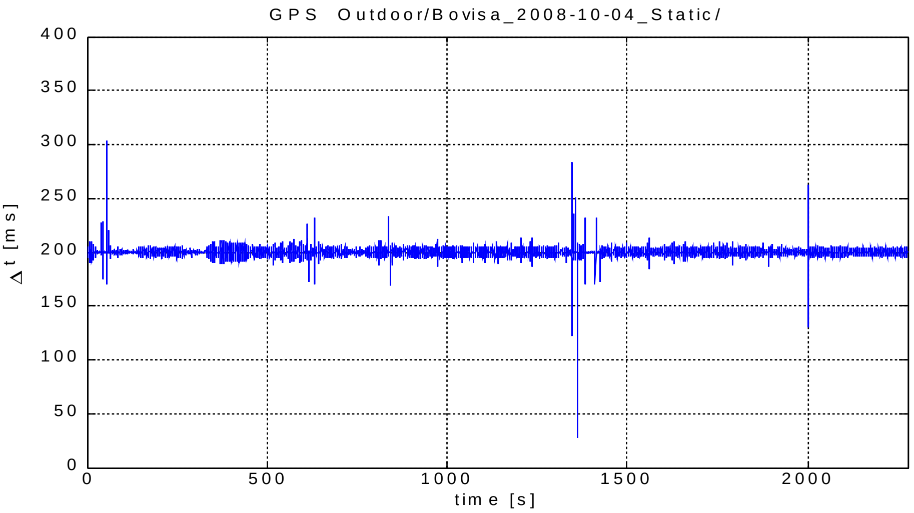

FRONTAL Outdoor/Bovisa_2008-10-04_Static/
Δt [ms]
time [s]


SVS_L Outdoor/Bovisa_2008-10-04_Static/
Δt [ms]
time [s]

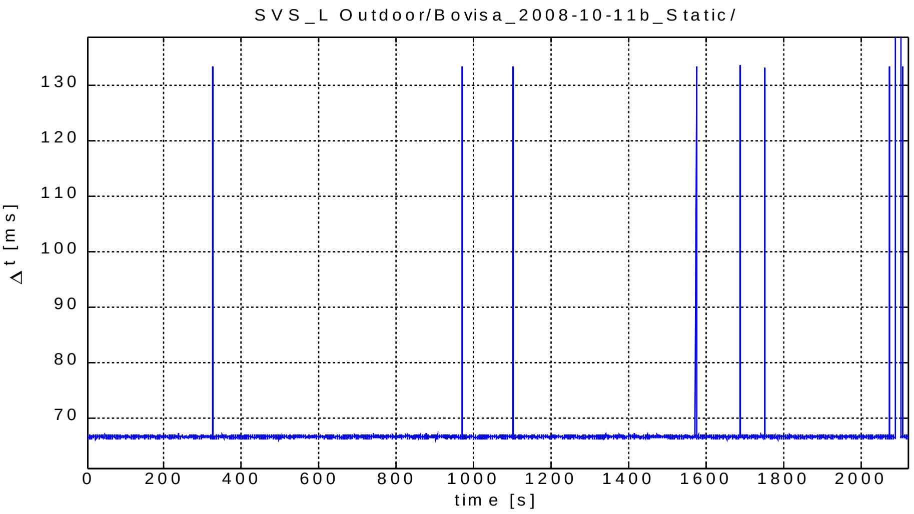

SVS_R Outdoor/Bovisa_2008-10-04_Static/
Δt [ms]
130
120
110
100
90
80
70
0
500
1000
1500
2000
time [s]

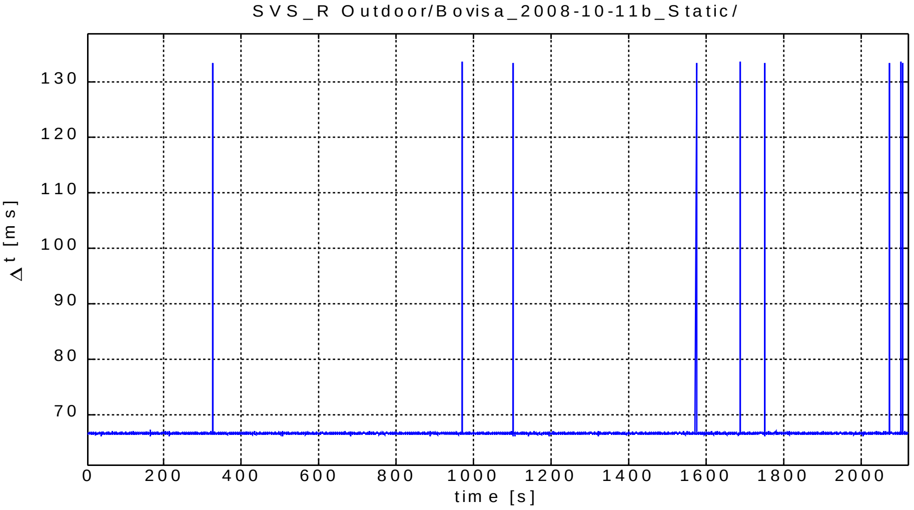

SVS_T Outdoor/Bovisa_2008-10-04_Static/
X: 1466
Y: 1.28e+004
Δt [ms]
12000
10000
8000
6000
4000
2000
0
500
1000
1500
2000
time [s]

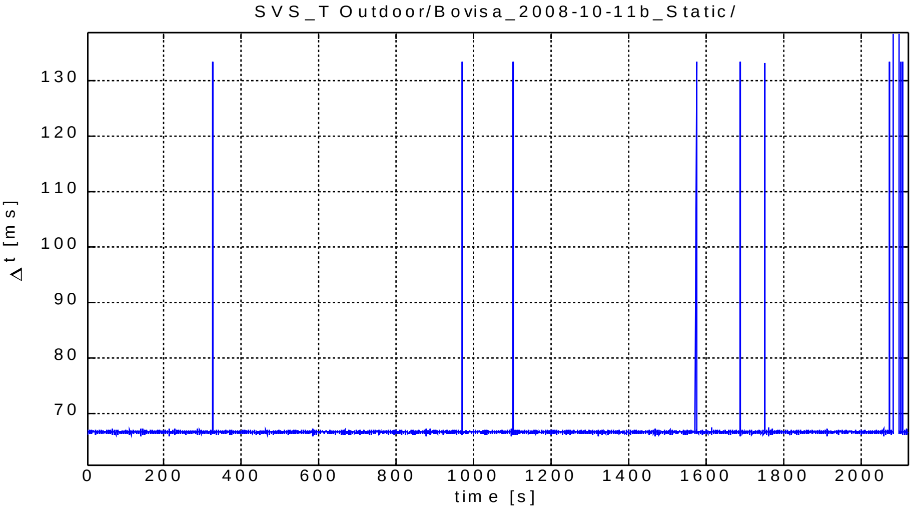

PANORAMIC Outdoor/Bovisa_2008-10-04_Static/
Δt [ms]
100
90
80
70
60
50
40
0
500
1000
1500
2000
time [s]



Timing results for Bovisa_2008-12-11b_Static



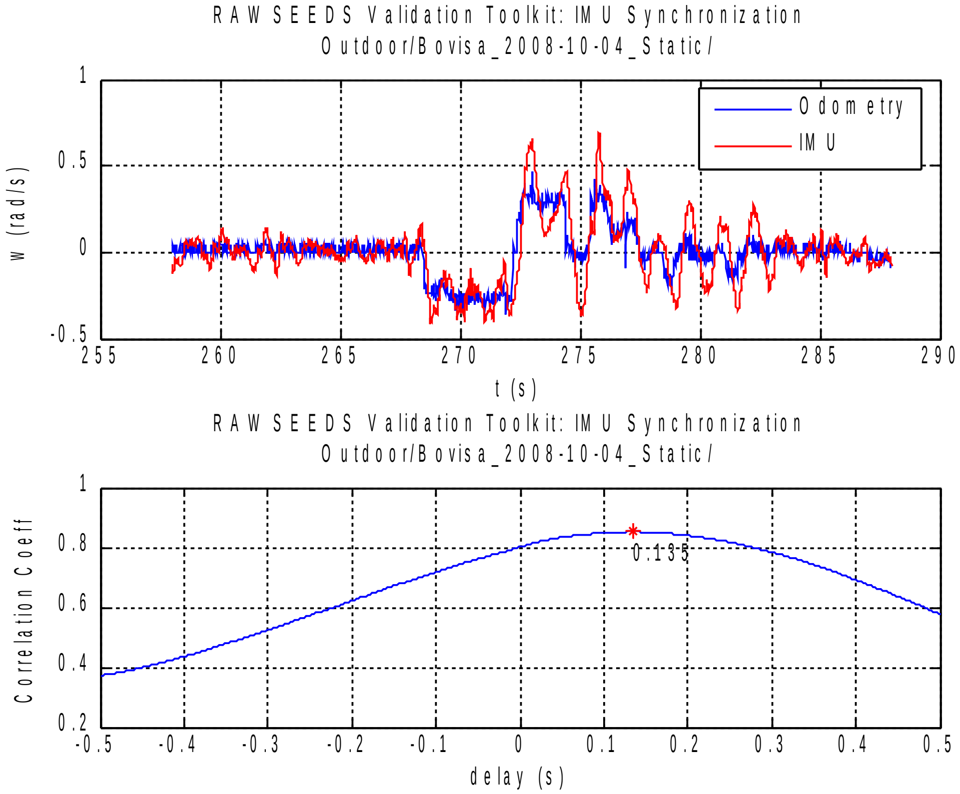

SVS_R Outdoor/Bovisa_2008-10-11b_Static/
Δt [ms]
130
120
110
100
90
80
70
0
200
400
600
800
1000
1200
1400
1600
1800
2000
time [s]


SVS_T Outdoor/Bovisa_2008-10-11b_Static/
Δt [ms]
130
120
110
100
90
80
70
0
200
400
600
800
1000
1200
1400
1600
1800
2000
time [s]

4.5.2. Odometry

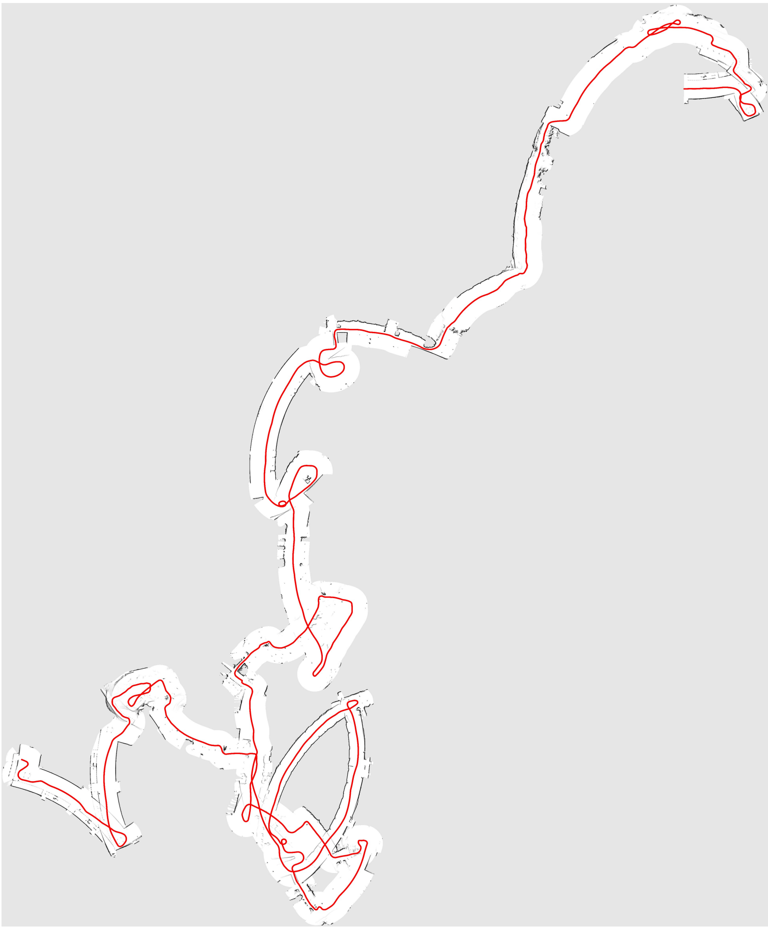
1) Data is verified to be in compliance with the file specification and timestamped.

