RAWSEEDS

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

WorkPackage 3

Deliverable D3.1
Preliminary Data Certification

Project no. 045144

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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. Most of the effort in WP3 has been devoted to the design of the algorithms for data validation and their software implementation. Having prepared the data validation software ahead of time is allowing quick progress in WP3.

The validations performed have covered the datasets obtained in WP2 and made available to the consortium until September 15th, 2008. The datasets are being validated considering the four criteria defined in WP1: file format, timing, data overlap and data density and quality. The current status of the validation is summarized in the following table, where blank cells represent work in progress, and asterisks indicate defects that need to be corrected.

	Indoor			**Indoor & Outdoor**
Sensor data	**Session0**	**Session1**	**Session2**	**Session 20080901**
Odometry	Valid	Failed	Valid	Valid
IMU	Valid*	Valid*	Valid*	Valid*
SICK Laser	Valid	Failed	Valid	Valid
Hokuyo Laser	Valid	Valid	Valid	Not usable outdoors
Sonar Belt		Not available	Not available	Not available
Monocular Vision	Valid*	Valid*	Valid*	Valid*
Trinocular Vision	Failed	Failed	Failed	Failed
Panoramic Vision		Not available		
GPS	Not available	Not available	Not available	Valid

In general, the datasets obtained have good quality, although the accompanying documentation needs to be improved. Many defects detected are minor and can be corrected with post-processing of the datasets. The two major defects detected are: 1) severe data loss in Session1; and 2) the low quality of the camera calibrations performed, compared with the standard current practice. In our tests, the calibration has been found to be acceptable for monocular SLAM, but it seems to be too imprecise for trinocular or stereo SLAM.

Data acquisition for Session1 and camera calibration for all sessions need to be repeated. Section 4 of this document discusses the details of the most important defects found and provides recommendations for their correction.

2. Data validation methodology

The datasets are being 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. The timestamps will be checked to be monotonically non-decreasing. 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.
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.

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 and quality are validated by running line extraction software throughout the trajectory and building local maps with EKF-SLAM, using software developed by UNIZAR. The datasets are also processed to perform Graph-based SLAM, using software developed by ALUFR (Grisetti et al 2007, Grisetti et al 2008).

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

At the time of preparing this report, the extrinsic calibration of the sonar ring (locations of the sonar sensors on the robot) was not available, and only the file format and frequency of acquisition could be verified.

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) Accurate verification of the sonar synchronization is more difficult, because sonar returns are quite insensitive to robot rotation. We will try to verify it by correlating the variation of the frontal sonar returns with the speed of the robot in straight portions of the trajectory.

d) Data density and quality are validated by plotting the sonar returns on top of the SICK laser returns in different parts of the trajectory to detect possible malfunctioning of the sonar belt. This could also highlight gross errors in synchronization of the sonars with respect to the laser.

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.

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.

c) Data overlap:

i. It is first verified by visual inspection of the image sequences. Then the sequences are processed to obtain FAST corners, 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 2008), and data association based on JCBB (Neira and Tardos 2001). The Inverse Depth and JCBB combination first proposed by (Clemente et al 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 makes them useless for monocular SLAM. We call them “dark” frames; they are detected and enumerated.

d) 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.

e) Data density and quality:

   i. It is validated by running the FAST (Rosten and Drummond 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 Jean-Yves Bouguet. 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) Data overlap is first verified by visual inspection of the image sequences. Then the sequences are processed to obtain Harris corners, track them on the sequence and perform pure stereo SLAM, without using the robot odometry, using the software developed by UNIZAR (Paz et al., 2008).

c) 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.

d) 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.

e) 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. The calibration quality is further verified by running stereo SLAM software on the dataset.

8) Panoramic Vision:

The validation methodology will be similar to monocular vision. At the time of writing this deliverable, the adaptations of the monocular software needed to validate panoramic vision is not finished. This report contains only preliminary validation results.

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 deliverable 3.2 we plan to obtain angular velocity from the panoramic images and compare it to the angular velocities obtained by the IMU using cross-correlation.

d) Data density and quality will be validated by running feature extractors 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) The synchronization of the GPS with the rest of the system is verified by estimating from GPS data the robot heading and its derivative, the robot angular velocity. The angular velocities obtained by GPS and the IMU are compared by cross-correlation.

c) 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.

3. Data validation results

At the time of preparing this deliverable, the datasets available and the sensor streams provided in each dataset were:

Data Files Available									
Session		**0**		**1**		**2**			**20080901**
Round		**2**	**3**	**1**	**2**	**1**	**2**	**3**	
Sensor	Odometry	Yes	Yes	Yes	Yes		Yes	Yes	Yes
	IMU	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sick_Front	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sick_Rear	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Hokuyo_Front	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Hokuyo_Rear	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sonar_Belt	Yes	Yes						
	EYE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	SVS_L	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	SVS_R	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	SVS_T	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	VSTONE	Yes	Yes			Yes	Yes	Yes	Yes
	GPS								Yes

The datasets Session0 to Session2 correspond to indoor trajectories, while Session 20080901 corresponds to a mixed indoor/outdoor trajectory. In the following sections we summarize the results obtained during the validation process of the four datasets. The results are presented in more detail in the first dataset. In the rest of cases, only the most important novelties discovered are detailed.

3.1. Validation of Session0

The validations performed so far are summarized in the following table, where blank cells represent work in progress, and asterisks indicate defects that need to be corrected.

Sensor	**File Format**	**Timing**	**Data overlap**	**Data density and quality**
Odometry	Valid	Valid*	Not applicable	Valid
IMU	Valid	Valid*	Not applicable	Valid
SICK Laser	Valid	Valid	Valid	Valid
Hokuyo Laser	Valid	Valid	Valid	Valid
Sonar Belt	Valid			
Monocular Vision	Valid	Valid	Valid	Valid* Calibration has low precision
Trinocular Vision	Valid	Valid	Valid	Failed Calibration not usable
Panoramic Vision				
GPS	Not available	Not available	Not available	Not available

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.

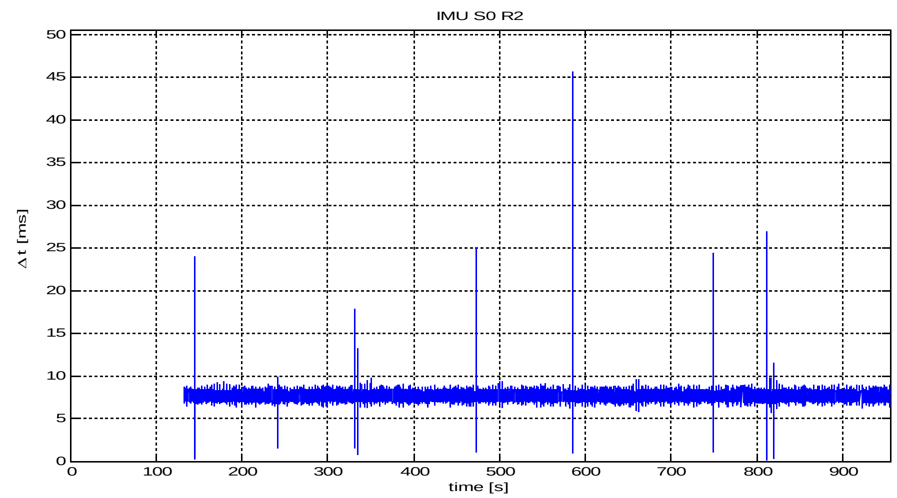
3.1.1. Basic time properties

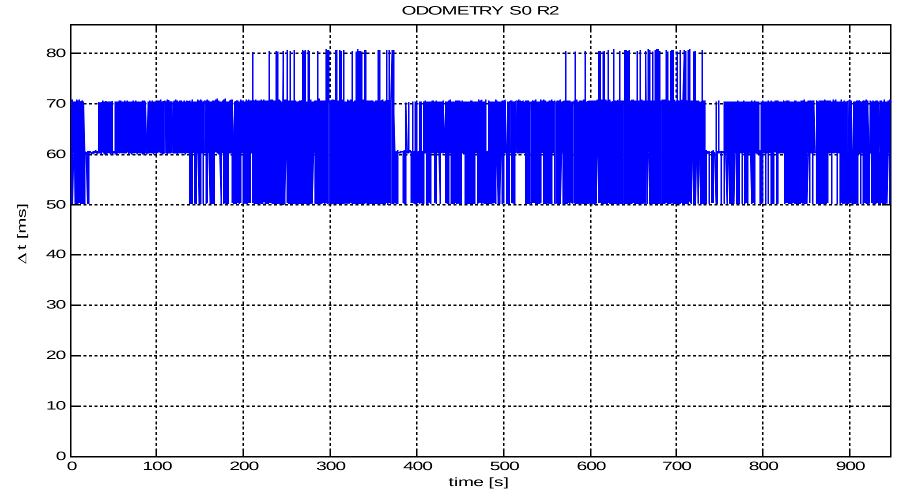
The following tables summarize the main timing characteristics of the data streams obtained from the different sensors (F: mean acquisition frequency, T: mean period, Tmax: maximum time interval between two consecutive acquisitions, Delay: mean delay with respect to IMU time base, std Delay: standard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

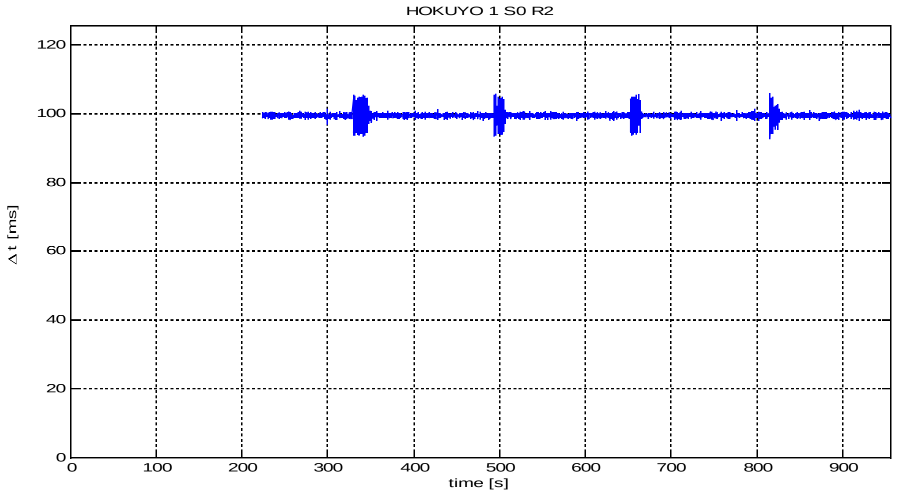
Session0 Round2										
	IMU	Odometry	Sick 1	Sick 2	Hokuyo 1	Hokuyo 2	Monocular	Trinocular	Panoramic	Sonar
F (Hz)	122.8	16.6	76.9	76.9	10.1	10.1	30.0	15.0	15.0	
T (ms)	8.1	60.4	13.0	13.0	99.5	99.4	33.4	66.6	66.6	
Tmax (ms)	45.6	80.8	24.3	23.0	110.7	111.1	44.3	67.2	66.9	
Delay (ms)	--	-151.4	-3.6	-1.5	-46.5	-32.3	33.2			
std Delay (ms)	--	32.7	2.5	3.5	3.5	7.1	21.5			

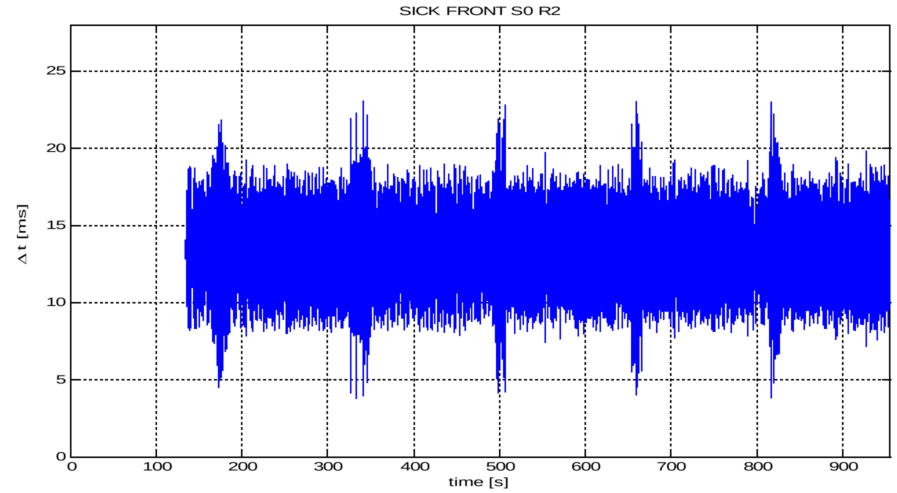
Session0 Round3										
	IMU	Odometry	Sick 1	Sick 2	Hokuyo 1	Hokuyo 2	Monocular	Trinocular	Panoramic	Sonar
F (Hz)	122.8	16.6	76.8	76.8	10.1	10.1	30.0		15.0	
T (ms)	8.1	60.4	13.0	13.0	99.5	99.4	33.4		66.6	
Tmax (ms)	52.3	84.3	25.0	22.8	114.5	111.2	41.6		67.0	
Delay (ms)	--	-138.8	-3.6	-0.5	-81.0	--	66.5			
std Delay (ms)	--	36.8	5.3	5.8	--	--	10.6			

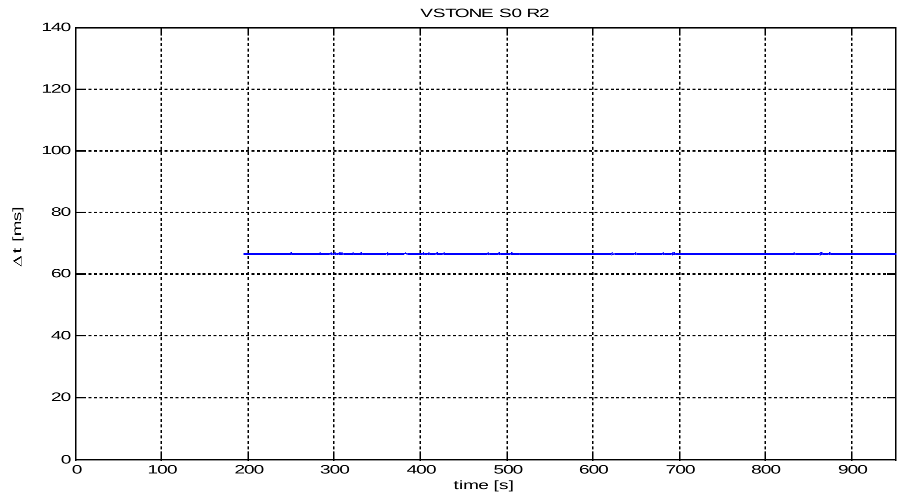
The delays will be discussed in more detail in the following subsections. With respect to the periods, if for a sensor stream Tmax is bigger than 2*T, most probably some data acquisitions have been lost. This can be seen more clearly in the following figures that plot the time separation between every pair of consecutive acquisitions. For this dataset, only IMU presents some data gaps.