2) Timing: See Table Section 4.5.1. the synchronization is validated by computing the angular velocities and the correlation with corresponding IMU measurements. The figure above shows that delay is still high.

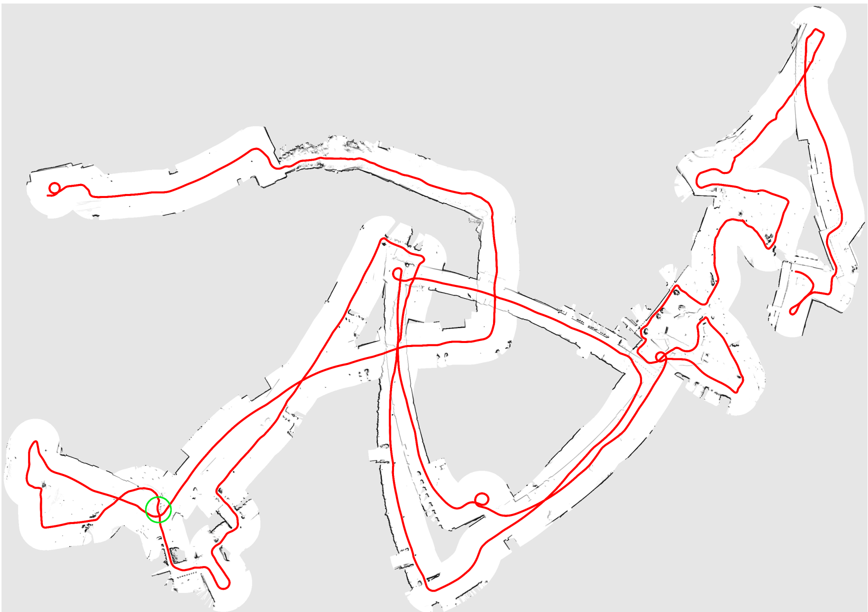


Synchronization by correlation with IMU angular velocities

3) Data quality: It is noted that the odometry in the datasets has a bias and does not provide a zero mean error — as most SLAM approaches assume. This fact can be seen in the map odometry figures provided for Outdoor Static sessions. The corridors are not straight but show a bias to the left hand side, that can be corrected by calibration. Wheel slippage has been detected at some points of the trajectory, marked in green in the following figures. This does not invalidate the datasets because SLAM algorithms must be able to cope with this problem in real-life applications. However, the wheel slippages should be documented in the information accompanying the datasets, to warn the users that they are specially challenging.

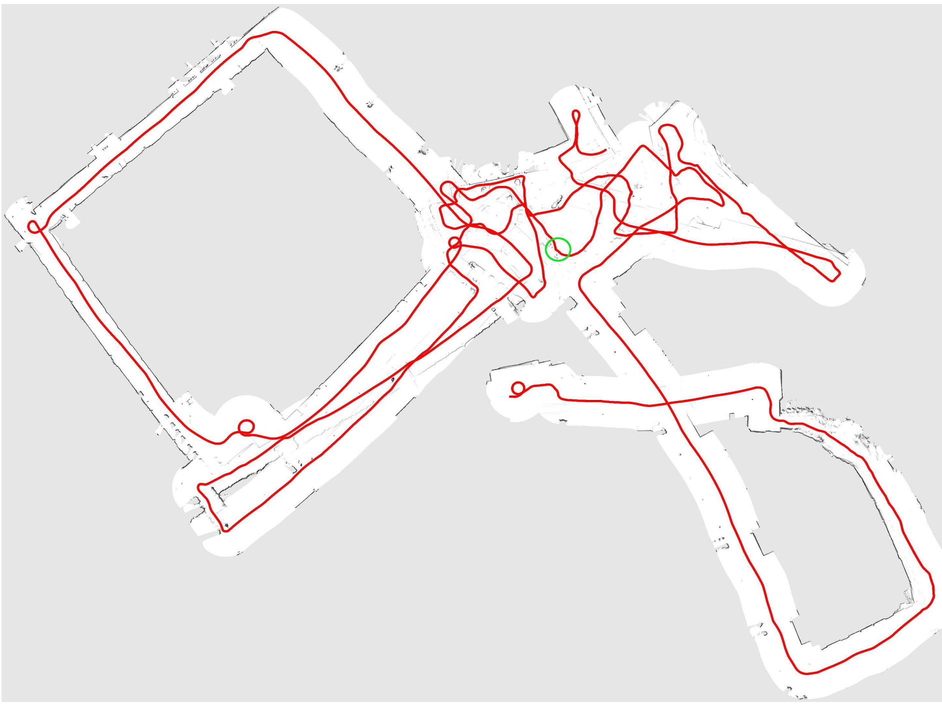


Outdoor/Bovisa 2008-10-04 Static: Maps raw odometry



Outdoor/Bovisa 2008-10-11b Static raw odometry: Map based on raw odometry. Wheel slippage is marked by a green circle in the map.

Outdoor/Bovisa 2008-10-04 Static: Maps generated from laser scans using improved odometry.



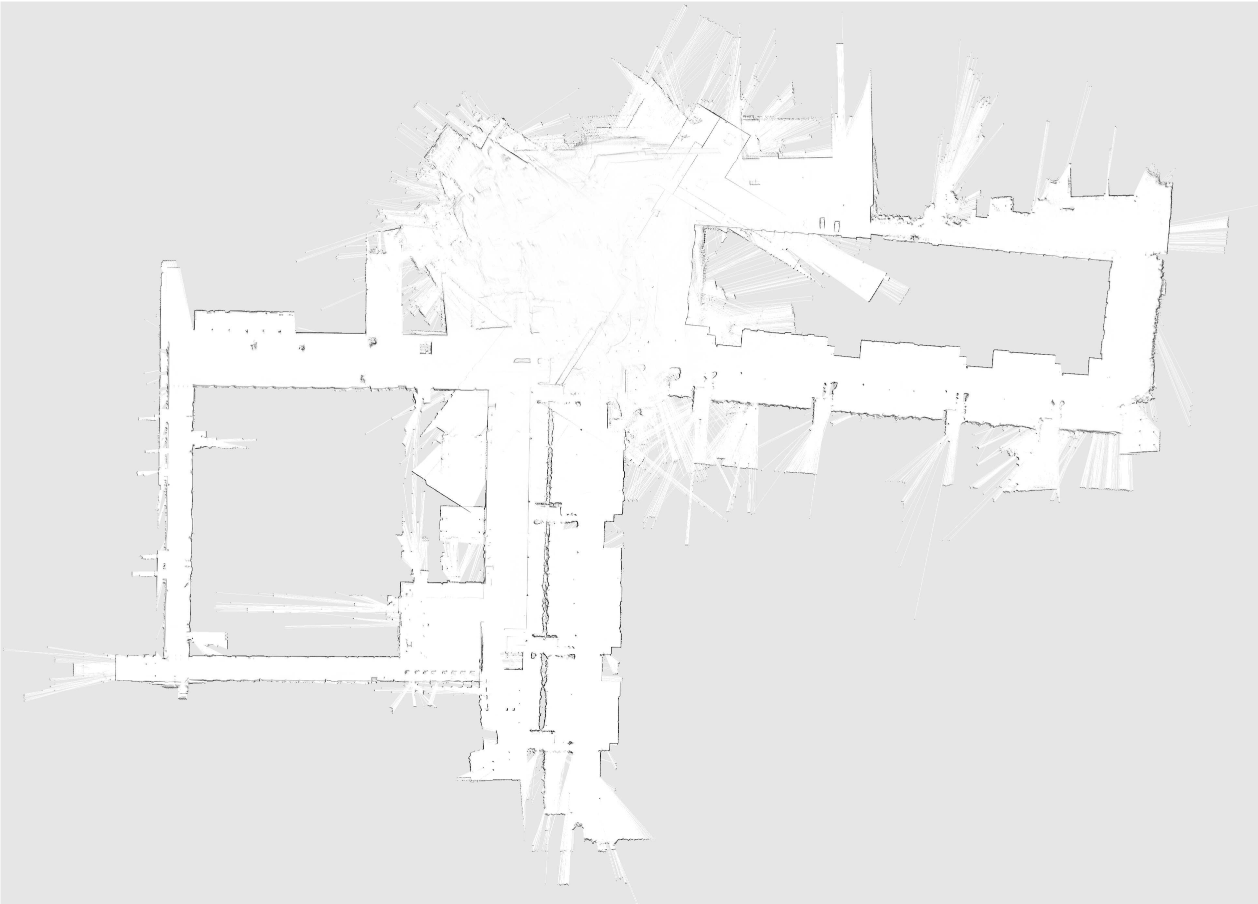
Outdoor/Bovisa 2008-10-11b Static improved odometry: Scan matching. Wheel slippage is marked by a green circle in the map.

4.5.3. SICK Laser

1. Data density and quality is validated by using ALUFR software which provides a Graph SLAM solution.

Resulting Graph SLAM map of Outdoor/Bovisa 2008-10-04 Static. The marked problematic areas are discussed in the next Figure.

The left picture shows a minor misalignment. The scans of this region are poorly aligned across all provided log files that went through that region. There is few observable structure in the 50 x 50 meter park for the laser range finder and a scan matching algorithm. But there are SLAM techniques that should be able to cope with that. The right picture shows a strange trajectory which leads to a misalignment. It looks like the robot got stuck at this position or had some problems with the underground. But again this should be manageable with some SLAM approaches.



Resulting Graph SLAM map of Outdoor/Bovisa 2008-10-11b Static

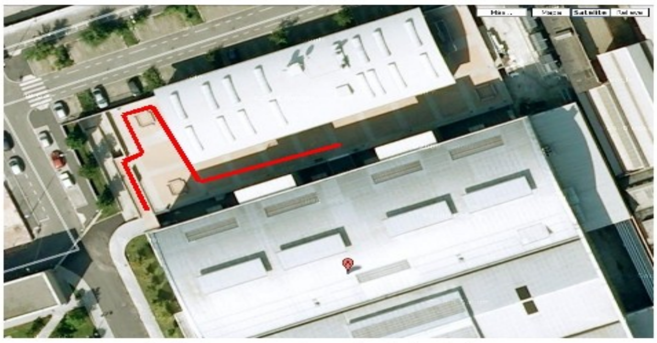
Furthermore, the trajectory of the robot when moving through the park area might be suboptimal for mapping approaches. The reason is that partially only very few structure is visible that could be used for correcting odometry errors. This might lead to locally blurred maps in that area. This, however, are issues a good SLAM approach should be able to compensate.


Map misalignment

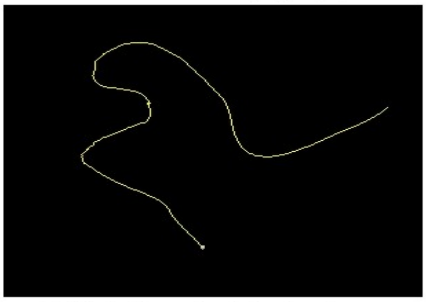
The blue trajectory is provided by the GraphSLAM algorithm, while the red is a hand corrected trajectory, which is closer to the true trajectory. The odometry misses a change of direction in the region marked by a green circle. The corresponding part of the trajectory is also marked in the google earth image. It looks like the error is nearly 90 degree.

4.5.4. Monocular Vision

1) Data is verified to be in compliance with the file specification and timestamped.
2) Timing: nominated frequency has been validated. See Table in section 4.5.1
3) Data overlap: we run monocular SLAM to validate the existence of sufficient environment features. The application of JCBB algorithm detects spurious features successfully and filter them out without any problem.



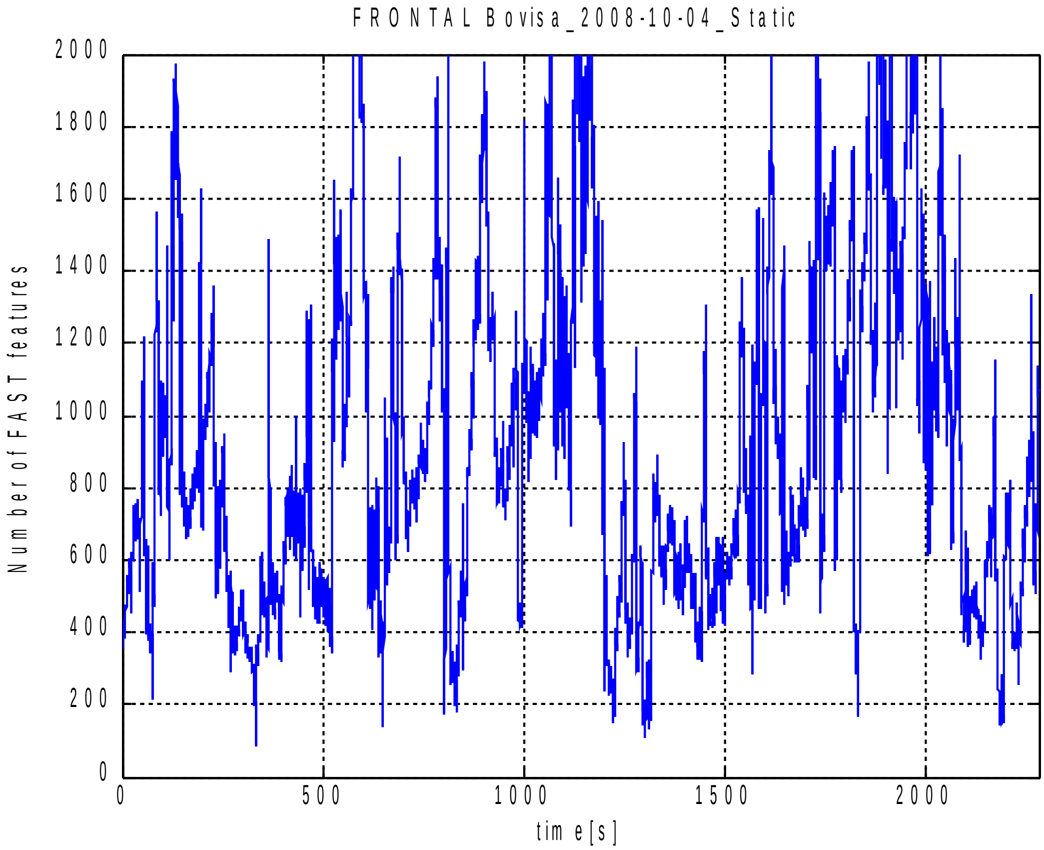
(a) Approximated trajetory



(b) Estimated trajectory

(c) Estimated trajectory and reconstructed points

Next figure shows the number of FAST features along the sequence. It can be seen that the density of features is higher with respect to the density observed in indoor experiments.

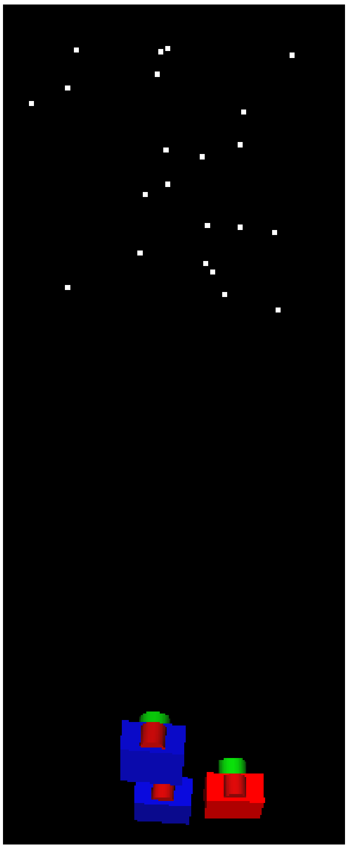


The calibration parameters are the same that for Mixed datasets.

4.5.5. Trinocular vision

1) Data is verified to be in compliance with the file specification and timestamped.
2) Timing: nominated frequency has been validated. See Table in section 4.5.1. We found a large data gap (12,8s) when evaluating the delta times along the top camera sequence. This correspond to 192 lost frames.
3) Data quality: In order to verify the relative position between cameras of the trinocular sensor, we performed a 3D reconstruction of one scene. The results for dataset Bovisa 2008-10-11b Static are shown in the following figure:

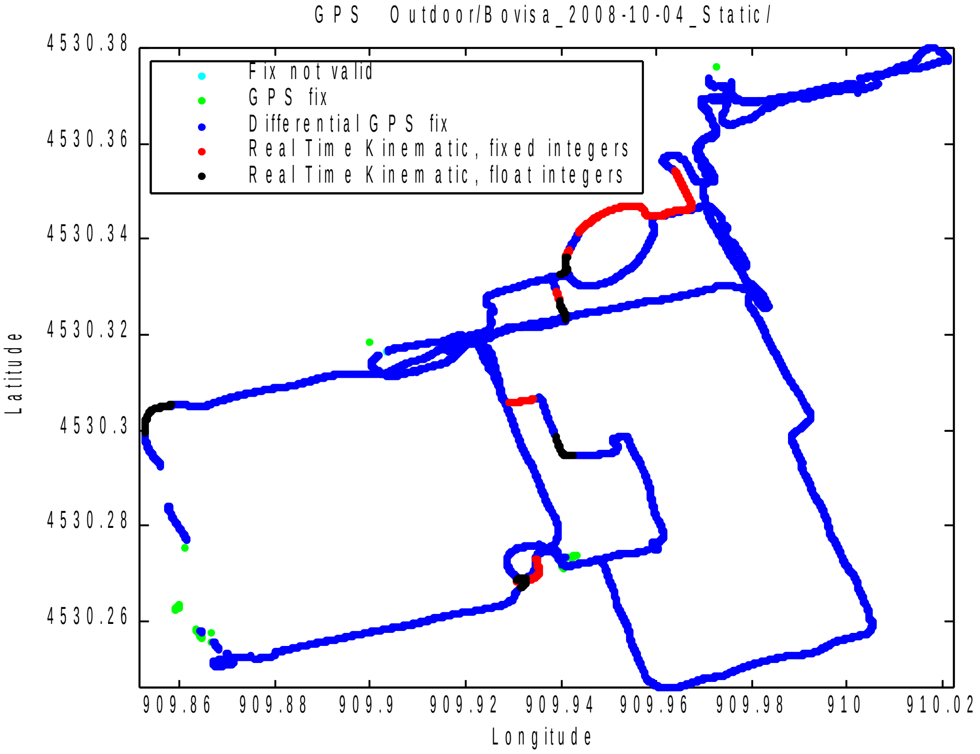
L: 1223740238.646717 T: 1223740238.646819 R: 1223740238.646921



3D reconstruction for frame 13612 of the dataset Bovisa 2008-10-11b Static. The SVS L image corresponds to the red camera. It does not correspond to the left image.

4.5.6. GPS

1)Data density and quality are validated by plotting the robot positions obtained from GPS. For these datasets we verify that GPS data covers sufficiently the outdoor parts of the trajectory.



GPS raw data

Planed trajectories on google Earth

4.6. Validation of Outdoor-Dynamic Session

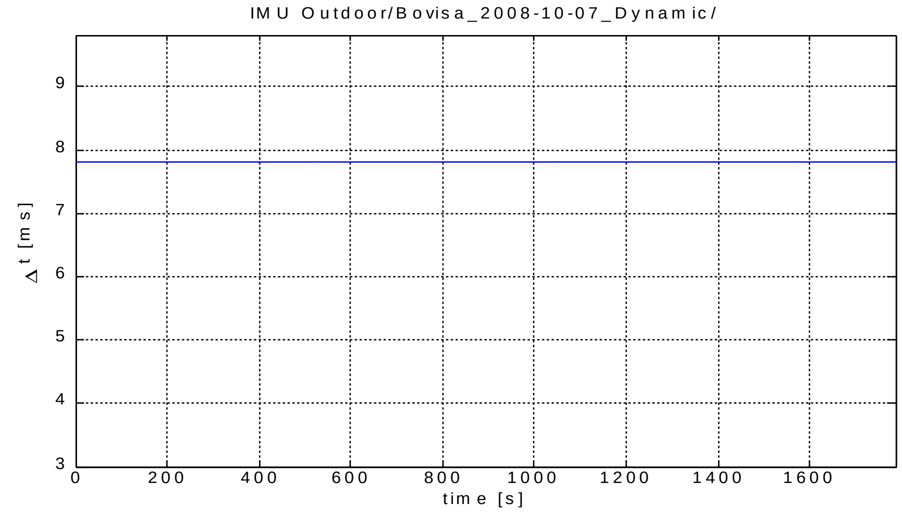
4.6.1. Basic time properties

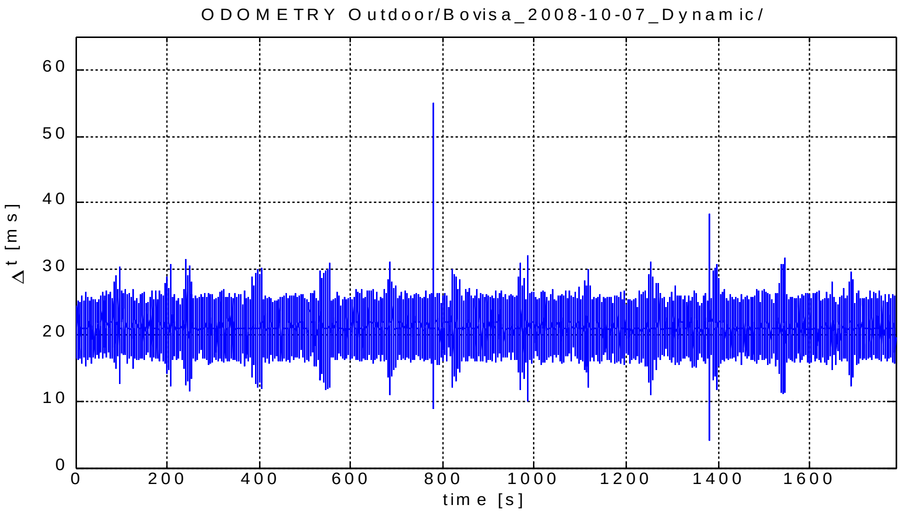
The following tables summarize the main timing characteristics of the data streams obtained from the different sensors (F: mean acquisition frequency, T: mean period, Tmax: maximum time interval between two consecutive acquisitions, Delay: mean delay with respect to IMU time base, std Delay: standard deviation of the delay). Cells highlighted in yellow represent data loss or synchronization issues, cells marked with '--' could not be computed.

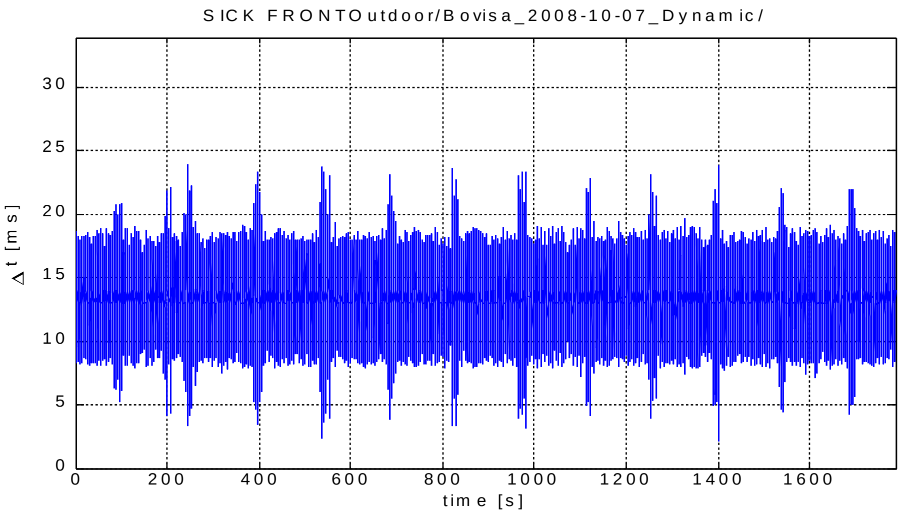
Outdoor/Bovisa_2008-10-07_Dynamic										
	IMU	Odometry	Sick R	Sick F	Hokuyo 1	Hokuyo F	Frontal	Trinocular	Panoramic	GPS
F (Hz)	127,97	47,62	76,84	76,84	10,1	10,05	29,9	15	15	5
T (ms)	7,8	20,99	13,01	13,01	99,1	99,44	33,5	66,65	66,68	199,92
Tmax (ms)	7,8	55,12	24,50	23,92	173,5	175,06	68,1	133,45	108,35	604,30
Delay (ms)	--	-98,00	54,08	51,38	--	--	-15,9	47,7	-34,6	--
std Delay (ms)	--	48,02	5,05	3,34	--	--	6,8	7,1	3,5	--