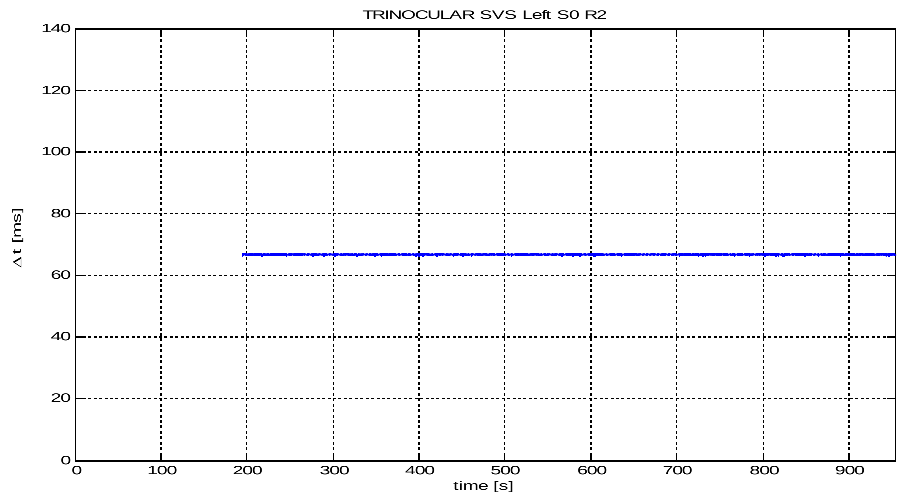


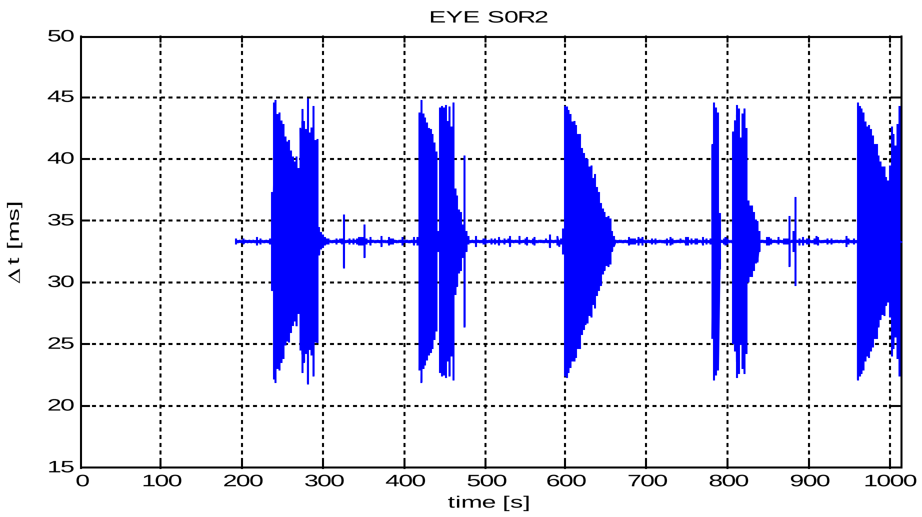

ODOMETRY S0 R2
Δ t [ms]
time [s]


HOKUYO 1 S0 R2
Δ t [ms]
time [s]


SICK FRONT S0 R2
Δ t [ms]
time [s]

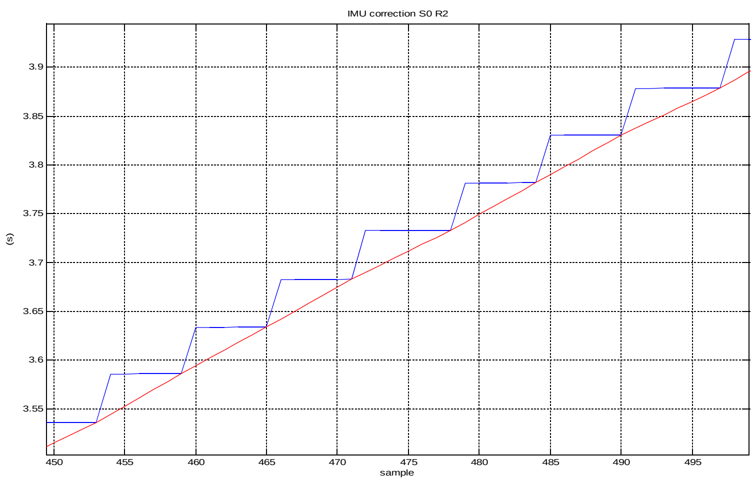

VSTONE S0 R2
140
120
100
80
60
40
20
0
Δt [ms]
0
100
200
300
400
500
600
700
800
900
time [s]


TRINOCULAR SVS Left S0 R2
140
120
100
80
60
40
20
0
Δt [ms]
0
100
200
300
400
500
600
700
800
900
time [s]


EYE S0R2
50
45
40
35
30
25
20
15
Δt [ms]
0
100
200
300
400
500
600
700
800
900
1000
time [s]

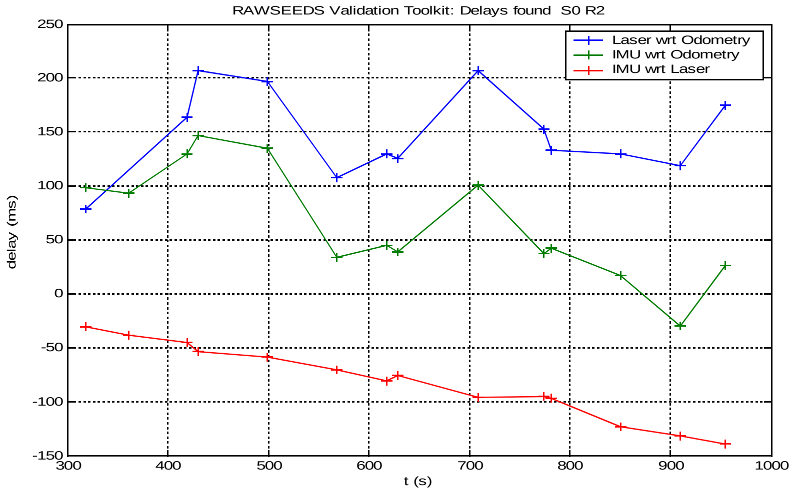
3.1.2. IMU

1) Data is verified to be in compliance with the file specification and timestamped. Although the nominal period for the IMU is 8.1ms, the timestamps acquired present jumps of 50ms (see blue plot in the figure). Given that the operation frequency of the sensor is very stable, the most probable source of the error is IMU data buffering in the computer. This defect can be easily overcome by a simple post-processing in the datasets performing a linear interpolation of the timestamps as shown in the figure (red plot).

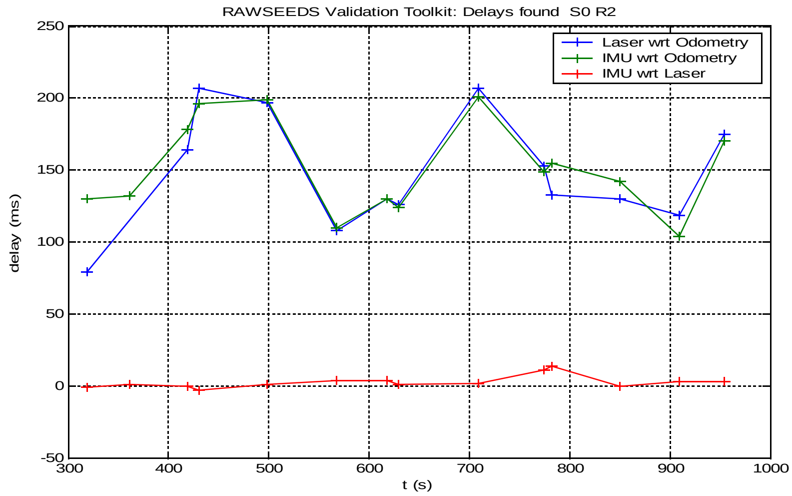


Original IMU timestamps (blue) and corrected timestamps (red)

The interpolation provided in the dataset files IMU_STRETCHED is not correct. As it can be seen in the following figures, the times provided in IMU_STRETCHED present a continuous drift throughout the dataset, that disappears when the correct interpolation (as shown in the previous figure) is computed.



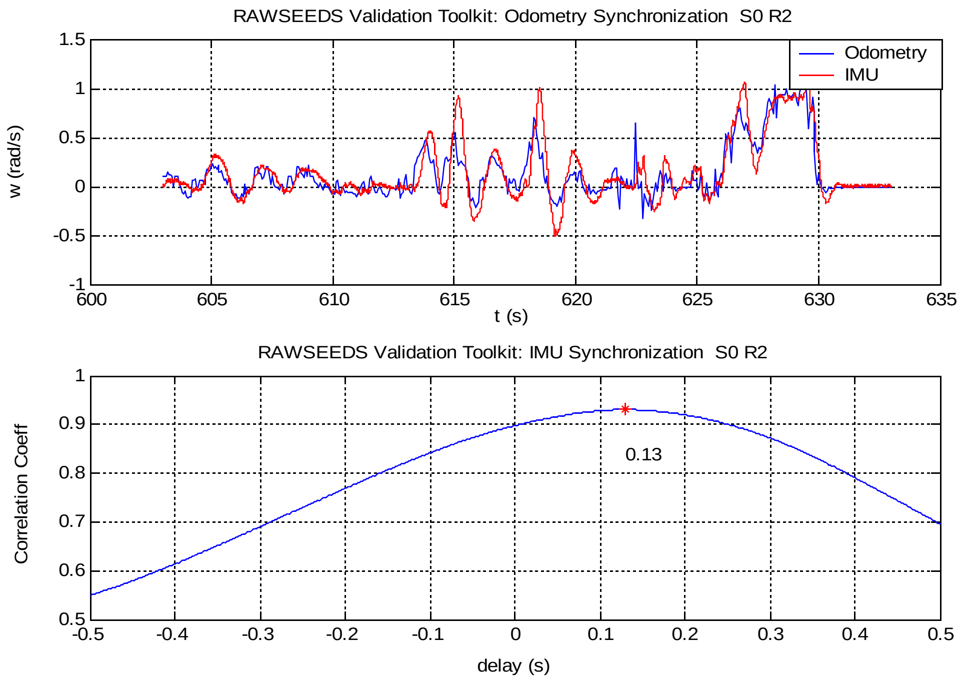
Delays between sensors with the interpolation provided in IMU_STRETCHED



Delays between sensors with the correct interpolation

3.1.3. 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 some 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.

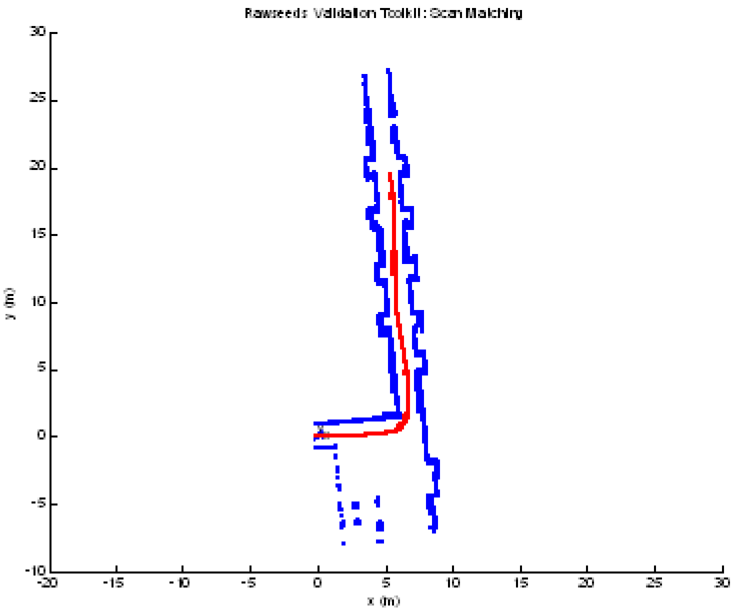


Validation of IMU and odometry synchronization

3) By inspecting the above figure it seems that the calibration of the odometry (conversion between wheel turns and the linear and angular displacements) could be improved. A suggested technique is acquiring a dataset in an easy-to-map environment, determining the robot motion using scan matching, and use this to estimate the odometry parameters by least square fitting.

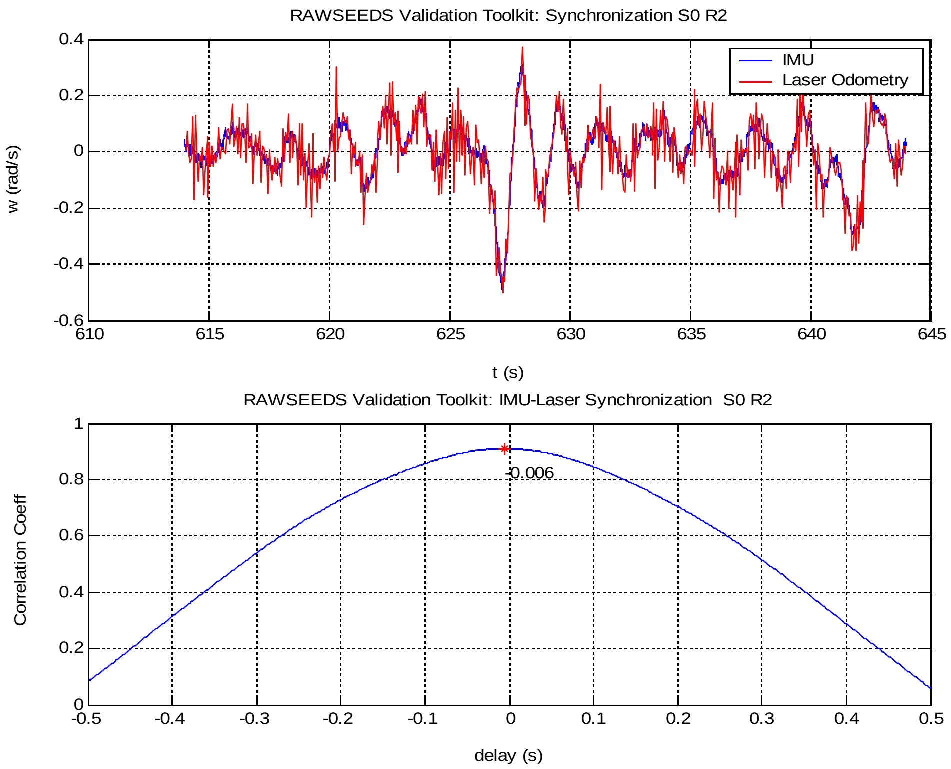
3.1.4. SICK Laser

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.



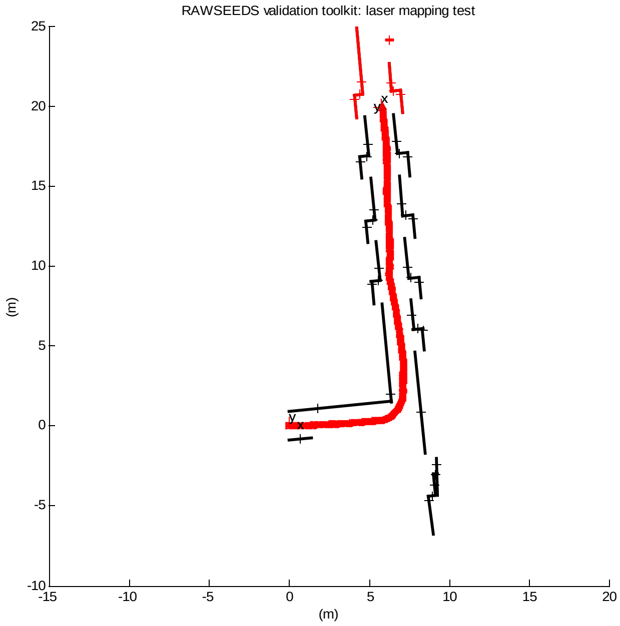
Validation of SICK laser overlap using scan matching on Session0

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 5ms, and do not pose any problems for SLAM.