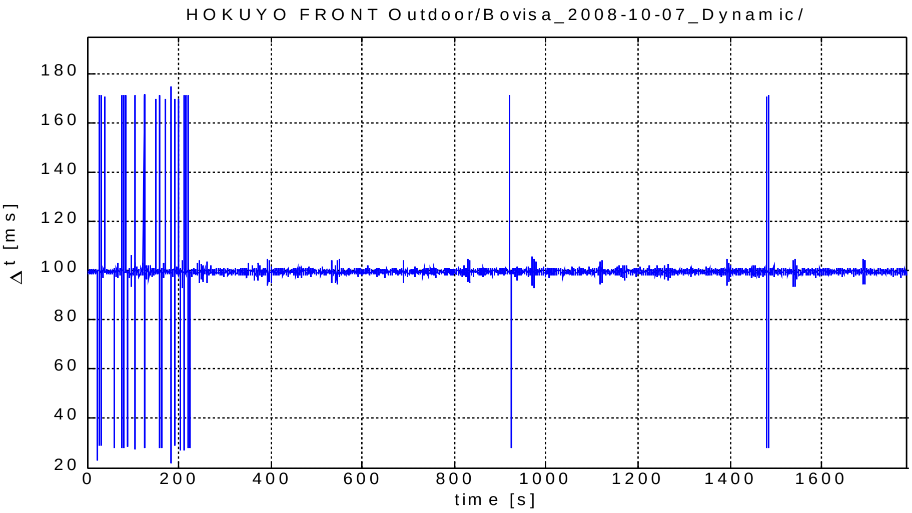
For this dataset we formulate the following conclusions:

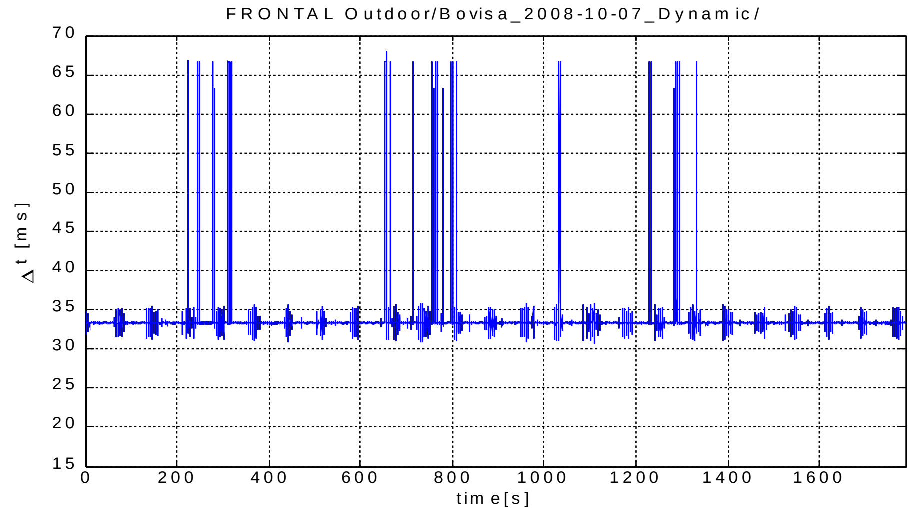
1. Sporadic gaps are found for HOKUYO and SICK.
2. GPS presents some oscillations.
3. Cameras timing present delta time gaps. However they do not represent data loss and can be used for SLAM.

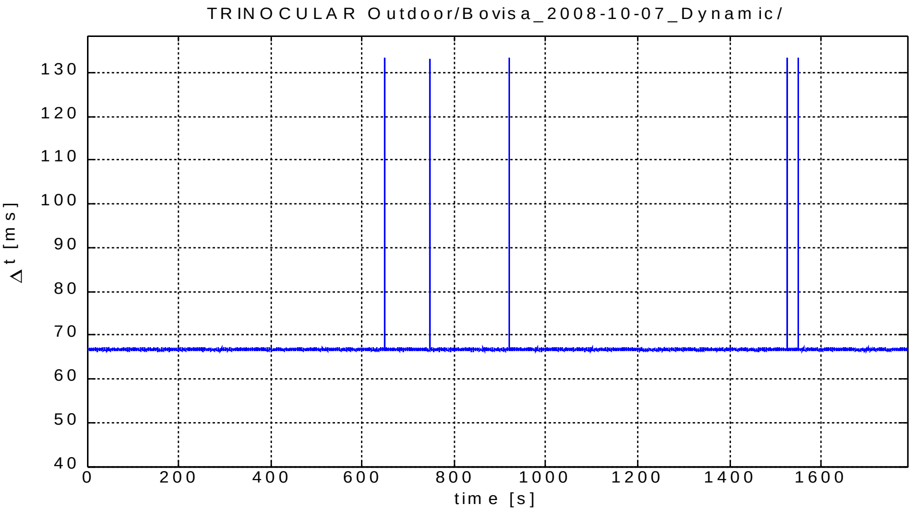

IMU Outdoor/Bovisa_2008-10-07_Dynamic/
Δt [ms]
time [s]

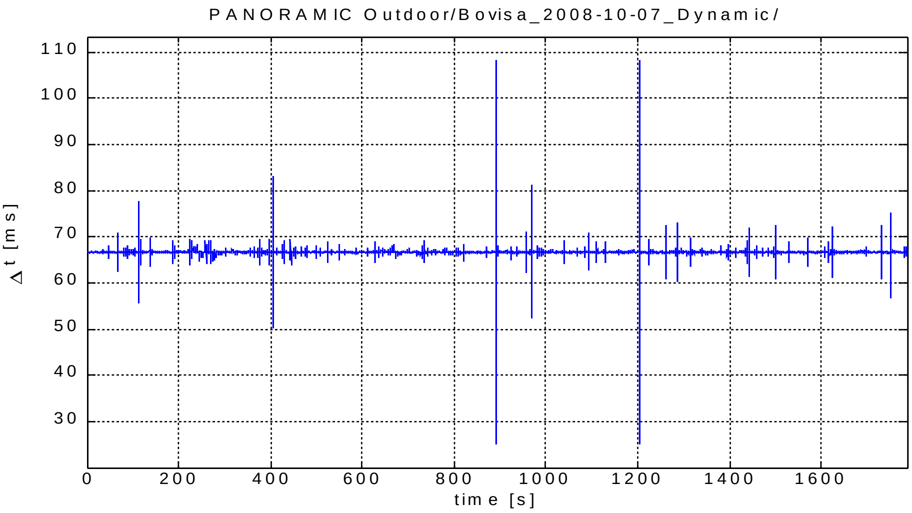

ODOMETRY Outdoor/Bovisa_2008-10-07_Dynamic/
Δt [ms]
time [s]

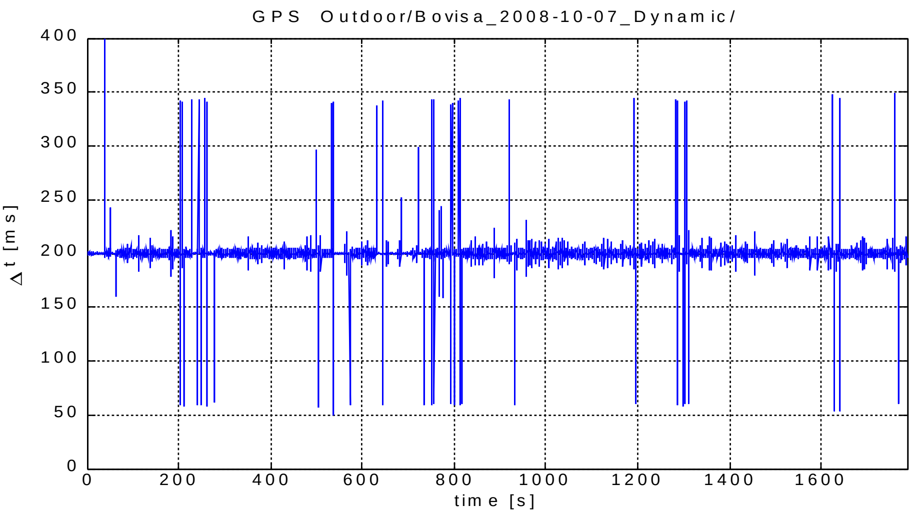

SICK FRONTOutdoor/Bovisa_2008-10-07_Dynamic/
Δt [ms]
time [s]


HOKUYO FRONT Outdoor/Bovisa_2008-10-07_Dynamic/
Δt [ms]
time [s]


FRONTAL Outdoor/Bovisa_2008-10-07_Dynamic/
Δt [ms]
time[s]

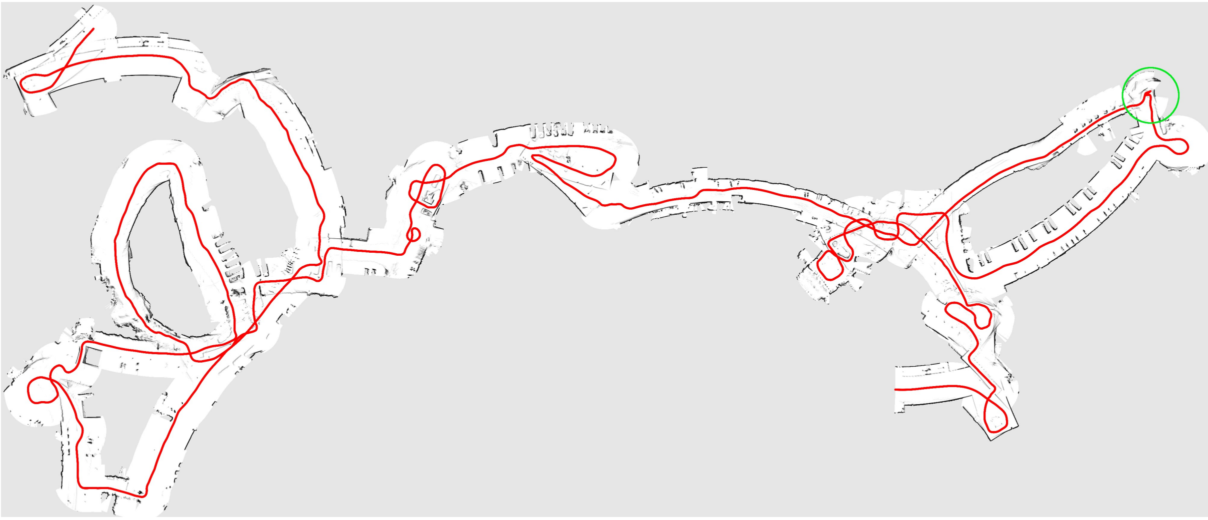

TRINOCULAR Outdoor/Bovisa_2008-10-07_Dynamic/
Δt [ms]
time [s]


PANORAMIC Outdoor/Bovisa_2008-10-07_Dynamic/
Δt [ms]
time [s]
110
100
90
80
70
60
50
40
30
0
200
400
600
800
1000
1200
1400
1600


GPS Outdoor/Bovisa_2008-10-07_Dynamic/
Δt [ms]
time [s]
400
350
300
250
200
150
100
50
0
200
400
600
800
1000
1200
1400
1600

4.6.2. Odometry

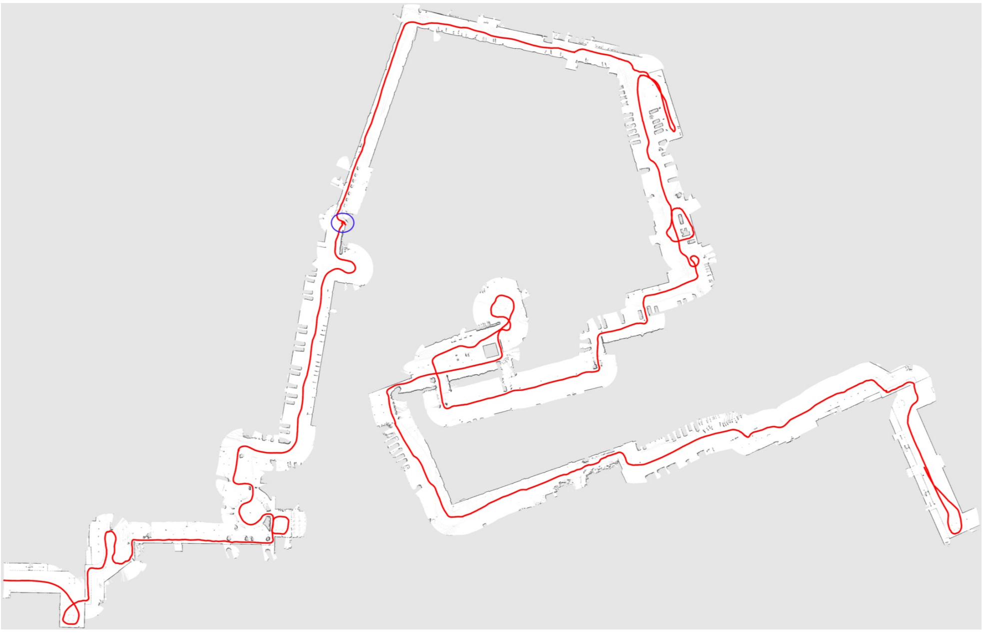
1) Data is verified to be in compliance with the file specification and timestamped.
2) Data Quality: At the position labeled in the figure, the robot made a right turn of approximately 90 degree. Due to wheel slippage, the odometry information shows instead a turn to the left hand side. This does not invalidate the datasets because SLAM algorithms must be able to cope with this problem in real-life applications. However, the wheel slippages should be documented in the information accompanying the datasets, to warn the users that they are specially challenging.