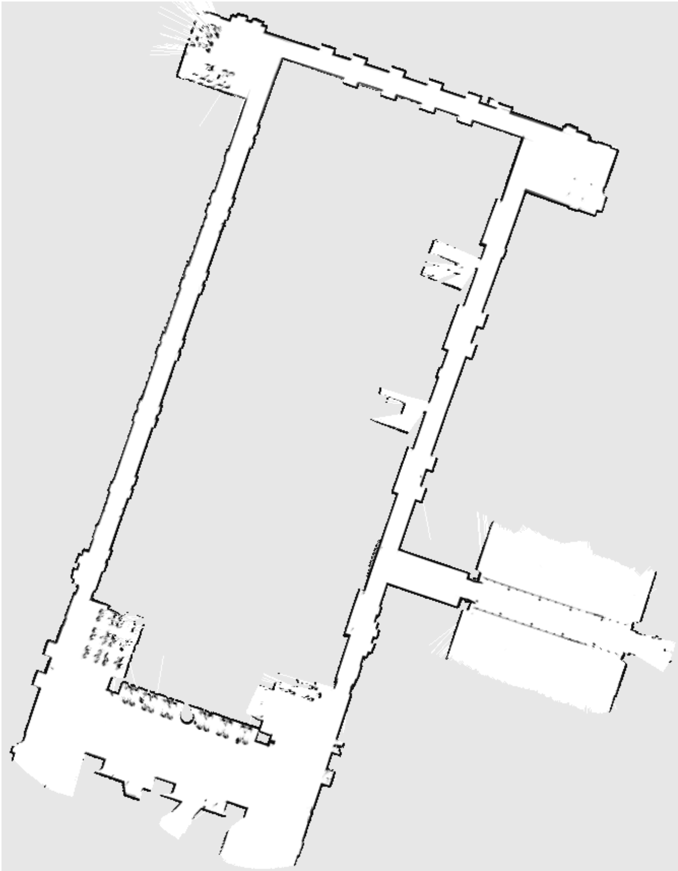
Validation of the SICK laser synchronization by cross-correlation of the angular velocities obtained from laser odometry and IMU

4) Data density and quality are validated by running line extraction software throughout the trajectory and building maps using EKF-SLAM and graph-based SLAM. The validation has been successful, as shown in the following figures. However, if Session0-Round2 is used alone, there is insufficient overlap to close the loop.



EKF-SLAM with laser segments using SICK laser in Session0

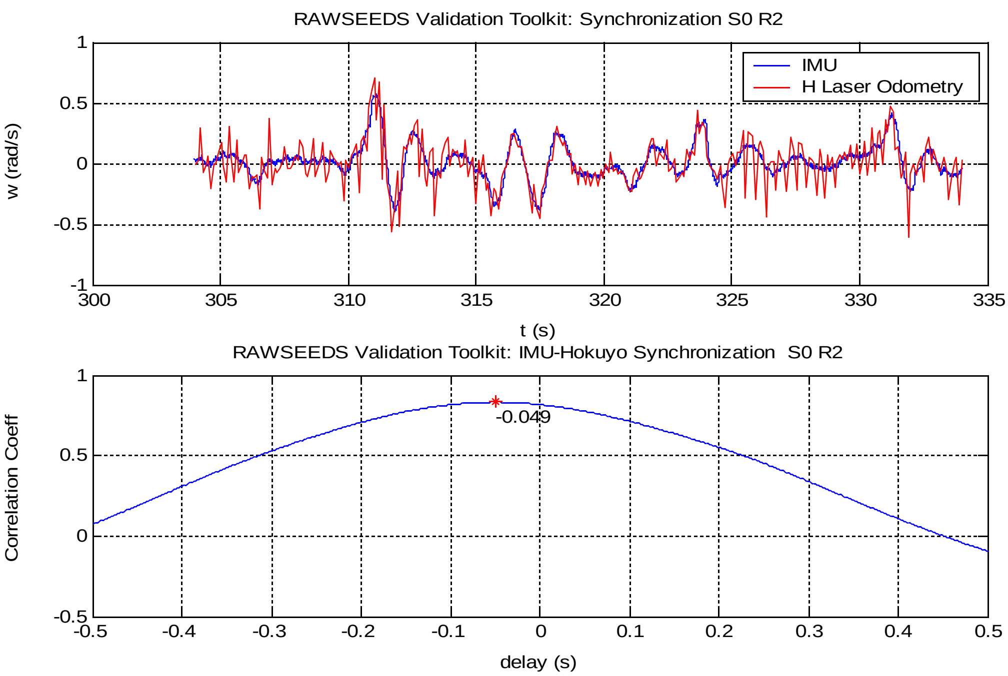
Graph-based SLAM using SICK laser in Sesion0-Round2



Graph-based SLAM using SICK laser in Sesion0-Round3

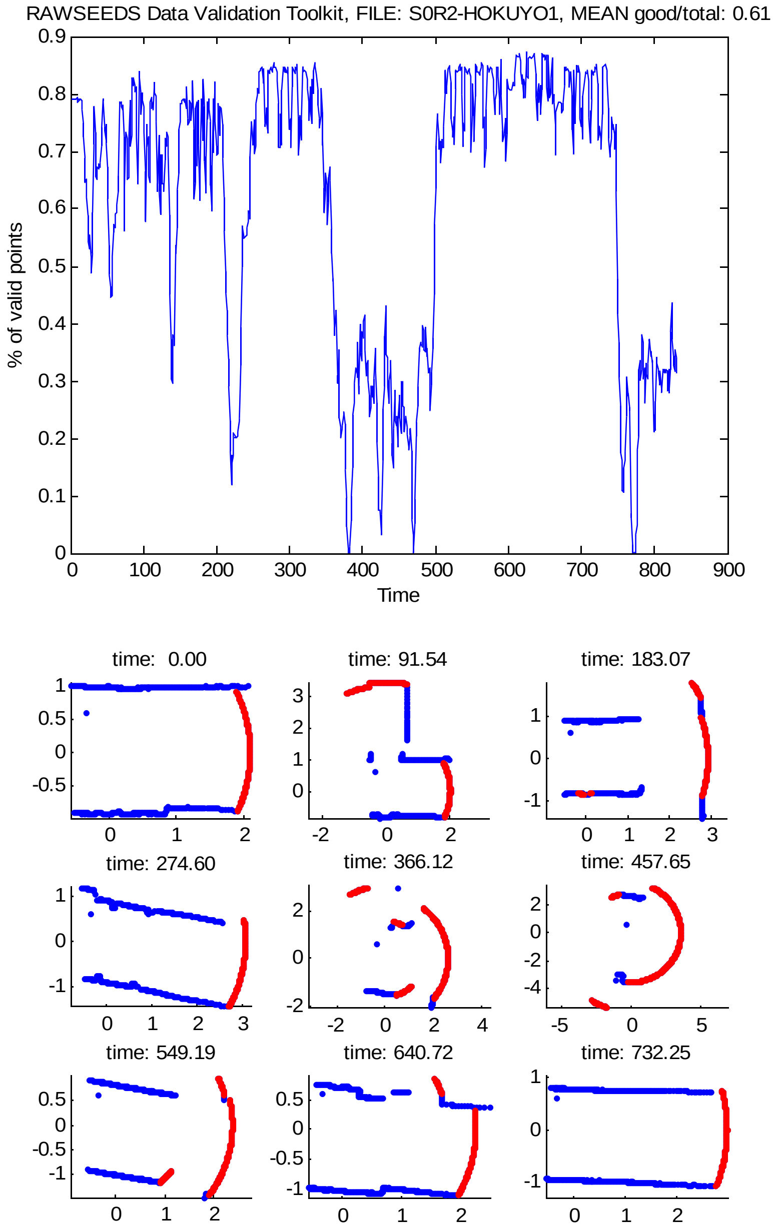
3.1.5. Hokuyo Laser

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, scan laser 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. The delay has been found to be between 40ms and 80ms, which can correspond to sensor and data transfer latencies, and does not pose a serious problem for SLAM.



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.



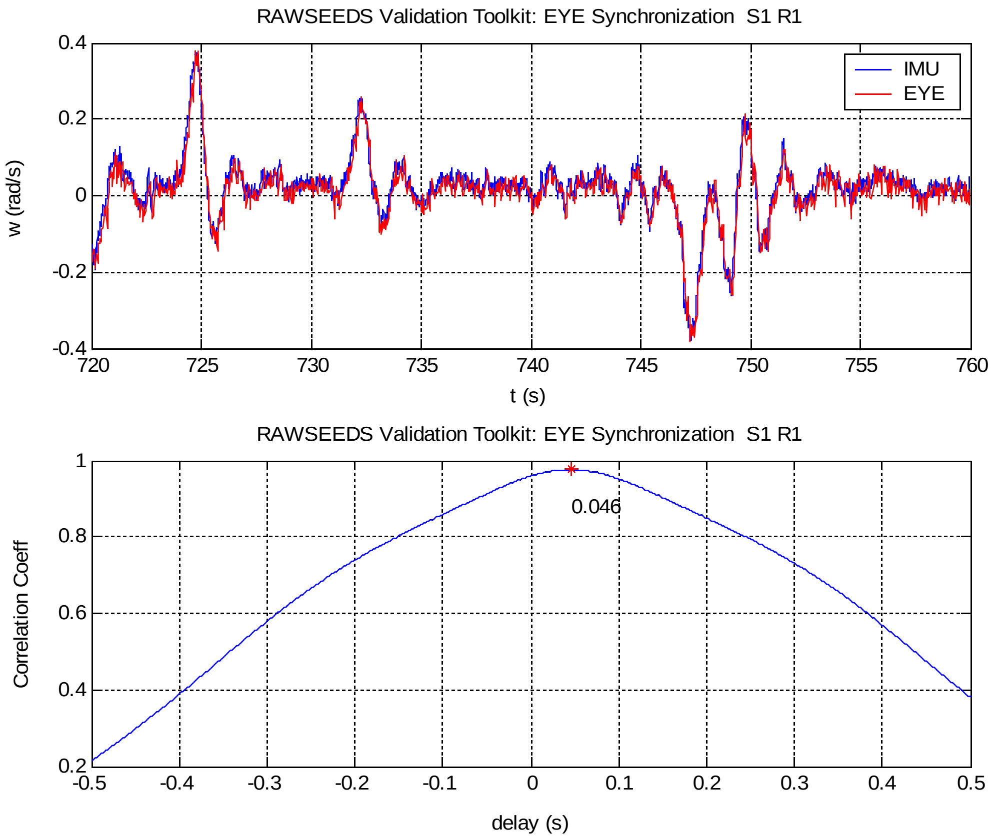
Valid (blue) and invalid (red) points from the Hokuyo laser throughout the dataset

3.1.6. Sonar Belt

At the time of preparing this report, the extrinsic calibration of the sonar belt (locations of the sonar sensors on the robot) was not available, and only the file format and frequency of acquisition could be verified.

3.1.7. Monocular Vision

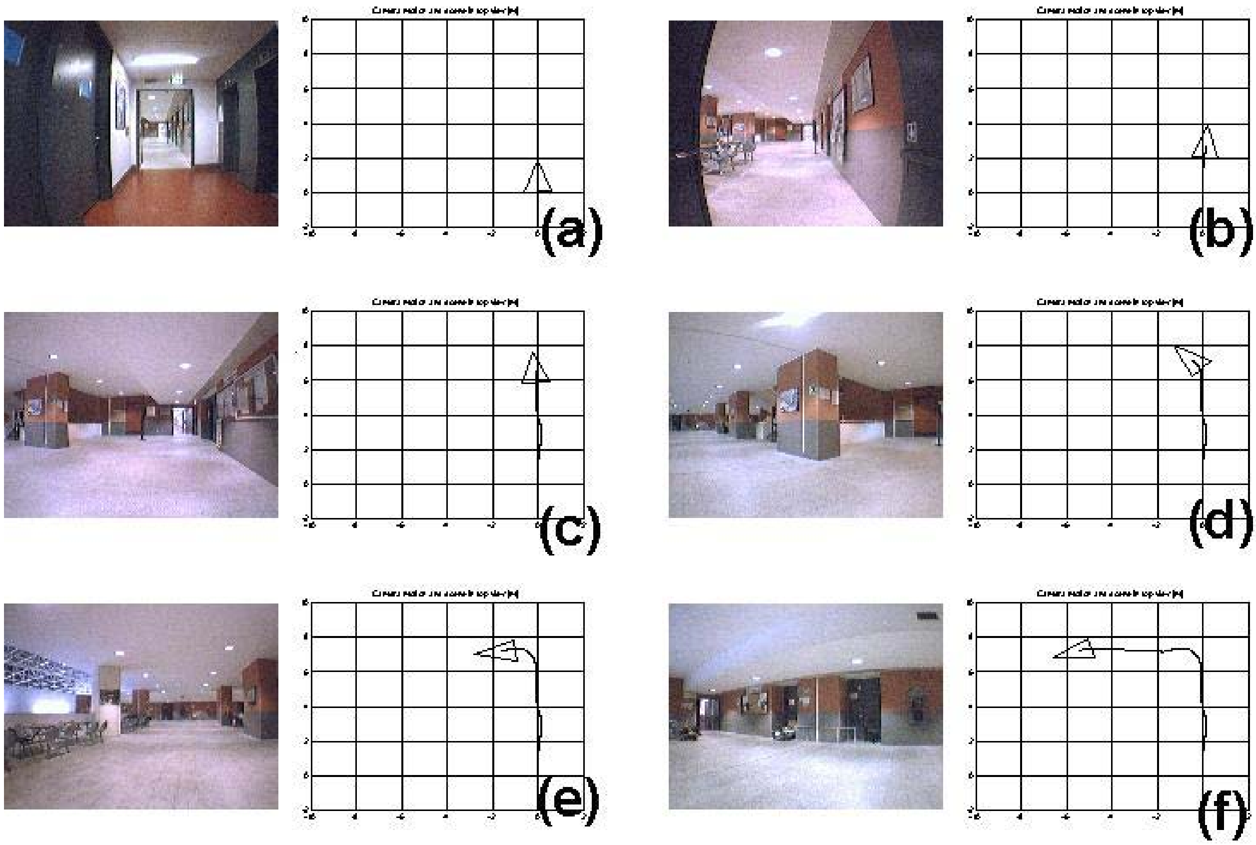
1) Data is verified to be in compliance with the file specification and timestamped File format: all image files are readable.
2) Timing: see table in section 3.1.1. The synchronization of the vision data is verified by selecting several portions of the trajectory with high angular velocity. The angular velocities obtained by pure visual SLAM and IMU are compared by cross-correlation, as shown in the figure. The delay of monocular vision is found to be around 40ms, which can correspond to sensor and data transfer latencies, and does not pose any problems for SLAM.



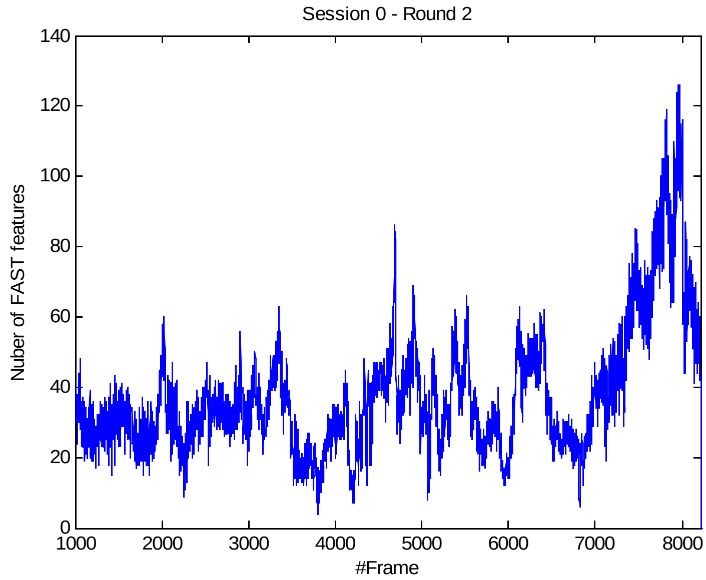
Validation of monocular vision synchronization

3) Data overlap:

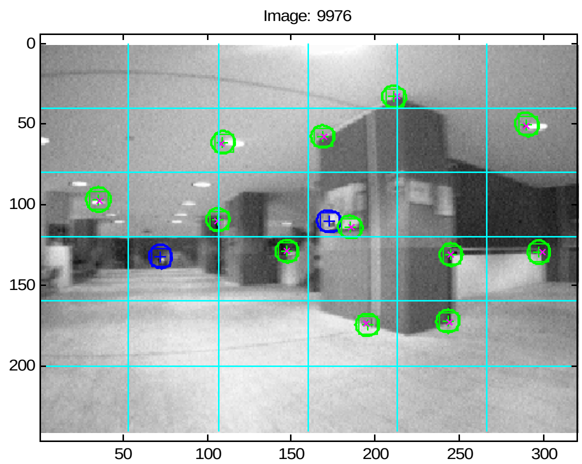
   It has been verified that the sequence can be processed by standard inverse depth + JCBB monocular SLAM. The next figure shows an example after processing 4249 images, from image 10191 to 14440 in Session 0 – Round 2. There are no dark frames in Session 0 – Round 3. The first ~500 frames are rather dark and might be difficult to track features in them.