Bovisa 2008-10-07 Dynamic: Major error in the odometry is marked by a green circle.

4.6.3. SICK Laser

1) Data is verified to be in compliance with the file specification and timestamped.
2) Data overlap and data density: It was verified running the Graph SLAM algorithm. In this case, the wheel slippage could not be corrected even with the recalibrated odometry.

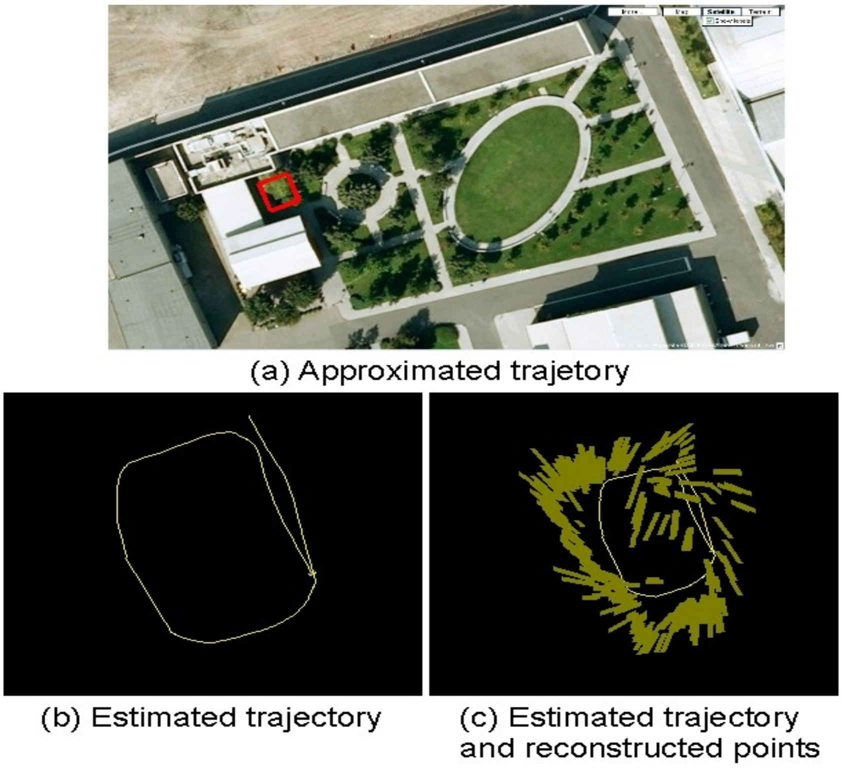


Resulting GraphSLAM map of Bovisa 2008-10-07 Dynamic. There is a major error in the odometry marked by a blue circle.

Planed trajectory of the robot. The robot turned right at the green marked position

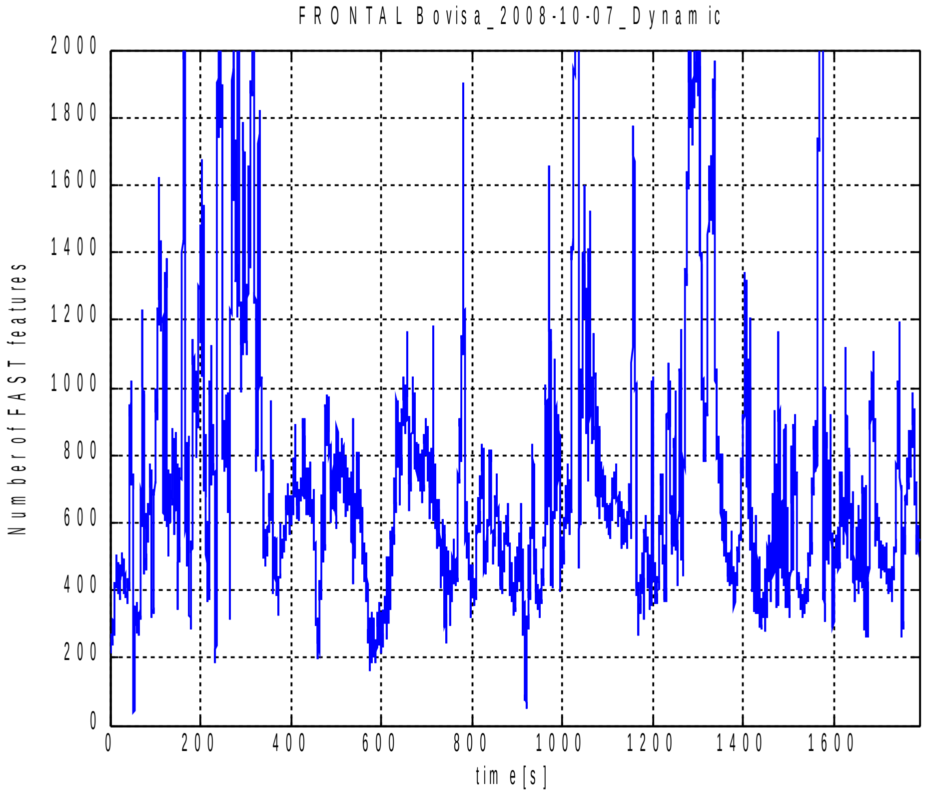
4.6.4. Monocular Vision

1) Data is verified to be in compliance with the file specification and timestamped.
2) Timing: nominated frequency has been validated. See Table in section 4.6.1
3) Data overlap: we run monocular SLAM to validate the existence of sufficient environment features. The figure shows the estimation results in a part of sequence *Outdoor/Bovisa_2008_10_07Dynamic.*



Map obtained from dataset Outdoor/Bovisa_2008_10_07Dynamic

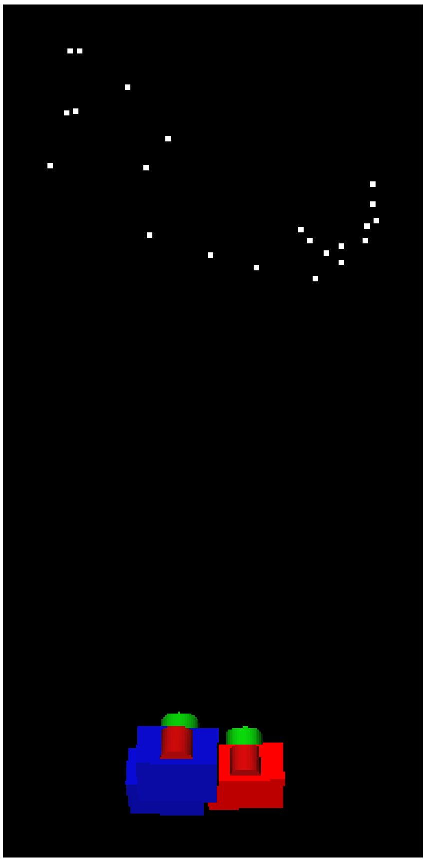
The number of fast features along the path is shown in following figure. Similar to previous datasets, the density increases in outdoor scenarios.


FRONTAL Bovisa_2008-10-07_Dynamic
Number of FAST features
time [s]
2000
1800
1600
1400
1200
1000
800
600
400
200
0
0
200
400
600
800
1000
1200
1400
1600

4.6.5. Trinocular Vision

1) Data is verified to be in compliance with the file specification and timestamped.
2) Timing: nominated frequency has been validated. See Table in section 4.6.1
3) Data Quality: Performing a 3D reconstruction on dataset Bovisa 2008-10-07 Dynamic we found that the cameras are interchanged. The problem is latent in the remaining outdoor datasets. The next figure exemplifies this incoherence.

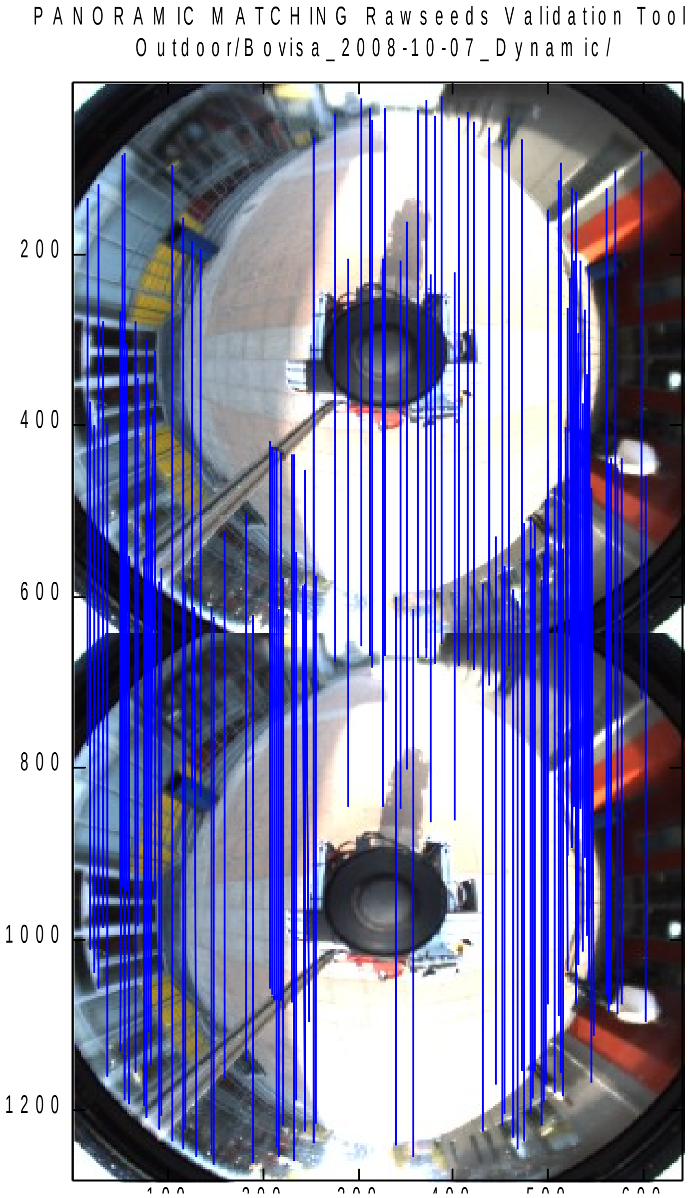
L: 1223390937.874085 T: 1223390937.873685 R: 1223390937.873889



3D reconstruction of frame 1798 of the dataset Bovisa 2008-10-07 Dynamic. The SVS L image corresponds to the red camera. Note that the left images does not correspond to the left camera.