4) Data density and quality: the next figure shows the number of FAST features extracted from frames 1000 to 8216 in Session 0 – Round 2. Feature density is considered good enough for feature-based monocular SLAM. Some low density frames correspond to blurred images due to high rotation velocity. Frames 5070 and 6820 in the sequence re two examples. Other minima correspond to low textured areas, such as frame 4206.



Data density and quality are also validated by running the Harris corner extractor throughout the image sequence. We have found that some parts of the dataset, mainly in the corridors, have low feature density, making them very challenging for pure visual SLAM. This will be taken into account in WP4 to define Benchmark Problems with different levels of difficulty. We have also found that in quick turns the images appear blurred, but the extraction of feature points is still successful. The suggested corrective action is to increase the camera shutter speed, if the ambient light is sufficient. Otherwise, the robot rotation speed should be reduced.



Example of blurred image and Harris corners obtained

5) 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 images were not properly acquired and the precision of the calibration obtained is below the usual standards for this type of cameras. More details on this defect, and suggestions about how to correct it are given in section 4.

   In any case, the main question is whether this defect does invalidate the monocular vision dataset or not. To answer this question we have further verified the dataset by running monocular SLAM software developed at UNIZAR (Civera et al. 2008) on large portions of the dataset, using the available calibration. As conclusion, the precision of the calibration, although improvable, is enough for monocular SLAM.

3.1.8. 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 3.1.1. There are no frames lost in the trinocular sequence. Once the calibration problems are solved, the synchronization of the vision data will verified by comparing the angular velocities obtained by stereo SLAM and IMU.
3) Calibration: The dataset does not provide calibration for the external parameters (the cameras relative position and orientation). The calibration images provided have been found of too low quality to perform the extrinsic calibration. More details about this important issue are given in section 4.4.

3.1.9. 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 3.1.1. There are no frames lost in the panoramic sequence.
3) At the time of writing this deliverable, the adaptations of the vision software needed to perform further validations is not finished.

3.2. Validation of Session1

The validations performed so far are summarized in the following table, where blank cells represent work in progress, and asterisks indicate defects that need to be corrected.

Sensor	**File Format**	**Timing**	**Data overlap**	**Data density and quality**
Odometry	Valid	Valid*	Not applicable	Failed Severe data loss
IMU	Valid	Valid*	Not applicable	Valid
SICK Laser	Valid	Valid	Valid	Failed Severe data loss
Hokuyo Laser	Valid	Valid	Valid	Valid
Sonar Belt	Not available	Not available	Not available	Not available
Monocular Vision	Valid	Valid	Valid	Valid* Calibration has low precision
Trinocular Vision	Valid	Valid	Valid	Failed Calibration not usable
Panoramic Vision	Not available	Not available	Not available	Not available
GPS	Not available	Not available	Not available	Not available

In this dataset there is severe data loss in odometry and laser SICK data. In consequence, this dataset can only be useful for pure visual SLAM, without using odometry. The whole dataset must be reacquired.

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 Session0 are described, e.g. the Hokuyo laser is not mentioned here. This means that considerations similar to the ones exposed in Session0 also apply here.

3.2.1. 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, and blank cells represent work in progress.

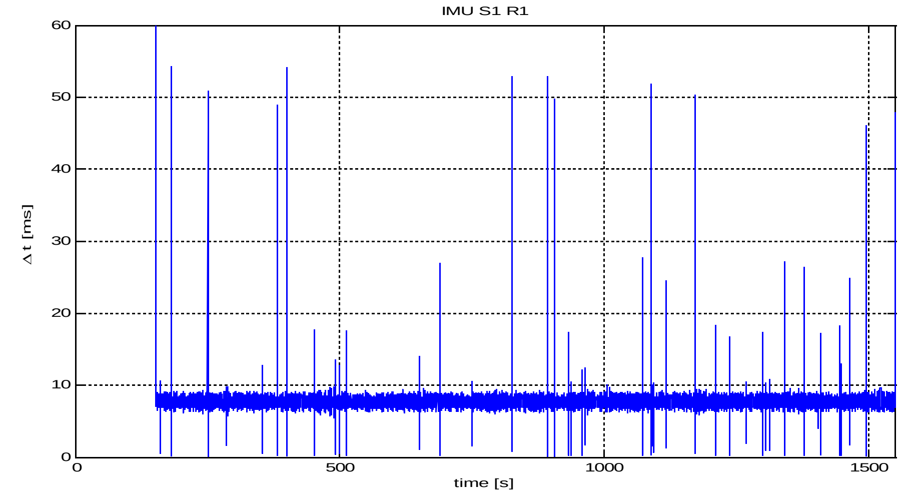
Session1 Round1									
	IMU	**Odometry**	**Sick 1**	**Sick 2**	**Hokuyo 1**	**Hokuyo 2**	**Monocular**	**Trinocular**	**Panoramic**
F (Hz)	123.5	19.9	78.9	76.9	10.0	10.1	30.0	15.0	--
T (ms)	8.1	50.3	13.0	13.0	99.5	99.5	33.3	66.7	--
Tmax (ms)	54.2	493.2	2019.4	20253.0	107.0	111.8	38.8	67.1	--
Delay (ms)	--	-146.5	-4.1	-4.9	--	--	47.0		--
std Delay (ms)	--	39.4	5.6	4.4	--	--	3.5		--

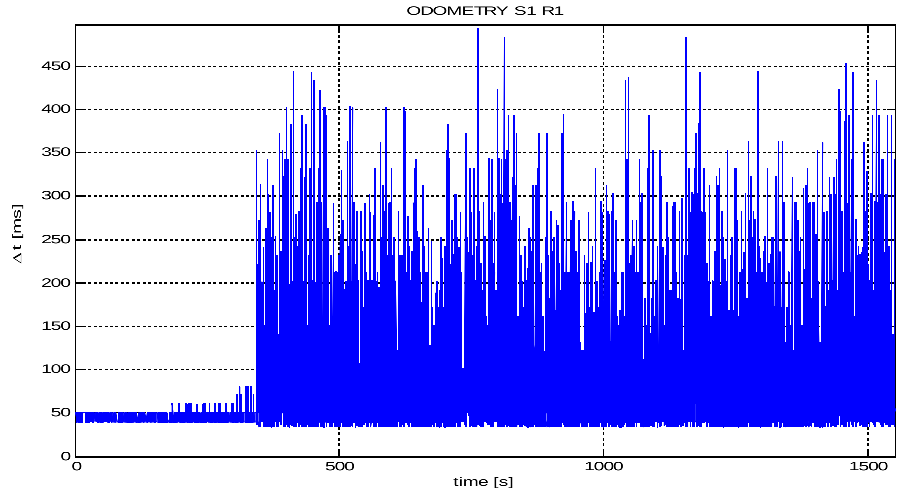
Session1 Round2									
	IMU	**Odometry**	**Sick 1**	**Sick 2**	**Hokuyo 1**	**Hokuyo 2**	**Monocular**	**Trinocular**	**Panoramic**
F (Hz)	123.3	19.9	76.9	76.9	10.1	10.1	29.9	15.0	--
T (ms)	8.1	50.3	13.0	13.0	99.5	99.4	33.4	66.7	--
Tmax (ms)	53.8	392.3	1164.7	1174.0	107.9	166.6	33.6	67.1	--
Delay (ms)	--	-185.6	-5.1	-7.3	--	--	-542.9		--
std Delay (ms)	--	29.0	5.3	4.4	--	--	28.4		--

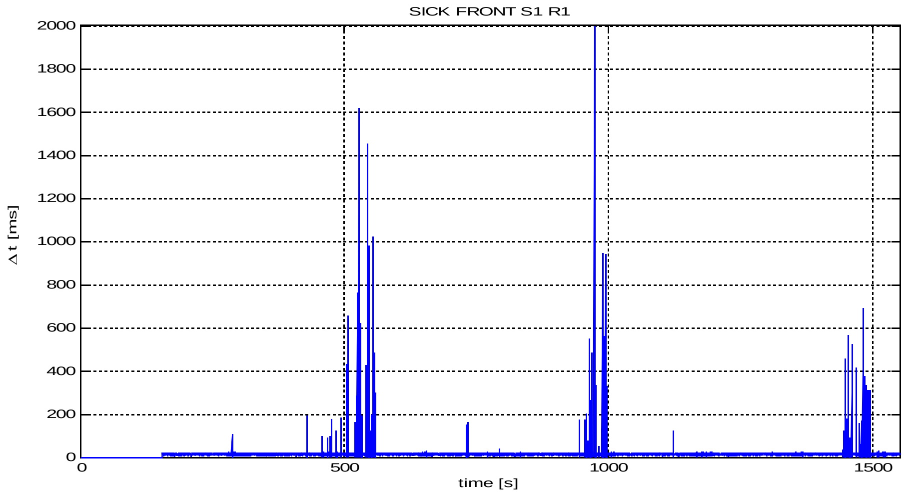
The delays are similar to Session0. With respect to time periods, when for a sensor stream Tmax is bigger than 2*T, most probably some data have been lost. This can be seen more clearly in the following figures that plot the time separation between every pair of consecutive acquisitions.

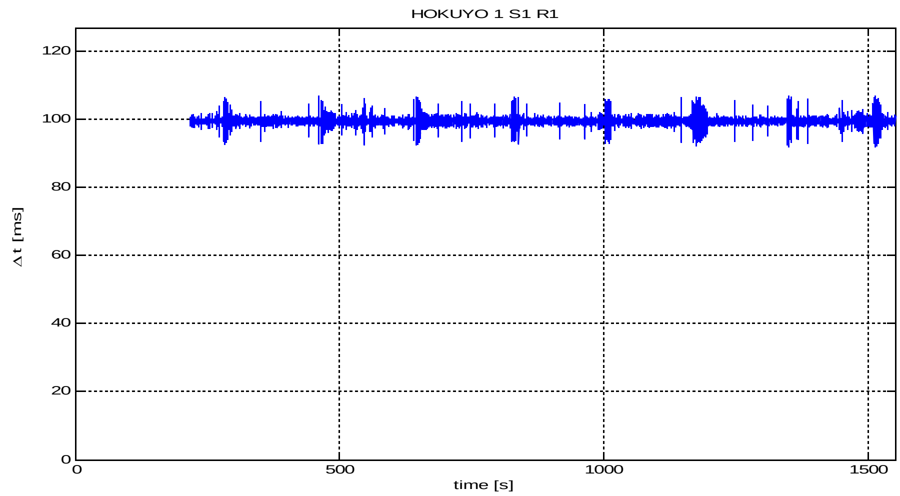
The conclusions for this dataset are:

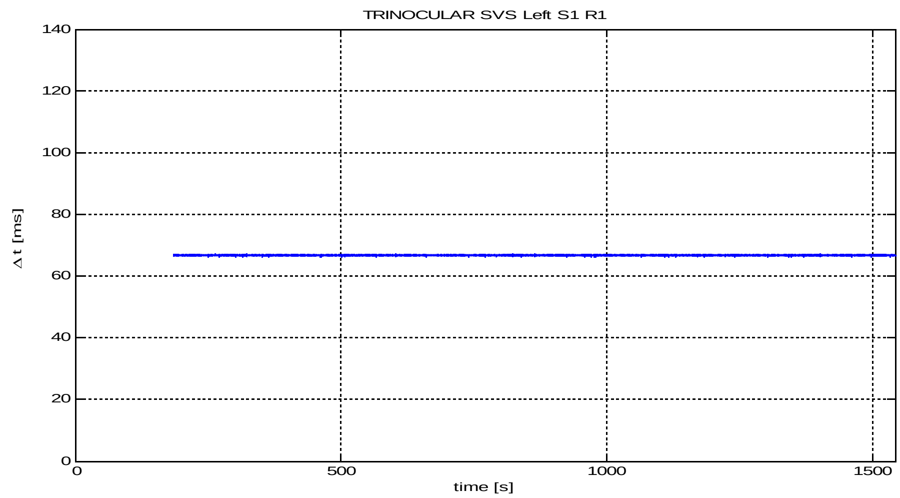
1) IMU presents some sporadic data loss
2) After a certain instant in Round 1, odometry presents repeated data gaps of 0.5 seconds, which make odometry unusable for SLAM.
3) SICK laser presents several data gaps for periods between 1 and 20 seconds, which make it unusable for SLAM.
4) Hokuyo laser is correct, with minor period oscillations.
5) Monocular vision in Round2 is desynchronized by 0.5 seconds.
6) There are no panoramic vision images.

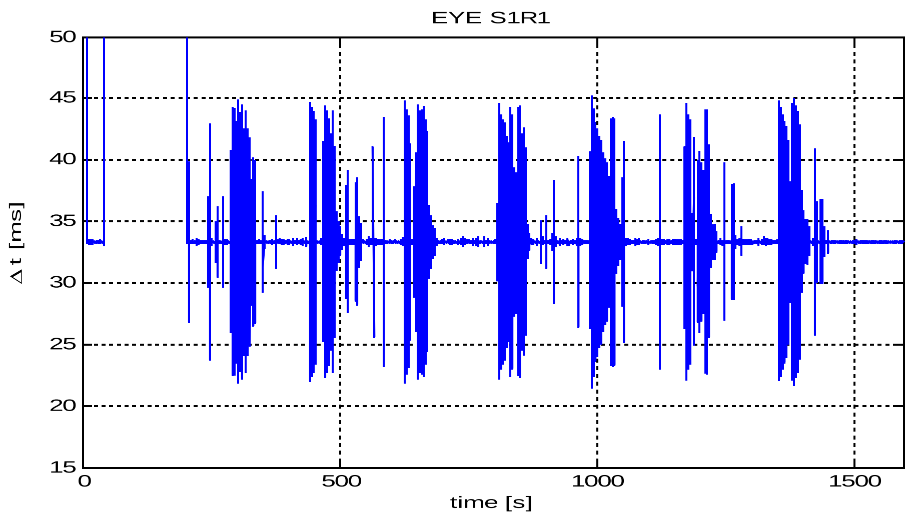

IMU S1 R1
Δ t [ms]
time [s]
0
10
20
30
40
50
60
500
1000
1500


ODOMETRY S1 R1
Δ t [ms]
time [s]
0
50
100
150
200
250
300
350
400
450
500
1000
1500


SICK FRONT S1 R1
Δ t [ms]
time [s]
0
200
400
600
800
1000
1200
1400
1600
1800
2000
500
1000
1500