4.6.6. Panoramic Vision

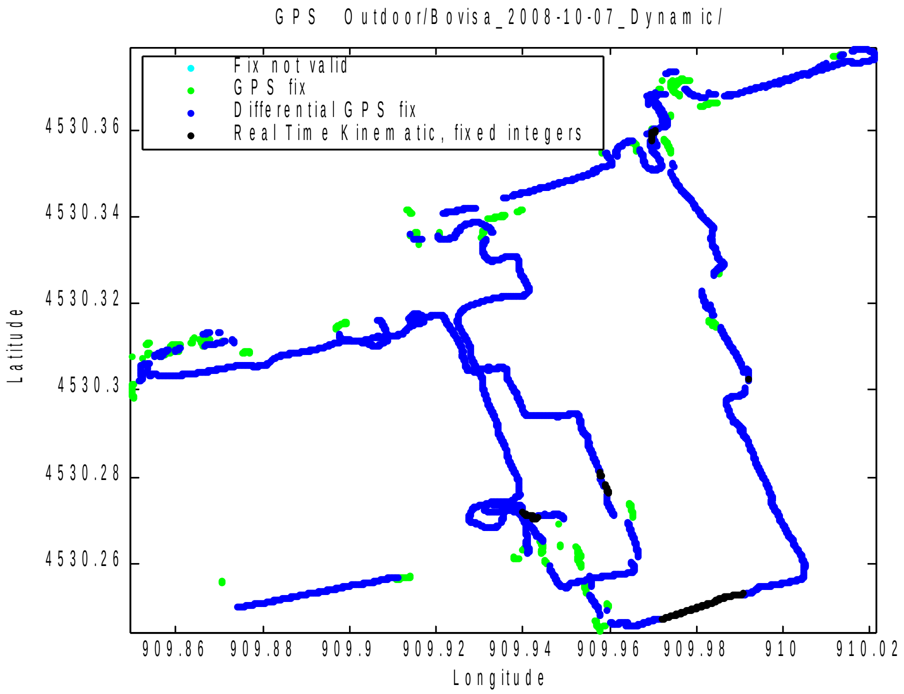
1) Data is verified to be in compliance with the file specification and timestamped.
2) Timing: nominated frequency has been validated. See Table in section 4.6.1
3) Data density and quality: we evaluate the quality of the images and we conclude that they are in compliance with the characteristics of SURF detector and matching algorithm. For this dataset the density of features is guaranteed to be enough for future localization proofs.



Example of SURF matching on an Outdoor scenario

4.6.7. GPS

1)Data density and quality are validated by plotting the robot positions obtained from GPS. For these datasets we verify that GPS data covers sufficiently the outdoor parts of the trajectory.



GPS raw data

Planed trajectories on google Earth

5. Recovery of the defects found in the preliminary validation

Most of the important defects listed in the deliverable "D3.1 preliminary data certification" have been successfully corrected in the new datasets. This section reviews these defects and analyzes their recovery in the new datasets.

5.1. Dataset documentation

Summary

In the preliminary validation, the documentation of the datasets was incomplete. The documentation has been corrected and completed in deliverables D2.1 and D2.2. Some minor improvements are proposed below.

Detailed Description

The requirements of dataset documentation listed in deliverable D3.1 have been fulfilled, providing all the information required. In particular, the extrinsic parameters of the sensor respect to a common reference as well as the description of the planed trajectories are well described in deliverables ***D2.1*** and ***D2.2*** which describe the new structure adopted to organize the datasets with common characteristics***.***

The major part of the minor issues found in file formats have also been addressed. This actions successfully improved the readability of the new acquired datasets. A few details that can be improved, related to the images format used, are:

- Trinocular images in dataset Mixed/Bovisa_2008-10-04_Static are stored using .pgm format, while the rest of visual streams use the .png format. To maintain the homogeneity of the datasets, all images should be stored in .png format, that includes lossless compression.
- Each stream should be packed in a .tar archive, but the archive should not be compressed to .tar.bz2, because as the images are already compressed by the .png format, further compression does not reduce the size of the archives, but greatly increases the time required by the users to unpack the images.
- The image timestamps should be stored in a file separated from the .tar archive, in order to facilitate accessing this information without extracting the the images from the archive.

5.2. Timing and data loss problems

Summary

In the preliminary validation there was data loss, from minor to major, in all datasets. In the new datasets, the problem is solved. However, there are a few minor data gaps for some sensors, in some of the datasets.

Detailed Description

The time period for the different sensors suffers from minor oscillations during the acquisition of each dataset, that can be easily handled by most SLAM algorithms. In a few cases, several data acquisitions have been lost. A summary of the timing issues detected per sensor follows:

- Odometry: It is not perfectly synchronized with the rest of the sensors: it runs ahead of time by a value between 80ms and 150ms. It should be documented in the datasets to allow users to compensate the delay in their SLAM algorithms.
- Hokuyo laser: The period is quite stable in most of the sessions with sporadic oscillations. However, it still presents data loss in Mixed dataset Bovisa_2008-09-01_Static and and Outdoor dataset Bovisa_2008-10-04_Static. This is no important, since the Hokuyo lasers are not usable outdoors.
- Monocular and trinocular vision: there are period oscillation in some of the sessions with up to 3 consecutive frames lost. This does not constitute a problem for current visual SLAM algorithms.
- The Left and Top trinocular sequences in the outdoor dataset Bovisa_2008-10-11b have a gap of 12 seconds of frames lost. As the gap occurs at the end of the dataset, we consider the stream valid for SLAM. Another gap of 12 seconds appears in the Top camera in the middle of dataset Bovisa_2008-10-04. We consider the stream valid because it can be properly used for stereo SLAM. The gaps should be documented in the datasets.
- Panoramic vision has a gap of 3.5 seconds of frames lost in the mixed dataset Bovisa_2008-10-11a. We consider this stream valid because the error is found in the last part of the dataset and, according to our tests, it can be recovered with SLAM algorithms that used appropriate relocation techniques. The gap should be documented in the dataset.

Recovery actions

Document the data gaps in the datasets.

5.3. *Camera calibration*

5.3.1. Monocular calibration

Summary

In preliminary validations, the calibration errors in the monocular camera (3.48% error in focal length) were too large and deliverable D3.1 gave recommendations to reduce them. In the new datasets, these recommendations have been taken into account and accurate calibrations with errors of 0,20% have been achieved.

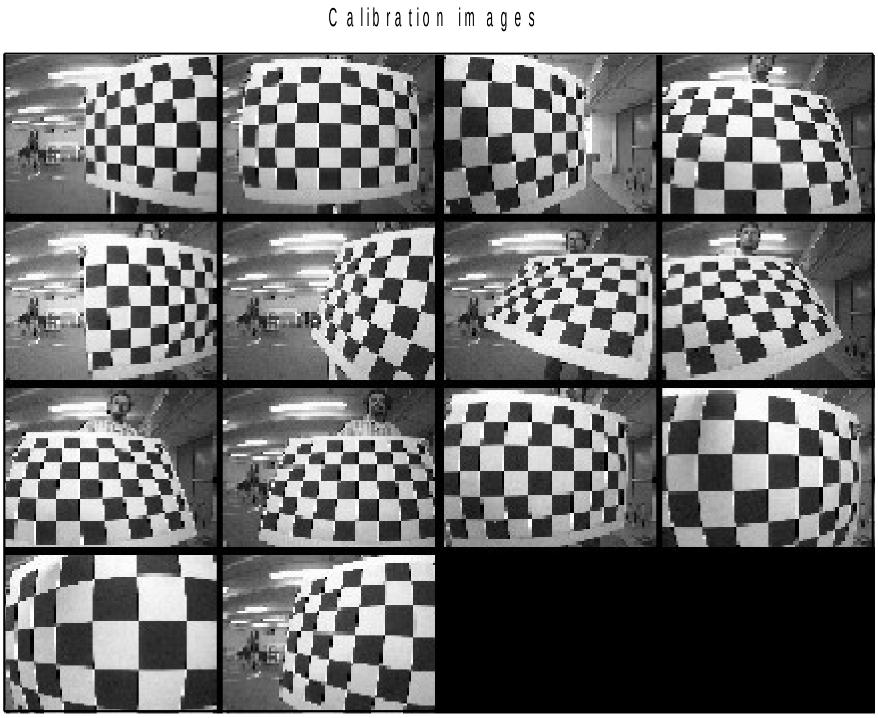
Details

In this section we detail the monocular calibration results obtained. Notice that the EYE camera used in old datasets has been now, more appropriately, renamed FRONTAL camera. The Matlab camera calibration toolbox (Bouget, 2008) has been used to evaluate the quality of the calibration provided, comparing with the example given in the toolbox. The old calibration analysed in D3.1 had a poor quality with errors of 3.48% in the focal length, compared to the 0.05% error in the toolbox example. Likely sources of error were image capture problems and over-parametrization.

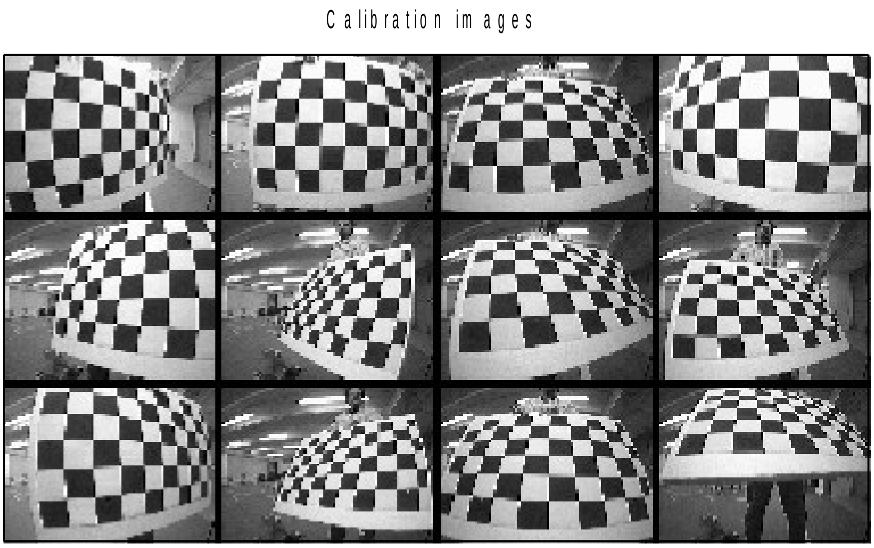
The recommendations issued in D3.1 have been taken into account to improve the calibration of FRONTAL camera in the acquisition of the new datasets. There are two different calibrations available, one for for the mixed and outdoor datasets and another for the new indoor datasets obtained in February. As it can be seen in the following table and figures, the calibration images have been chosen carefully to fulfil the optimization requirements, and the accuracy obtained is very good.

Datasets	f_value	f_error	Error %
Mixed and Outdoor	195,5473	0,3938	0,2014%
Indoor	194,8847	0,3847	0,1974%

FRONTAL calibration results



FRONTAL images used for calibration (Indoor datasets)



FRONTAL images used for calibration (Mixed and Outdoor datasets)

Indeed, the figures above demonstrate the use of correct calibration images for both indoor and Outdoor-Mixed datasets.

5.3.2. Trinocular calibration

Summary

In the preliminary data validations:

1) Intrinsic calibration parameters of the right camera had large errors (1,67% error in focal length) due to defects in the calibration process.
2) No extrinsic calibration parameters (relative transformations between cameras) were provided.
3) The recovery of the extrinsic calibration parameters gave low accuracy (2,59% errors in baseline) due to defects in the acquisition of the set of calibration images provided.

All this defects has been successfully corrected for the new dataset. Old and new calibrations are detailed in the following subsections.

Details

One of the problems of old calibrations is that the images used for the calibration of each camera were not synchronized and thus each set of images was only valid for independent camera calibration. The results of independent camera calibration had low accuracy, specially in the case of the right camera. Extrinsic stereo calibration was also tried running the stereo_gui.m program of the MATLAB toolbox to obtain the relative transformations between left and right cameras. The results were extremely poor, with errors of 2.59% in the baseline. One important problem was that the calibration pattern appeared too far from the cameras, with too small changes in orientation. Deliverable D3.1 suggested recovery actions for acquiring new calibration sequences that have been properly performed.

Calibration for Indoor Datasets (February):

The validation of this calibration shows that focal length error has been reduced to 0.06% providing very accurate intrinsic values.

Camera IndoorDatasets	f_value	f_error	Error %
Toolbox example	657	0,34	0,05%
SVS_L	660,4720	0,4059	0,0615%
SVS_R	664,7630	0,4027	0,0606%
SVS_T	662,6862	0,3908	0,0590%

Validation of intrinsic parameters of Calibration 3 (Indoor)

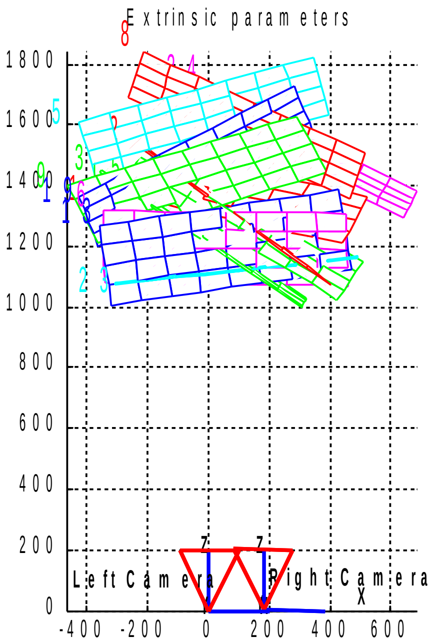
The extrinsic parameters have been also improved. The translation error is reduced to 0.08% compared to the 2.56% calculated before.

Camera coordinates	T value	T error	Error %
X position	-180,8425	0,1530	0,08%
Y position	-0,6073	0,1377	
Z position	-4,4141	0,1399	

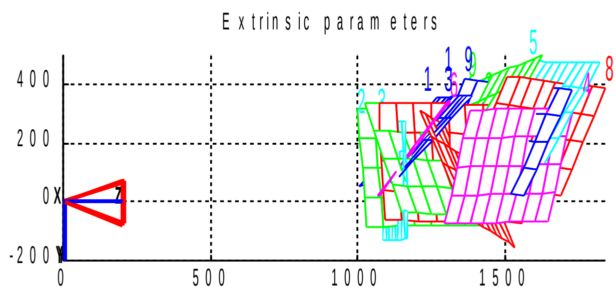
Camera coordinates	Om value	Om error	Error %
X position	0,0018	0,0001	
Y position	-0,0080	0,0001	
Z position	0,0056	0,0001	

Validation of extrinsic parameters of Calibration 3 (Indoor)

The corresponding 3D reconstruction shows the correct placement of the calibration pattern and the good quality of the calibration parameters.



Top view



Lateral view. There is not misalignment between cameras

Calibration for Outdoor and Mixed Datasets

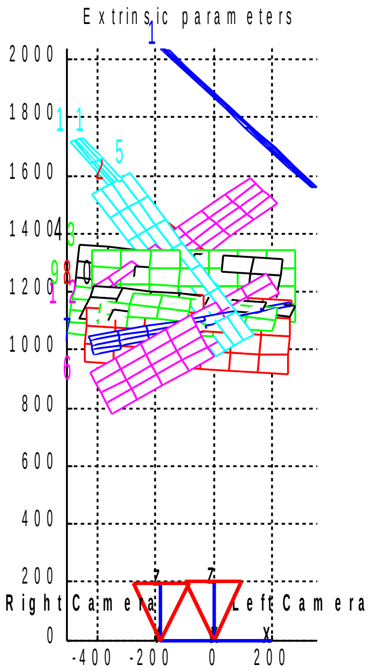
The validation of this calibration shows that focal length error has been reduced to 0.11% and baseline error to 0.13%, providing very accurate values.

Camera 2	f_value	f_error	Error %
Toolbox example	657	0,34	0,05%
SVS_L	669,1125	0,7495	0,1120%
SVS_R	664,0419	0,7481	0,1127%
SVS_T	665,9236	0,7127	0,1070%

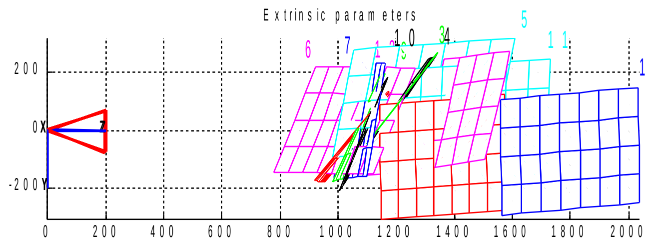
Camera coordinates	T value	T error	Error %
X position	181,06	0,24	0,13%
Y position	-0,33	0,22	
Z position	0,71	1,23	

Camera coordinates	Om value	Om error	Error %
X position	0,0010	0,0020	
Y position	0,0061	0,0032	
Z position	-0,0054	0,0002	

The corresponding 3D reconstruction shows the correct placement of the calibration pattern and the good quality of the calibration parameters. As it can be seen, the left and right camera are interchanged, a minor error that was also detected in the corresponding datasets.



Top view



Lateral view. There is not misalignment between cameras

5.3.3. Panoramic calibration

Summary

The panoramic calibration, not available for the preliminary validations, has been performed, obtaining good accuracy. However, the documentation about the calibration process needs to be improved.

Detailed description

Calibration of panoramic camera has been provided for this deliverable version. The main results are detailed in the following table:

Datasets	cc_x	cc_y	cc_x_error	cc_y_error	Error x %	Error y %
Mixed and Outdoor	326,14	313,86	1,45	0,00418	0,44%	0,0013%
Indoor	327,79	313,69	1,00161	0,00291	0,31%	0,0009%

Notice that the error percentage is less than 0,5%, which is considered adequate for this type of cameras.

Recovery actions

The documentation includes now a reference for the calibration process that was carried out, but this is still insufficient to fully understand the camera model used. We recommend to widen the calibration explanation for this sensor.

6. New defects found and recovery actions performed

6.1. Odometry Calibration

Summary

In the provided odometry nearly all straight corridors show a drift to the left hand side. This is a common problem with odometry that can be compensated with the calibration software developed by ALUFR.

Detailed Description

The seven datasets delivered in December 2008 were validated by running the laser graph-based SLAM software from ALUFR (Grisetti et al 2007, Grisetti et al 2008). This technique uses a novel constraint network-based approach that models poses of the robot during data acquisition as nodes in a graph. Using efficient optimization techniques developed in this project,we obtained mapping results that are the basis for the subsequent analysis. This technique obtains constrains for the robot poses using laser scan matching. However, in the areas of the environments were few laser information is available, the outcome of the algorithm relies essentially on the odometry information.

Based on the constraint network, we manually inspected the constraints that have been poorly optimized by our technique. A high error indicates a configuration of the network in which observations present contradictions. This facilitated the manual matching procedure by identifying the parts of the dataset with are likely to be erroneous. The identified parts have all been manually inspected and the individual transitions computed based on the odometry as well as the laser range finder data have been checked for consistency. Four of seven datasets could be processed by the algorithm obtaining good mapping results, as shown in the following table.

Dataset	**Odometry appropriate**	**Dataset Useful for Laser Mapping**
Indoor\Bicocca_Static_Daylight\Bicocca 2008-12-07a	passed	passed
Outdoor\ Bovisa_2008-10-04_Static	passed with minor problems	passed with minor problems
Outdoor\ Bovisa_2008-10-07_Dynamic	failed	failed
Outdoor\ Bovisa_2008-10-11b_Static	failed	failed
Mixed\ Bovisa_20080901_Static	passed	passed
Mixed\ Bovisa_20081006_Dynamic	passed	passed
Mixed\ Bovisa_20081011a_Static	passed	passed

For the outdoor dataset Bovisa 2008-10-04 Static, we identified two minor problems. First, the odometry is affected by high noise, especially in an area around the park. The problem we identified here was that the robots has only very few laser observation at that point and thus the drift cannot be compensated in an appropriate way by our techniques. As a result, minor inconsistencies can arise in maps of that area. Second, at one point, the robot appeared to be bumped against an object or a wheel was blocked for a short period of time. This causes substantially wrong odometry information and thus is likely to reveal mapping inconsistencies. The outdoor datasets Bovisa_2008-10-07_Dynamic and Bovisa_2008-10-11b_Static contain serious errors in the odometry information that seem to be caused by wheel slippage, and are discussed in the next section.

Recovery Actions

Odometry bias is a common problem with most mobile robots, typically due to the center of gravity not being on the geometrical center of the robot. ALUFR has developed a software package to perform the calibration and compensate for the inaccurate input data. To do so, laser range data is used to locally estimate an accurate map of the environment. Then, the calibration parameters are estimated by a probabilistic sampling technique in a way so that the odometry information is as close as possible to the trajectory reported by the mapping software.

Given that the velocity of the left and right wheels can be calculated by

$$v_r = \frac{tics_r * d_r * w_{dr}}{dt} \quad (1)$$

$$v_r = \frac{tics_l * d_l * w_{dl}}{dt} \quad (2)$$

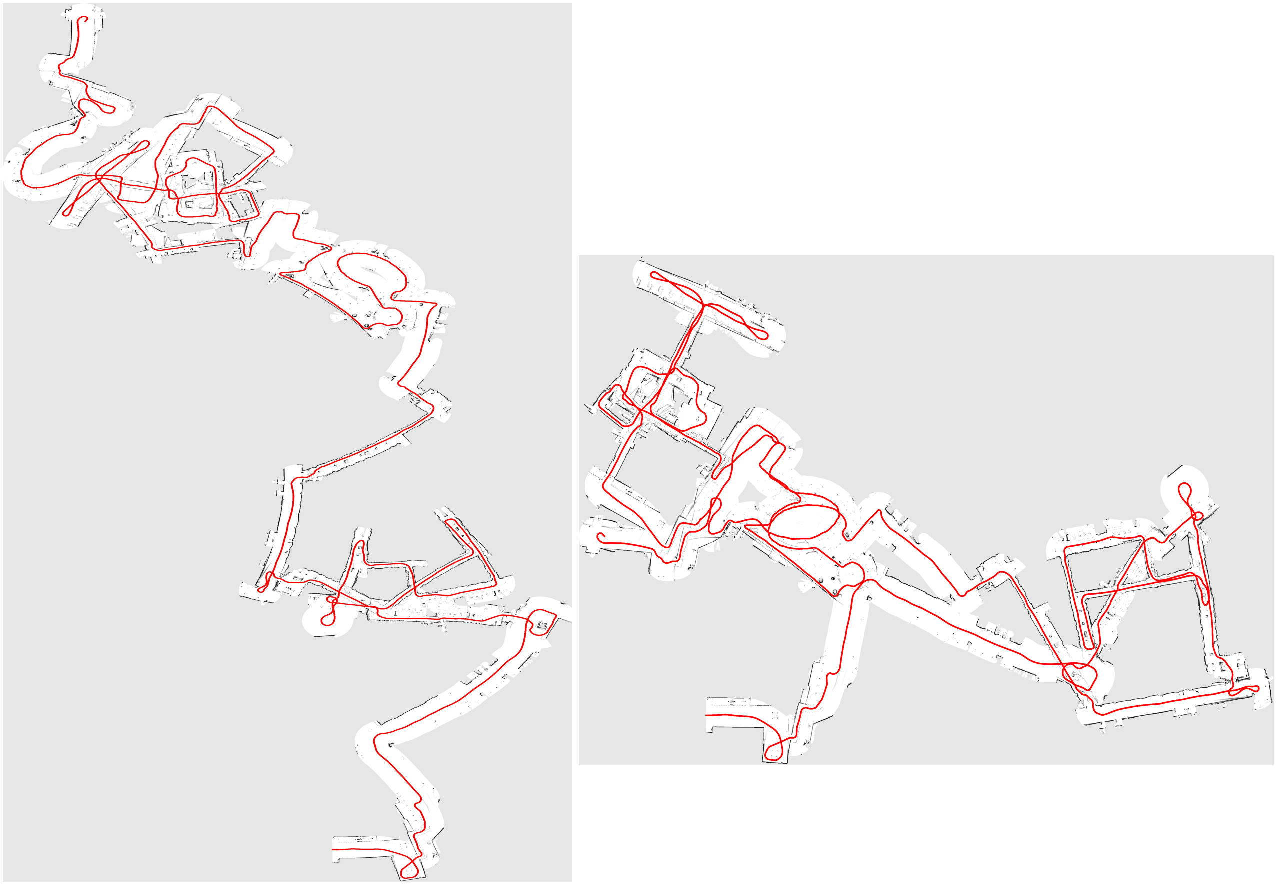
assuming that d_l and d_r are the tics to meter factors and that the drift can be modeled with the weights w_{dl} and w_{dr}.

Given this assumption, we determined the following parameters:

•Distance of wheels: $l = 0.393000$

$$d_l = 0.00000550\,;\, w_{dl} = 1.0050000\,;\, d_r = 0.00000550\,;\, w_{dr} = 1.0000000\,;$$

An example of the odometry bias and the correction obtained by applying the calibration parameters obtained is shown in the following figure.



Mixed/Bovisa 2008-10-11a Static: Map obtained using the laser scans and the robot odometry, before and after odometry calibration.

As conclusion, the dataset documentation should include the results of the calibration process to allow the users to improve the odometry.