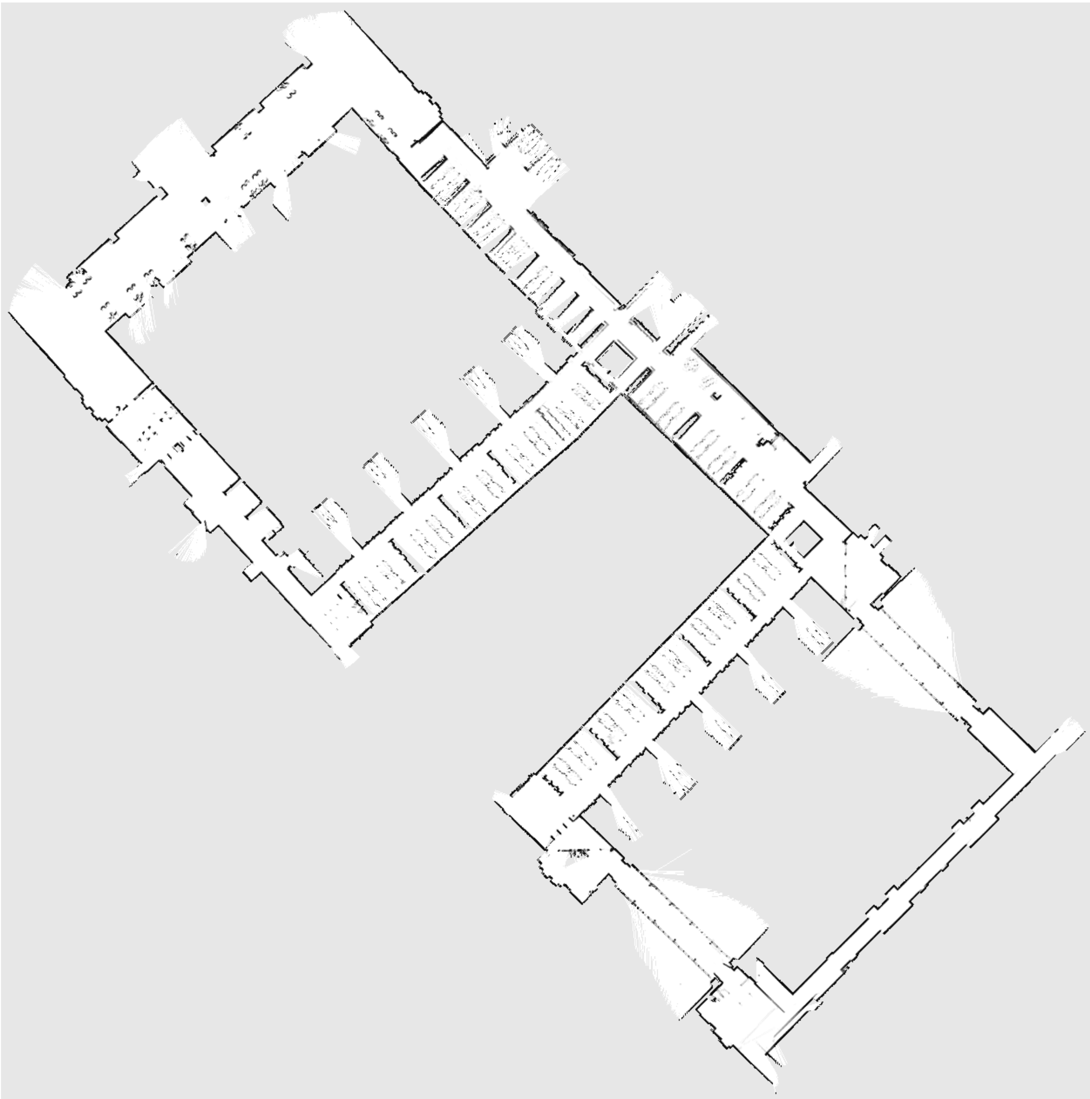

HOKUYO 1 S1 R1
Δt [ms]
time [s]
0
20
40
60
80
100
120
500
1000
1500


TRINOCULAR SVS Left S1 R1
Δt [ms]
time [s]
0
20
40
60
80
100
120
140
500
1000
1500


EYE S1R1
Δt [ms]
time [s]
15
20
25
30
35
40
45
50
0
500
1000
1500

3.2.2. SICK Laser

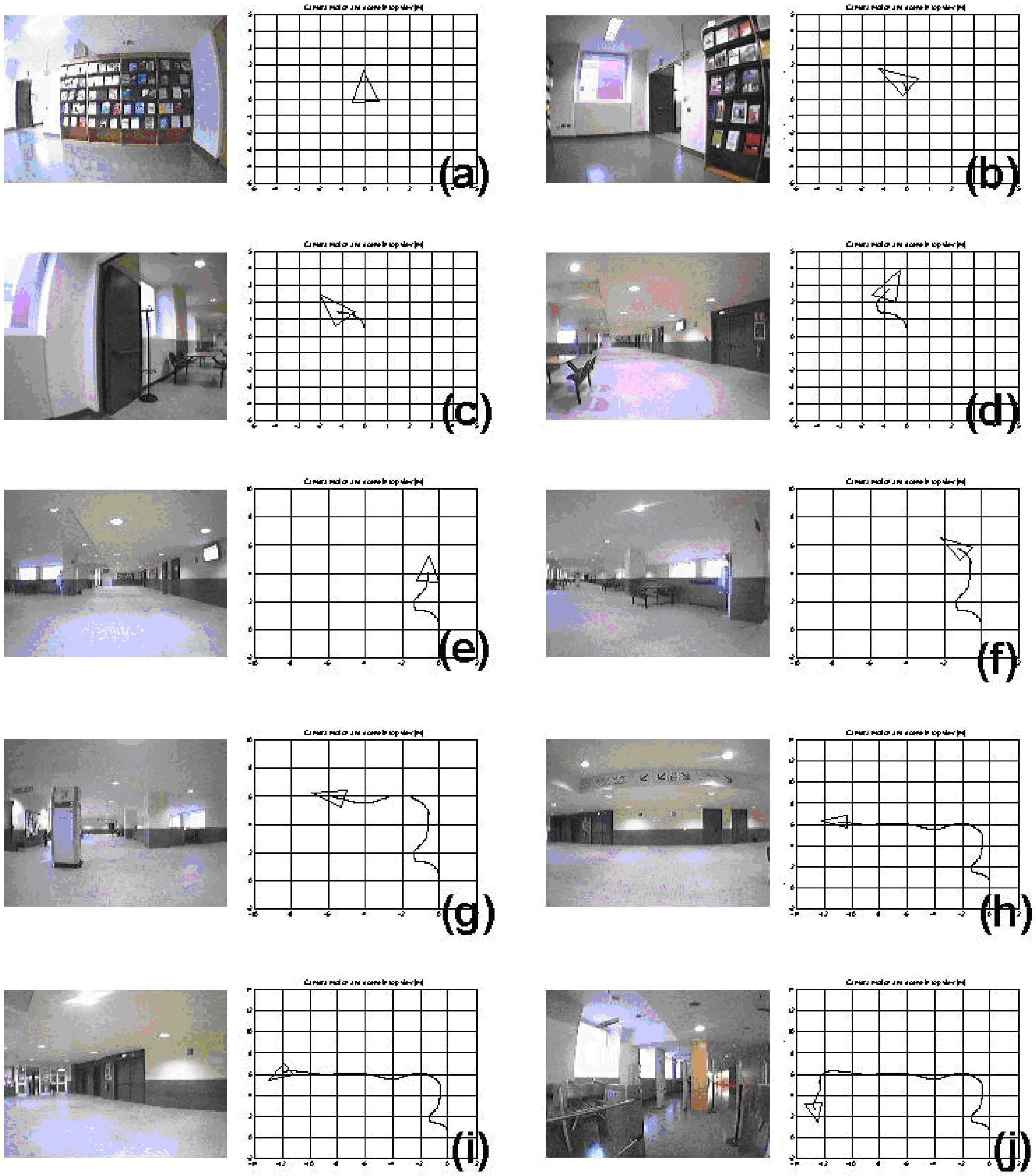
1) Data density and quality are validated by running laser scan matching to obtain the missing odometry data and then the graph-based laser SLAM software from ALUFR (Grisetti et al 2007, Grisetti et al 2008):



SLAM on dataset Session1-Round1

3.2.3. Monocular Vision

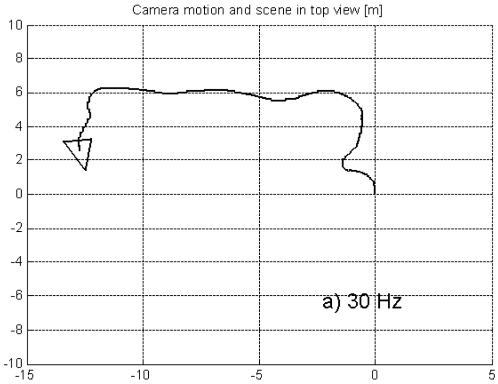
1) Data is verified to be in compliance with the file specification and timestamped File format: all image files are readable.
2) Timing: see table in section 3.2.1.
3) Data overlap:

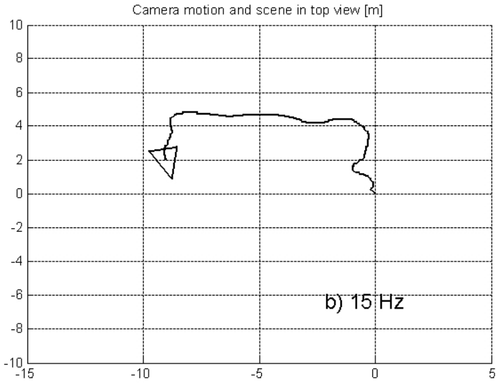


It has been verified that the sequence can be processed by standard inverse depth + JCBB monocular SLAM. The figure shows an example after processing

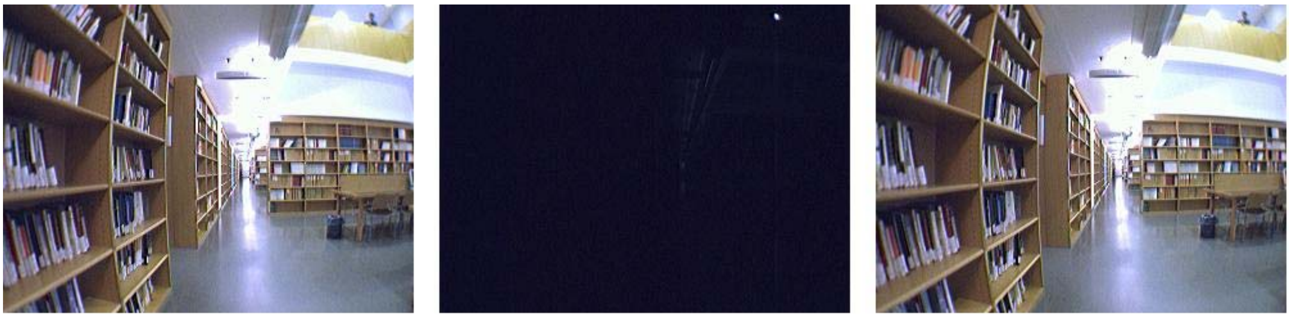
5366 images, from image 14101 to 19467 in Session 1 – Round 1; corresponding to a trajectory about 50 meters long.

We have also verified that the sequence is processable using only every other image, as can be shown in the following figure:





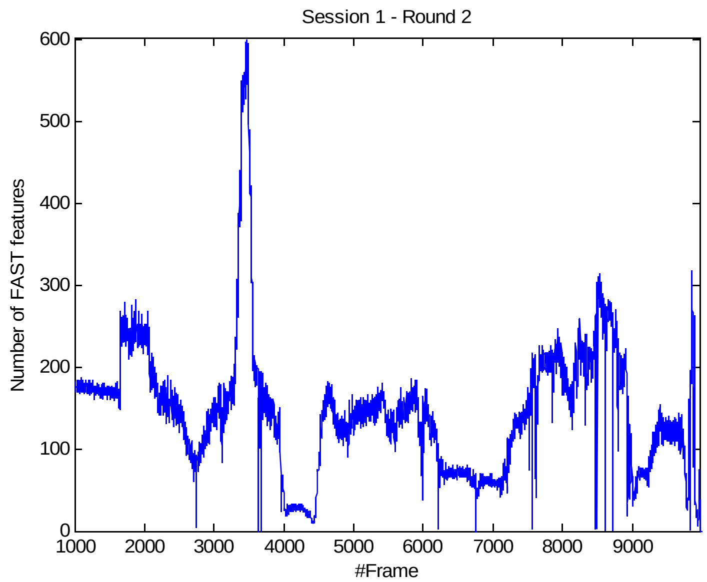
32 dark frames have been detected in Session 1 – Round 1 (evenly spaced about 1 out of 1500). 33 dark frames have been detected in Session 1 – Round 2 (evenly spaced about 1 out of 1500). An example of such dark frames is detailed in next figure, with the previous and next frames in the sequence.



Previous frame Dark frame Next frame

As dark frames are never consecutive, the 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 from frames 1000 to 9971 in Session 1 – Round 2. It is noticeable that feature density has been increased with respect to Session 0 from tens of features in Session 0 to hundreds of them in Session 1.



Low density frames correspond either to the reported "dark" frames, or to blurred images due to high rotation velocity. In the high rotation velocity cases, the effect is lower than in Session 0 due to the high density of features in the scene.

5) Calibration images used in this session do not fulfill the guidelines proposed by Bouguet, because the pattern is far from filling in the camera field of view and is parallel to the image plane. See section 4 for more details.

3.3. Validation of Session2

The validations performed so far are summarized in the following table, where blank cells represent work in progress, and asterisks indicate defects that need to be corrected.

Sensor	**File Format**	**Timing**	**Data overlap**	**Data density and quality**
Odometry	Valid	Valid*	Not applicable	Valid
IMU	Valid	Valid*	Not applicable	Valid
SICK Laser	Valid	Valid	Valid	Valid
Hokuyo Laser	Valid	Valid	Valid	Valid
Sonar Belt	Not available	Not available	Not available	Not available
Monocular Vision	Valid	Valid	Valid	Valid* Calibration has low precision
Trinocular Vision	Valid	Valid	Valid	Failed Calibration not usable
Panoramic Vision				
GPS	Not available	Not available	Not available	Not available

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.

3.3.1. 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, and blank cells represent work in progress.

Session2 Round1									
	IMU	Odometry	Sick 1	Sick 2	Hokuyo 1	Hokuyo 2	Monocular	Trinocular	Panoramic
F (Hz)	123.3	--	76.9	76.9	10.1	10.1	30.0	15.0	15.0
T (ms)	8.1	--	13.0	13.0	99.5	99.4	33.4	66.7	66.6
Tmax (ms)	52.6	--	1124.8	1131.4	106.7	106.8	44.8	67.1	66.7
Delay (ms)	--	--	-6.4	-3.5	--	-7.0	50.0		
std Delay (ms)	--	--	6.2	6.6	--	--	7.0		

Session2 Round2									
	IMU	Odometry	Sick 1	Sick 2	Hokuyo 1	Hokuyo 2	Monocular	Trinocular	Panoramic
F (Hz)	123.5	16.6	76.9	76.9	10.1	10.1	30.0	15.0	
T (ms)	8.1	60.4	13.0	13.0	99.5	99.4	33.4	66.7	
Tmax (ms)	54.6	80.9	986.7	983.6	170.7	107.3	2133.0	67.1	
Delay (ms)	--	-184.6	-8.9	-4.8	-48.7	-47.3	48.8		
std Delay (ms)	--	31.0	10.7	5.9	5.9	5.7	6.1		

Session2 Round3									
	IMU	Odometry	Sick 1	Sick 2	Hokuyo 1	Hokuyo 2	Monocular	Trinocular	Panoramic
F (Hz)	123.5	16.6	76.9	76.9	10.1	10.1	30.0	15.0	15.0
T (ms)	8.1	60.4	13.0	13.0	99.5	99.4	33.4	66.7	66.6
Tmax (ms)	55.2	81.1	1303.6	1293.4	106.5	107.6	44.7	67.1	66.9
Delay (ms)	--	-180.0	4.4	-0.7	--	-52.0	56.7		
std Delay (ms)	--	55.6	5.2	2.8	--	--	6.5		

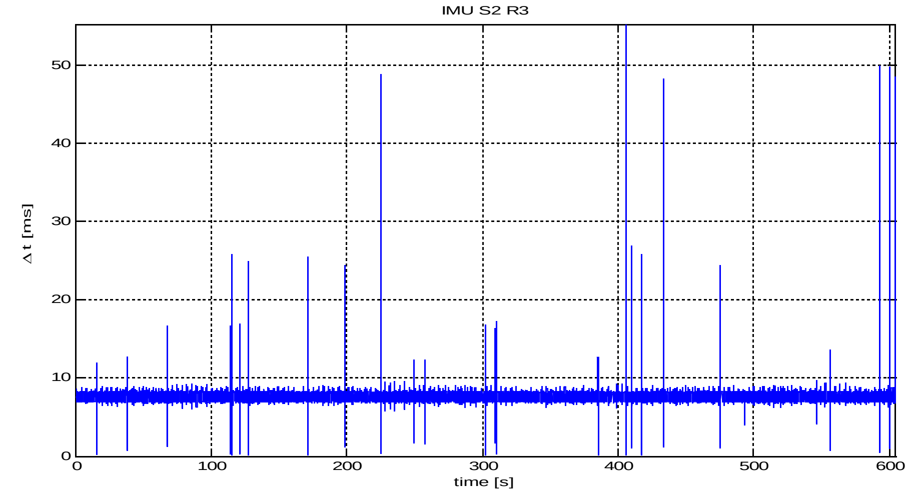
The delays are similar to Session0. With respect to time periods, if for a sensor stream Tmax is bigger than 2*T, most probably some data acquisitions have been lost. This can be seen more clearly in the following figures that plot the time separation between every pair of consecutive acquisitions.

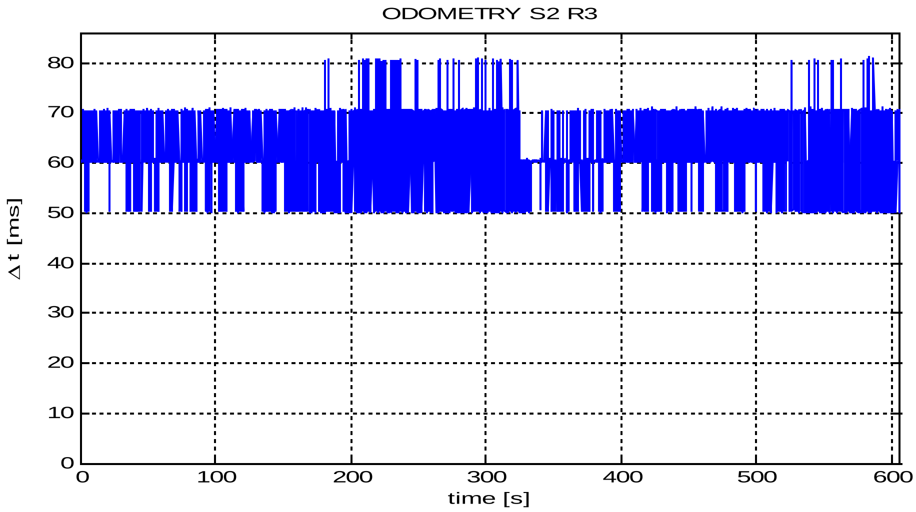
The conclusions for this dataset are:

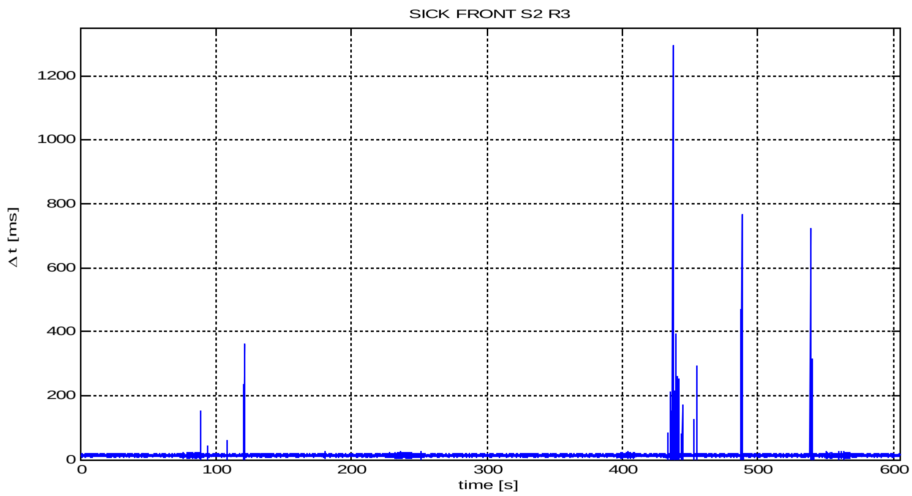
1) IMU and SICK present some sporadic data loss, that will not affect SLAM algorithms.

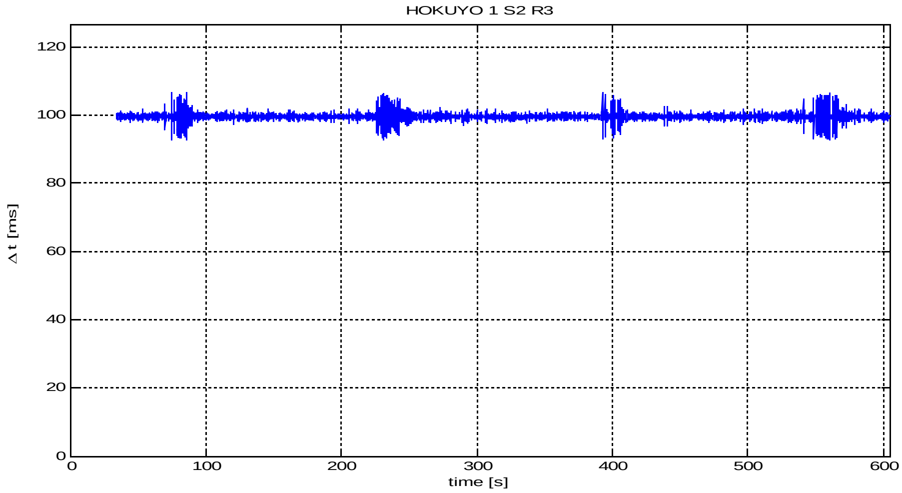
2) Odometry, Hokuyo laser are correct, with minor period oscillations.

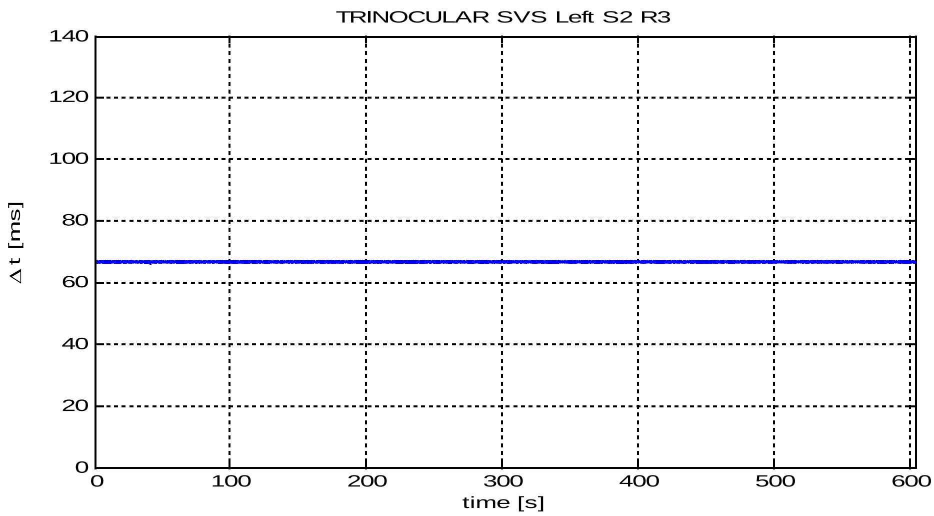
3) Monocular data presents a severe data loss of 63 frames (2,133 seconds) in frame 21363 from 28281, which makes the sequence unmanageable in its entire length for visual SLAM algorithms.

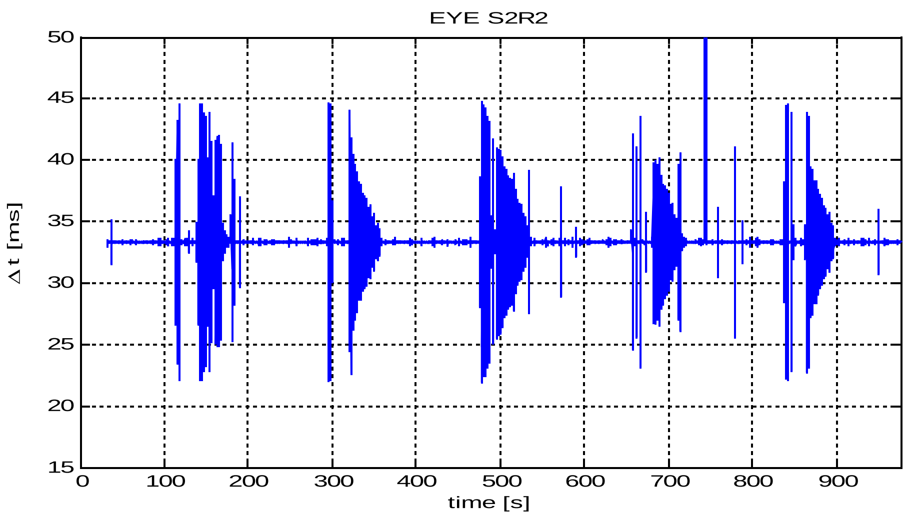

IMU S2 R3
Δ t [ms]
time [s]
0
10
20
30
40
50
0
100
200
300
400
500
600

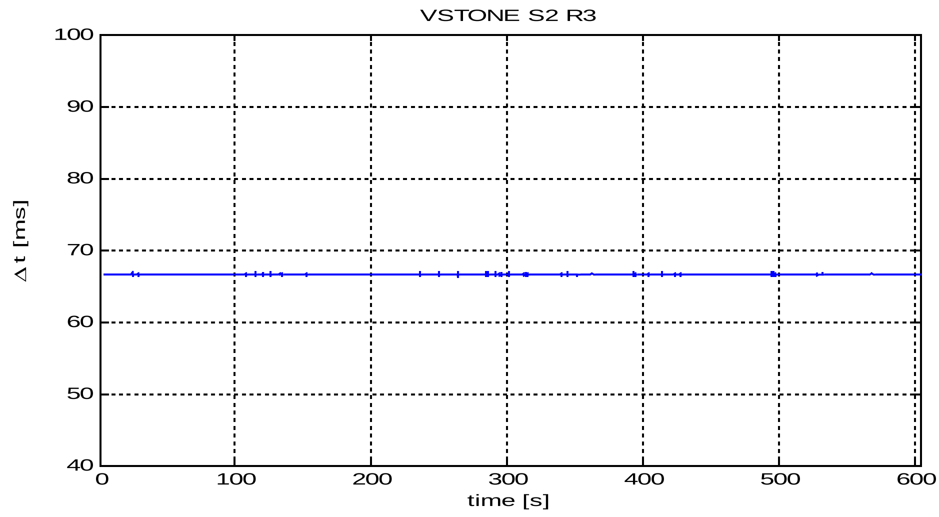

ODOMETRY S2 R3
Δ t [ms]
time [s]
0
10
20
30
40
50
60
70
80
0
100
200
300
400
500
600


SICK FRONT S2 R3
Δ t [ms]
time [s]
0
200
400
600
800
1000
1200
0
100
200
300
400
500
600


HOKUYO 1 S2 R3
Δ t [ms]
time [s]

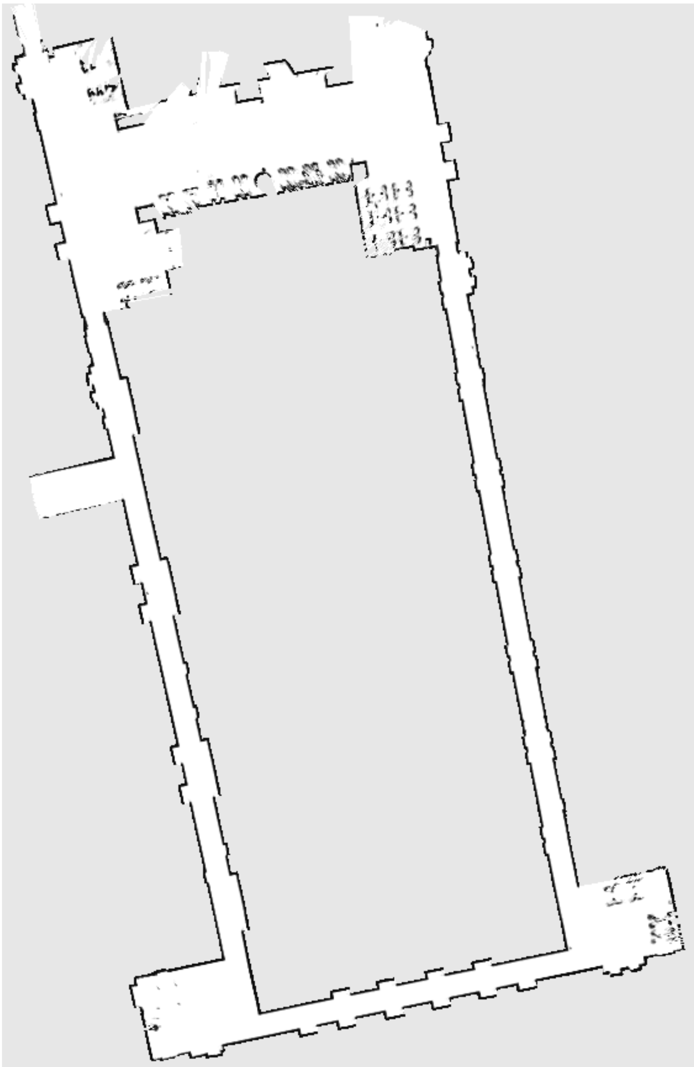

TRINOCULAR SVS Left S2 R3
Δ t [ms]
time [s]


EYE S2R2
Δ t [ms]
time [s]


VSTONE S2 R3
Δ t [ms]
time [s]
100
90
80
70
60
50
40
0
100
200
300
400
500
600

3.3.2. SICK Laser

1) Data density and quality are validated by running laser scan matching to obtain the missing odometry data and then 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:

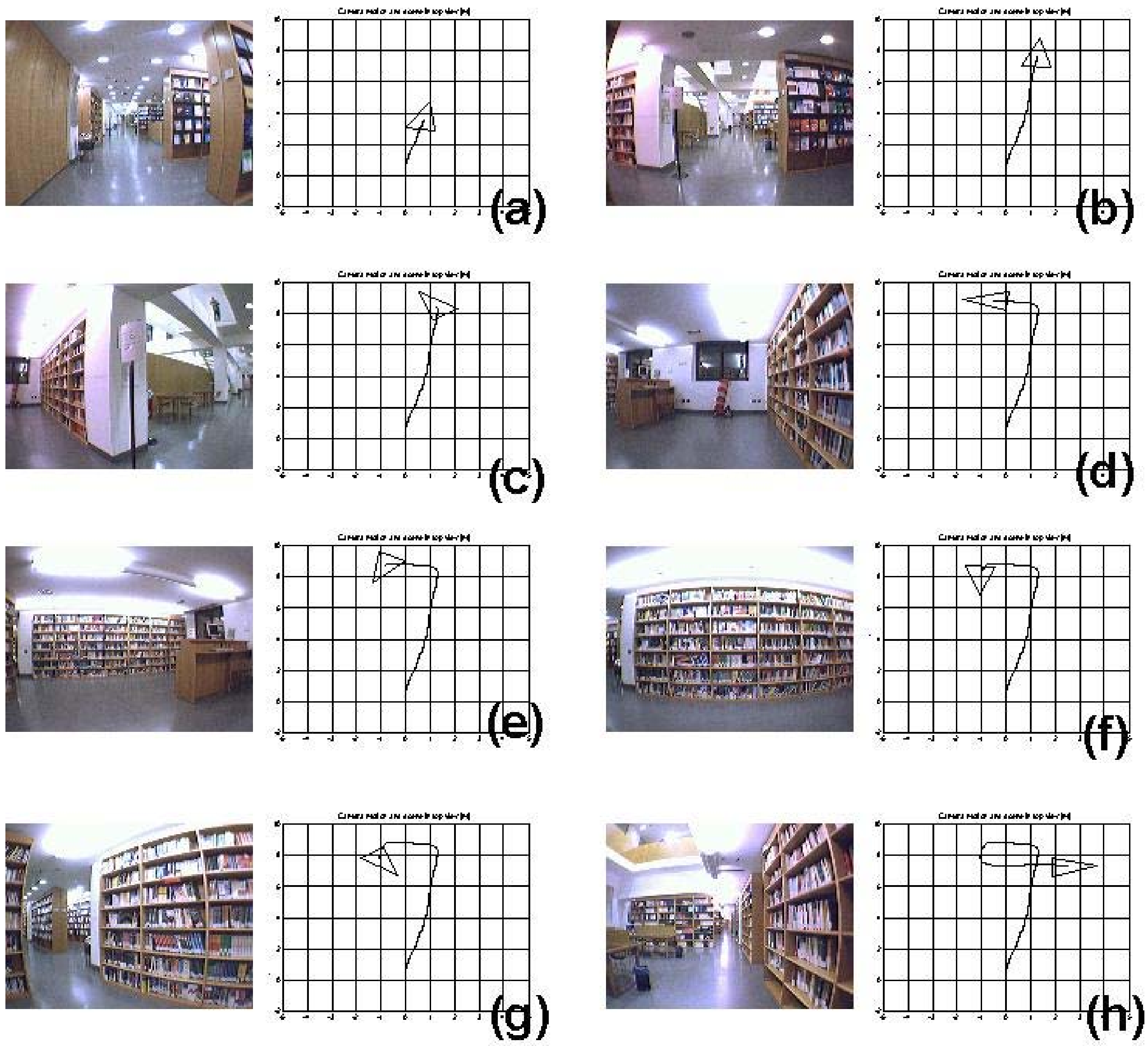


Graph-based SLAM on dataset Session2-Round3

Graph-based SLAM on dataset Session2-Round2

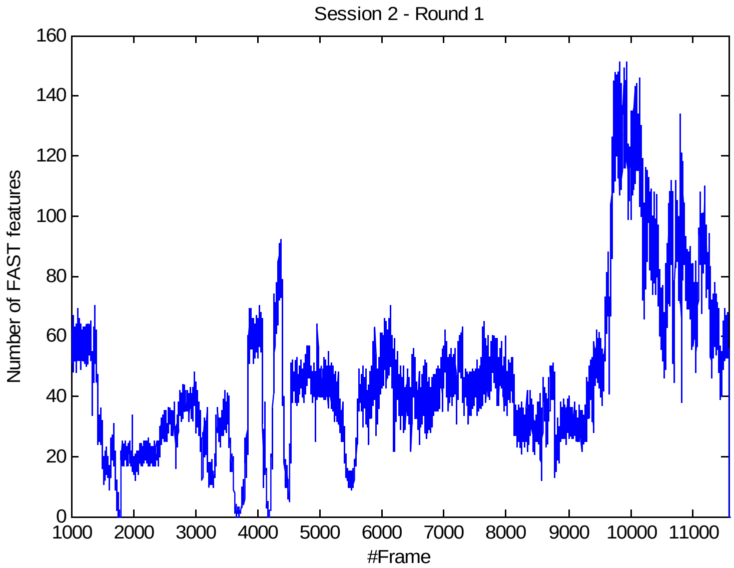
3.3.3. Monocular Vision

1) File format: All image files are readable.
2) Timing: See table in section 3.3.1.
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 after processing 6000 images, from image 19000 to 25000 in Session 2 – Round 1. 58 dark frames have been detected in this session and again evenly spaced, so they are not critical for visual SLAM algorithms.



4) Data density: Next figure shows the number of FAST features extracted from frames 1000 to 11571 in Session 2 – Round 1.

   There are some low density frames, corresponding to blurred images due to high rotation velocity, such as frame 8562 in the sequence. Other minima correspond to low textured areas, such as frame 5515. The first 5000 frames are not considered, as the robot is not moving during this period, so these images are useless.



5) Calibration images are the same than in Session 1, so the suggestions for improvement are the same. For more details, go to section 4.

3.4. Validation of Session 20080901

The validations performed so far are summarized in the following table, where blank cells represent work in progress, and asterisks indicate defects that need to be corrected.

Sensor	File Format	Timing	Data overlap	Data density and quality
Odometry	Valid	Valid*	Not applicable	Valid
IMU	Valid	Valid*	Not applicable	Valid
SICK Laser	Valid	Valid	Valid	Valid
Hokuyo Laser	Valid	Valid	Not usable outdoors	Not usable outdoors
Sonar Belt	Not available	Not available	Not available	Not available
Monocular Vision	Valid	Valid	Valid	Valid* Calibration has low precision
Trinocular Vision	Valid	Valid	Valid	Failed Calibration not usable
Panoramic Vision				
GPS	Valid		Not applicable	Valid

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.

3.4.1. Basic time properties

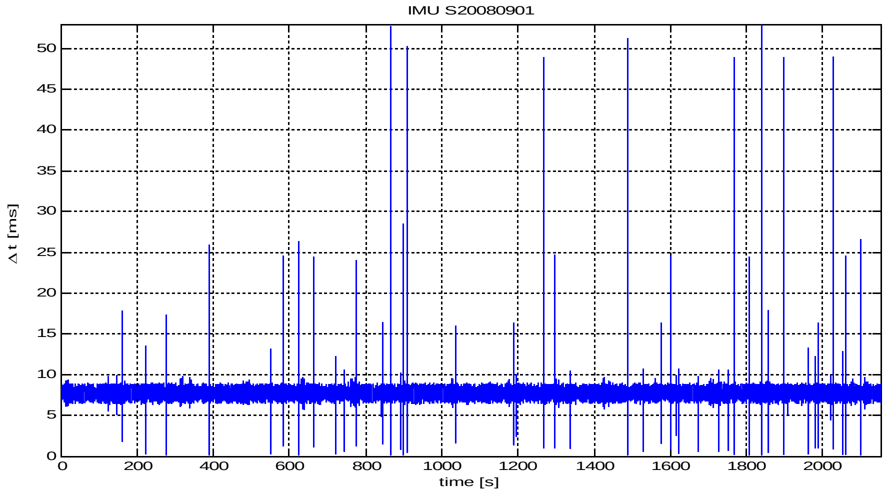
The following tables summarize the main timing characteristics of the data streams obtained from the different sensors (F: mean acquisition frequency, T: mean period, Tmax: maximum time interval between two consecutive acquisitions, Delay: mean delay with respect to IMU time base, std Delay: standard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

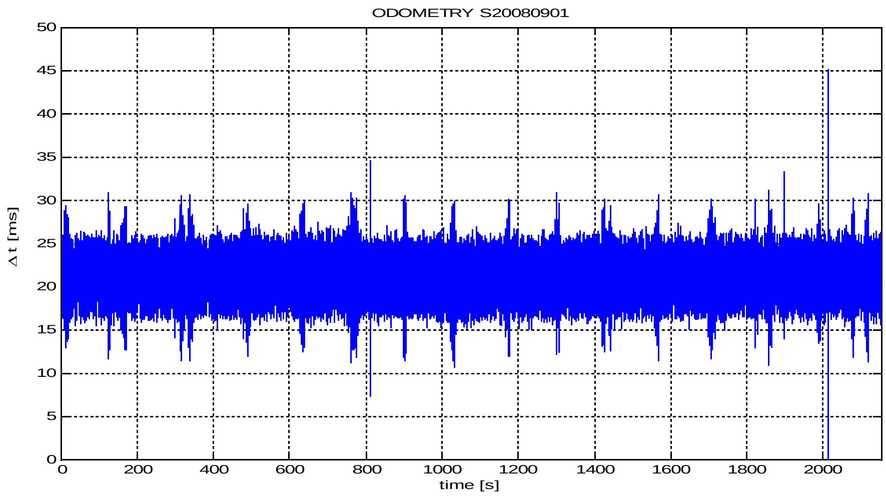
Session20080901 Round0										
	IMU	Odometry	Sick 1	Sick 2	Hokuyo 1	Hokuyo 2	Monocular	Trinocular	Panoramic	GPS
F (Hz)	122.8	47.6	76.8	76.9	10.1	10.1	30.0	15.0	15.0	5.0
T (ms)	8.1	21.0	13.0	13.0	99.3	99.0	33.4	66.6	66.7	200.1
Tmax (ms)	52.9	45.0	40.0	33.5	8831.2	173.6	133.3	133.3	110.0	314.8
Delay (ms)	--	-86.5	-3.6	-3.0	--	--	40.5			
std Delay (ms)	--	28.4	5.2	3.0	--	--	8.7			

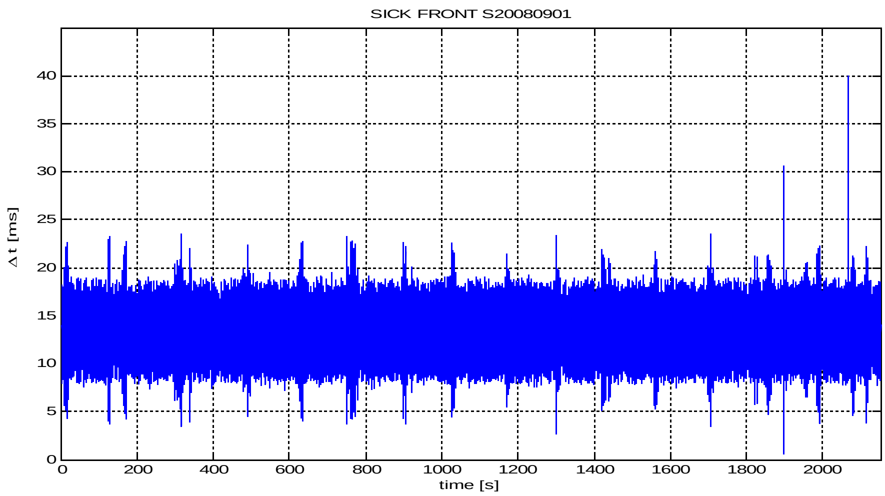
The odometry still runs ahead of time with respect to IMU, but the offset is smaller than in the indoor datasets. The rest of delays are similar. With respect to the periods, when for a sensor stream Tmax is bigger than 2*T, most probably some data has been lost. This can be seen more clearly in the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

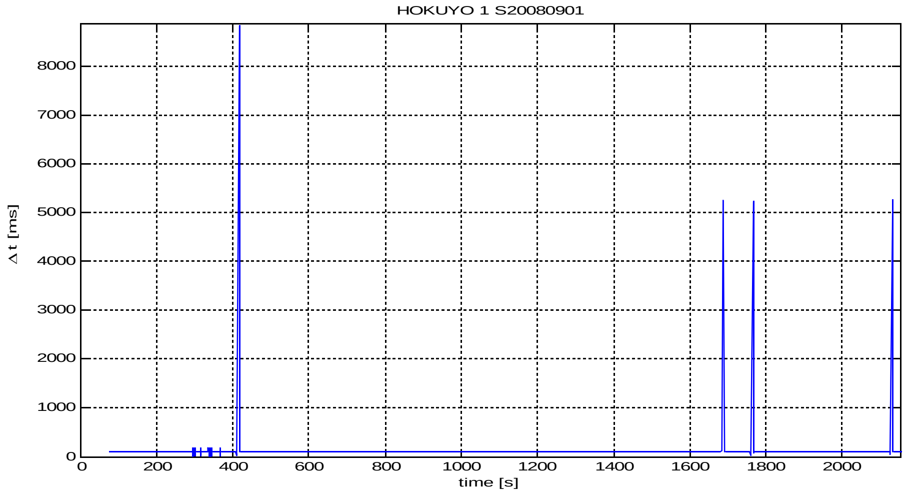
The conclusions for this dataset are:

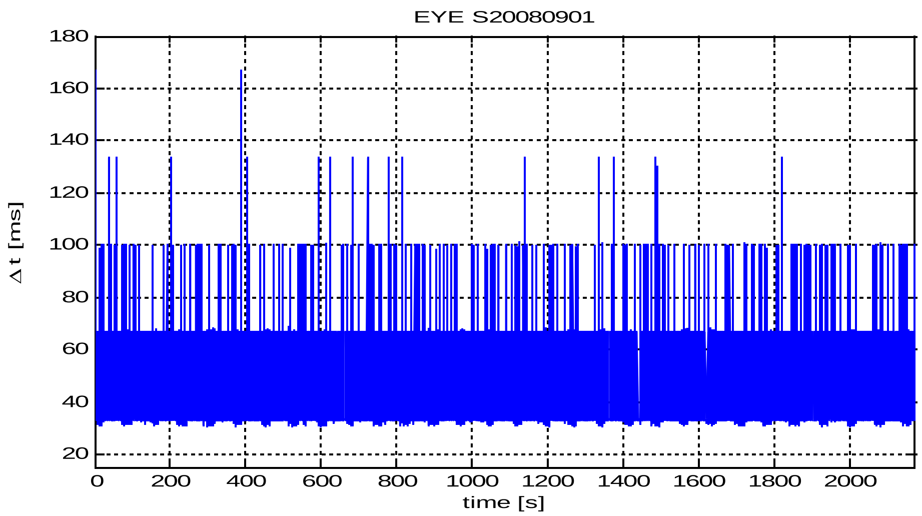
1) IMU presents some sporadic data loss, that will not affect SLAM algorithms.
2) Odometry, Sick laser, and GPS are correct, with some period oscillations.
3) Hokuyo laser presents data gaps of several seconds.
4) Monocular vision presents frequent loss of frames, as it can be seen in the figures below. About 1 out of every 15 images is lost, and two or even three consecutive frames lost are frequent.
5) Omnidirectional vision also presents some oscillations, but no data loss.

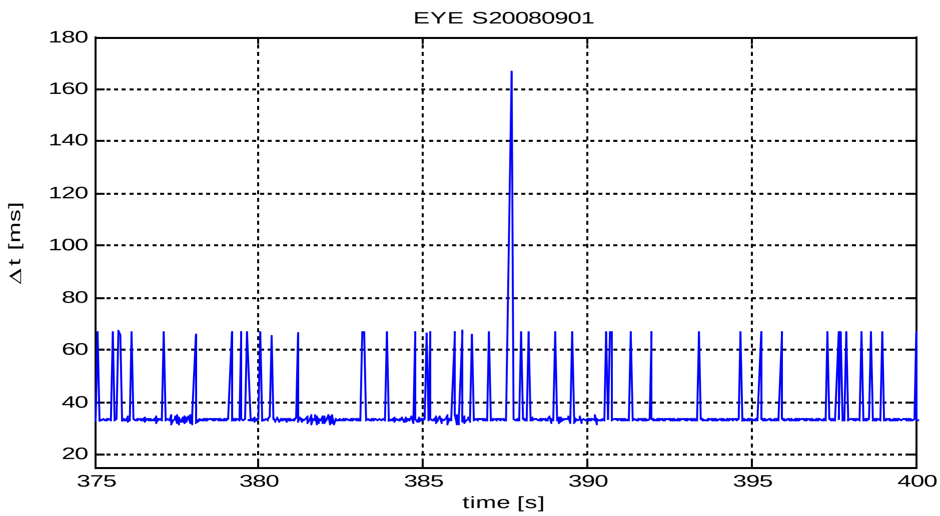

IMU S20080901
Δ t [ms]
time [s]

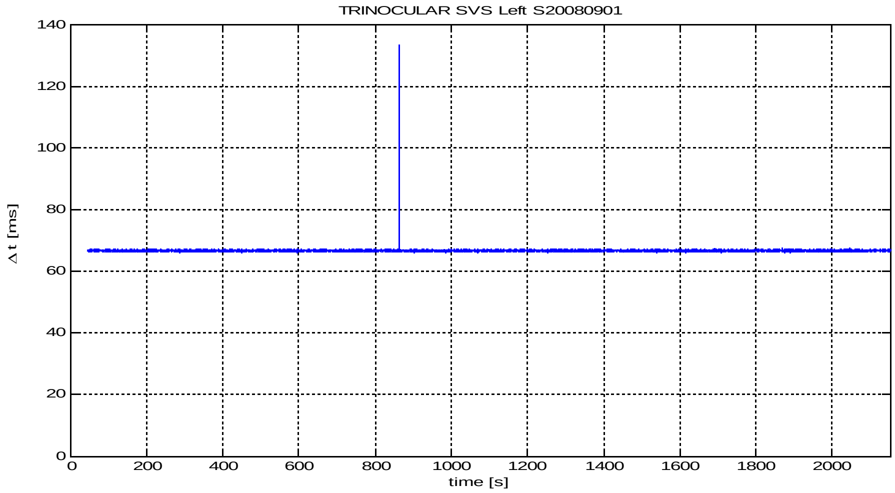

ODOMETRY S20080901
Δ t [ms]
time [s]