6.2. Wheel slippages

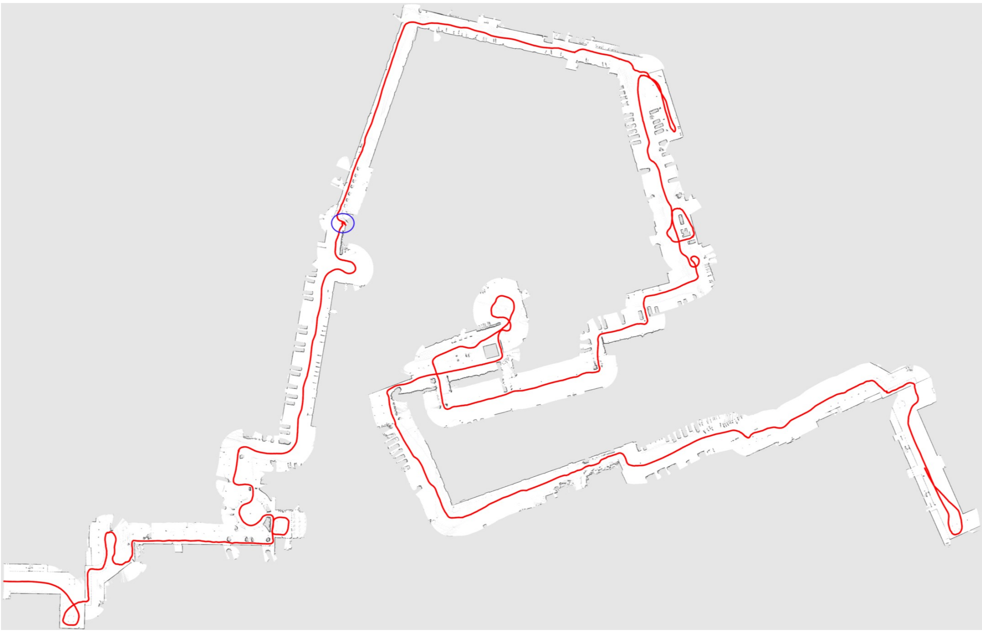
Summary

The outdoor datasets Bovisa_2008-10-07_Dynamic and Bovisa_2008-10-11b_Static contain serious errors in the odometry information that seem to be caused by wheel slippage.

Detailed Description

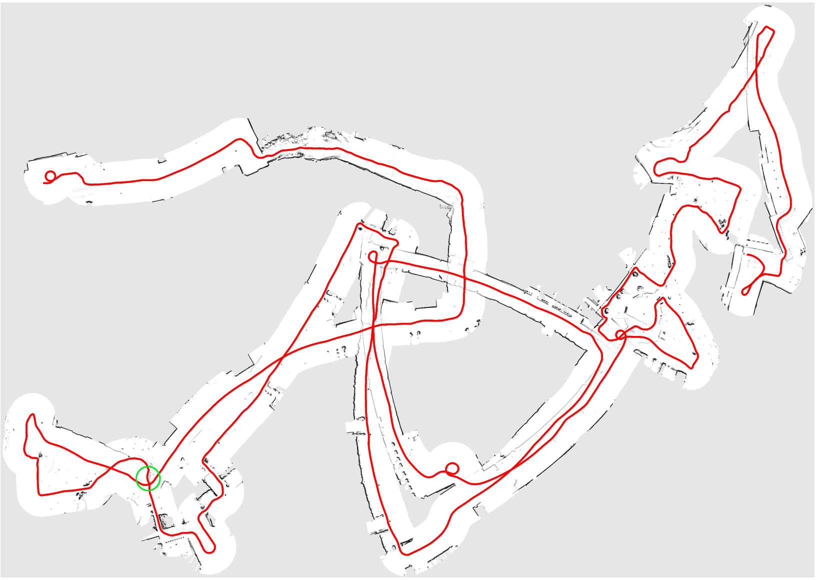
We believe that it is nearly impossible to compensate these errors using the laser-based SLAM techniques developed by ALUFR. In detail, we found the following errors:

- Bovisa 2008-10-07 Dynamic: At the position labeled, the robot made a right turn of approximately 90 degree. In the odometry information, however, shows a turn to the left hand side. This error is so large that we found it impossible to cope with this error.



Results of laser-based GraphSLAM of Bovisa 2008-10-07 Dynamic.

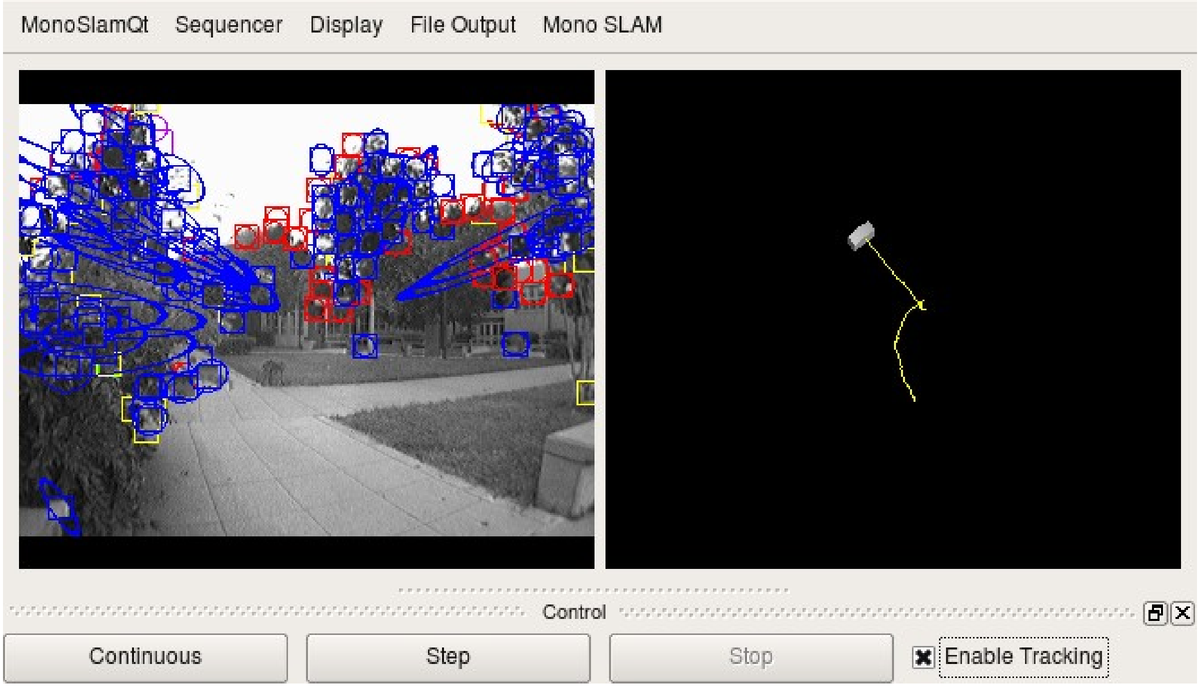
- Bovisa 2008-10-11b Static: At the position labeled, the robot performed a 90 degree turn to the left hand side. The odometry, however, does not report any turn. Again, this misinformation makes accurate map building nearly impossible for metric approaches.



Outdoor/Bovisa 2008-10-11b Static raw odometry: Map based on raw odometry. Wheel slippage is marked by a green circle in the map.

Even with manual adjustments, we were unable to obtain a consistent map of the space. We tried to compensate the wrong odometry information by ignoring it and only use the laser range finders to seek for better estimates using scan-matching. However, due to the lack of appropriate structure for matching, this turned out to be impossible using our laser-based SLAM methods.

However, although in these outdoor areas the laser information is scarce, visual SLAM techniques are able to extract hundreds of features, that allow to obtain consistent maps. The following figure shows the robot trajectory obtained using the visual SLAM technique of UNIZAR [Civera et al, TRO 2008], where the 90 degree turn to the left hand side is properly estimated.



Results of pure monocular SLAM in the wheel slippage of dataset Bovisa 2008-10-11b Static. The technique was able to correctly estimate the 90 degrees turn to the left.

Recovery Actions

As conclusion, we believe that wheel slippage is representative of the difficulties that a SLAM algorithm must face in real-life applications. This issue must be documented in the datasets and will constitute an interesting benchmark to asses the robustness of different SLAM algorithms.

Alternatively, we could also provide an “improved” version of the odometry data where the wheel slippage has been manually removed.

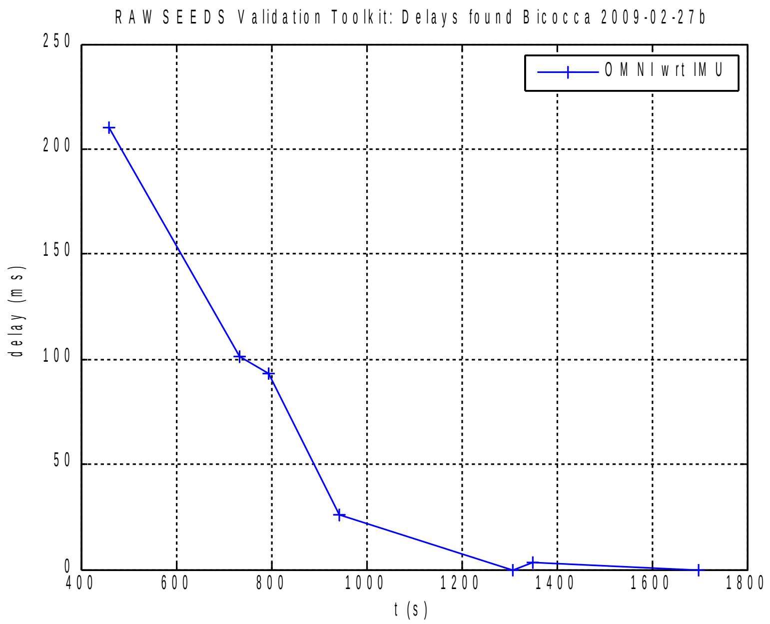
6.3. Synchronization errors in Bicocca_2009-02-27b

Summary

In the indoor dataset Bicocca_2009-02-27b, monocular, trinocular and panoramic cameras are not correctly synchronized with the rest of sensors.

Detailed Description

In the indoor dataset Bicocca_2009-02-27b, the timestamps of monocular and trinocular streams have periodic gaps of 1 second, but no frames were lost. This seems to be caused by the ptpd clock synchronization daemon that was used to synchronize the clocks of the different computers involved in the data acquisition. The timestamps have been manually corrected, eliminating the artificial timestamp gaps. However, the validation procedure has detected a significant residual error in the synchronization of monocular, trinocular and panoramic cameras, with errors up to 200ms. Additionally, the standard deviations of the delays are also large (20,8ms; 21,95ms and 78,4ms) making difficult an accurate compensation of the delays to perform SLAM. In the panoramic camera, the validation has also found a drift in the clock during the first part of the dataset, as shown in the following figure:



Recovery Actions

The validation results indicate that the different computers were not correctly synchronized, and the dataset has been discarded.

6.4. Invalid trinocular streams

Summary

In the indoor datasets acquired between 2008-12-06 and 2008-12-09 the image sequences of the three cameras that form the trinocular system are identical.

Detailed Description

This problem was totally unexpected because all the previous trinocular sequences were correct, including the sequences used for calibration. As the acquisition software developed by POLIMI was not changed, the bug has been reconstructed being related to the installation of an updated version of the firewire driver package. Unfortunately, the newer version caused the same image to be replicated in the three different memory areas of each acquisition thread. Those memory areas were then written to the three camera streams in the hard disk. As a results, the images coming from the other two cameras were not stored, being definitely lost.

Recovery Actions

- The datasets were declared invalid and WP2 was required to acquire new indoor datasets.
- The software bug was circumvented, and the new indoor dataset were acquired from 25 to 27 February 2009.
- Before making the datasets available to the consortium, a preliminary check was performed by POLIMI and UNIMIB to verify that:
  - All streams are present and there are no big data gaps.
  - The images from different streams are actually different (checked at the beginning, in the middle and at the end of the streams).
- A new validation procedure was added by UNIZAR in WP3, performing 3D scene reconstruction with Photomodeler using manually selected frames from each trinocular dataset. This allows to verify that the three images are correct and correspond with the calibration provided. This validation was also applied to the previous datasets, detecting that in some cases the left and right images were interchanged. The issue can be easily corrected by interchanging the filenames.
- The new indoor datasets have been successfully validated in WP3.

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