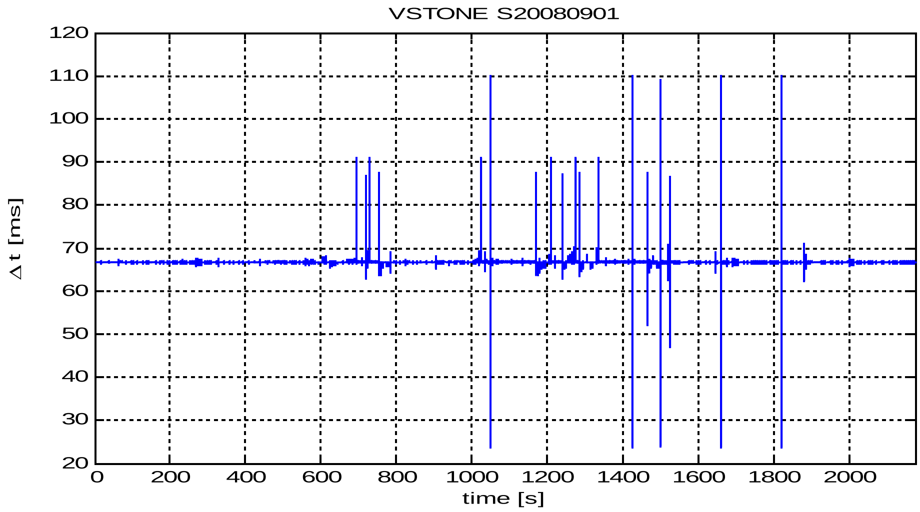

SICK FRONT S20080901
Δ t [ms]
time [s]

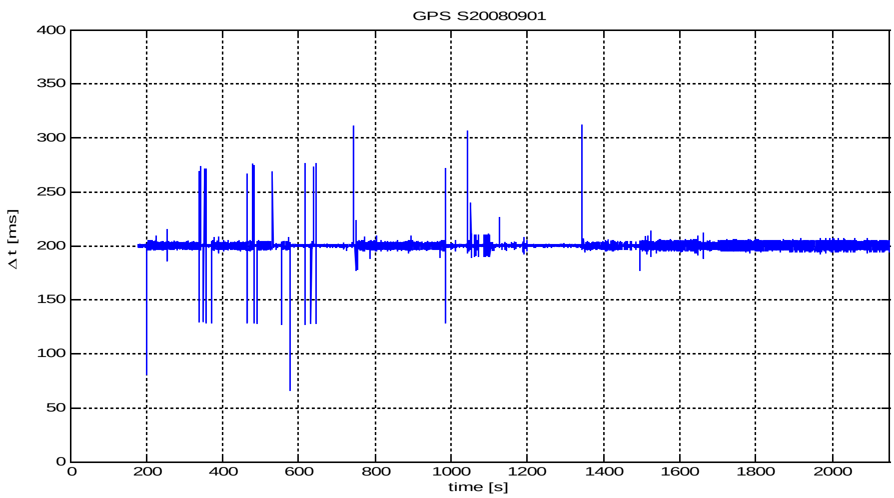

HOKUYO 1 S20080901
Δ t [ms]
time [s]


EYE S20080901
Δ t [ms]
time [s]


EYE S20080901
Δ t [ms]
time [s]


TRINOCULAR SVS Left S20080901
Δ t [ms]
time [s]


VSTONE S20080901
Δ t [ms]
time [s]


GPS S20080901
Δ t [ms]
time [s]

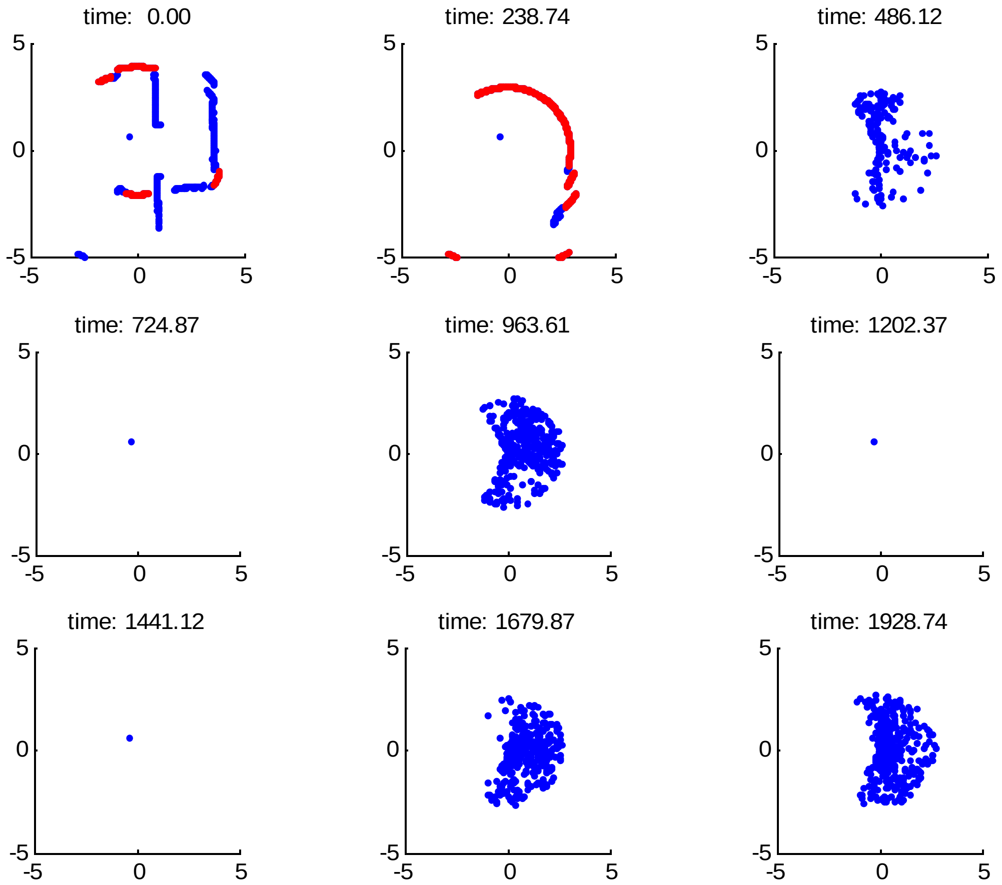
3.4.2. SICK Laser

1) Data density and quality are validated by running the laser SLAM software from ALUFR (Grisetti et al 2007, Grisetti et al 2008):

Graph-based SLAM on dataset Session20080901

3.4.3. 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 10000lux (a typical overcast day gives 10000-25000lux and bright sunlight gives 120000lux). 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 for SLAM in outdoor datasets taken in daylight.

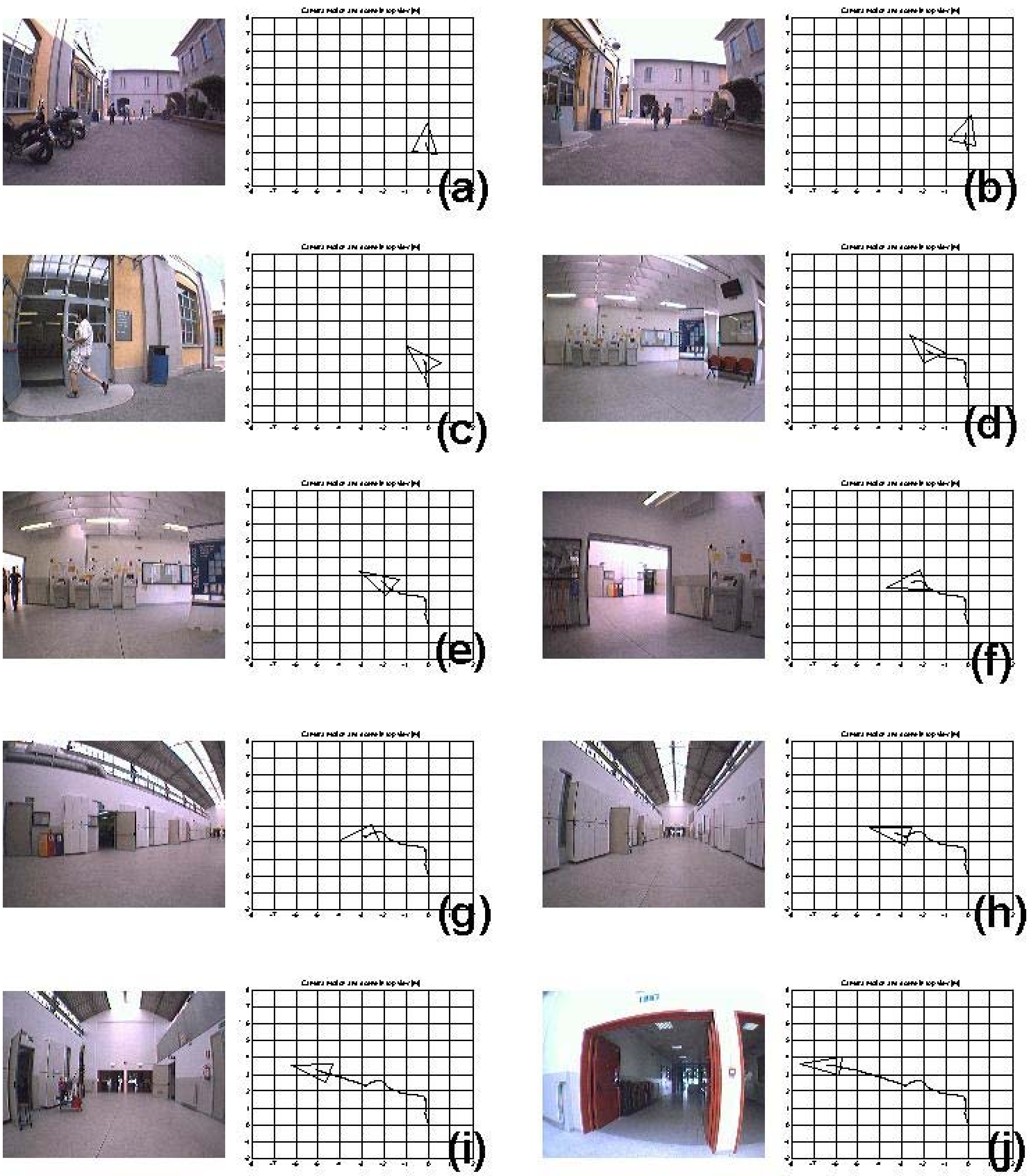


Points from the Hokuyo laser throughout the dataset Session20080901

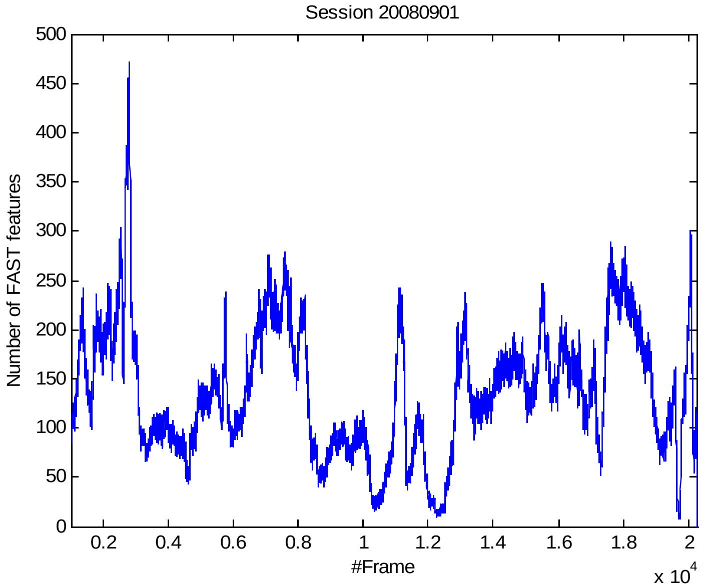
3.4.4. Monocular Vision

1) File format: All image files are readable.
2) Timing: see table in section 3.4.1.
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 20080901.



No dark frames have been detected in this sequence.



4) Data density: the next figure shows the number of FAST features extracted from frames 1000 to 20259 in Session20080901,

   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, from frame 10360 to 12250.

   Calibration is a bit closer to Bouguet's calibration toolbox guidelines because the calibration target is not always parallel and it appears a bit bigger in the images. In fact, 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 Session2 to 0,7% in Session 20080901.

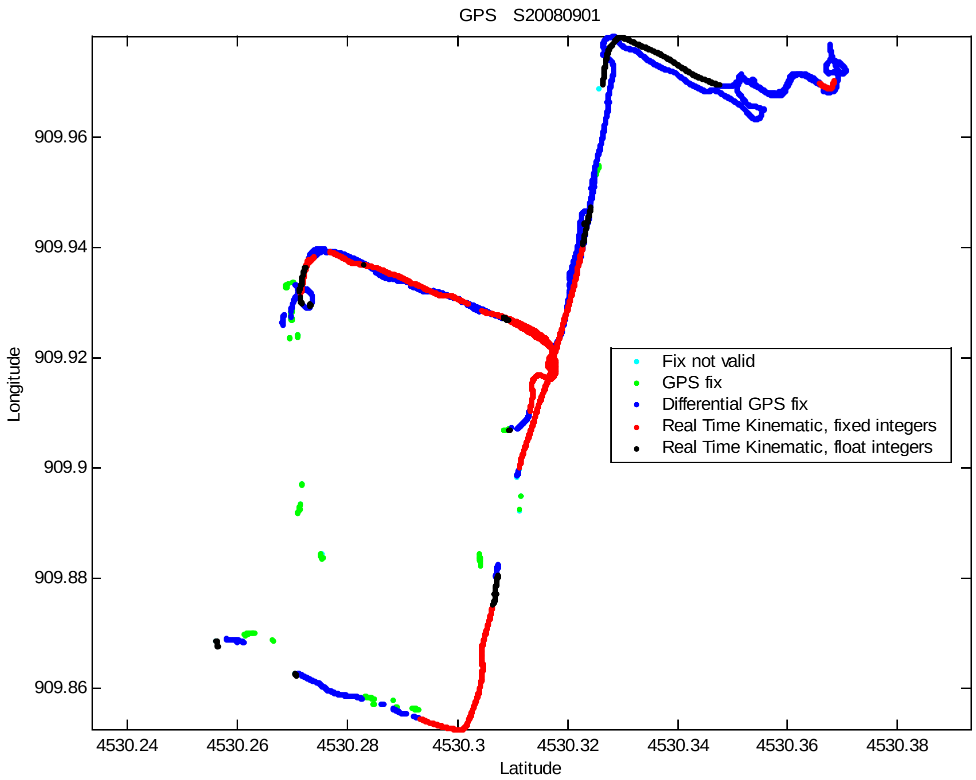
   Despite that the calibration target is bigger, it still does not fill the entire image. So, suggestions in section 4 still apply.

3.4.5. Trinocular Vision

1) Calibration: The dataset does not provide calibration for the external parameters (the cameras relative position and orientation). The calibration images provided have been found of too low quality to perform the extrinsic calibration. In this case, the calibration pattern used is bigger, but the calibration obtained is still not precise enough (see section 4.4).

3.4.6. 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.
2. The synchronization with other sensors is still not verified.



4. Defects found and recovery actions proposed

This section details the most important defects found during the validation of the available datasets and propose recovery actions to correct them, when possible. Guidelines should also be used to avoid defects in future dataset acquisitions.

4.1. Dataset documentation

Summary

The documentation of the datasets is incomplete.

Detailed Description

At the time of writing this deliverable, the only dataset documentation available is:

- “HOWTO document for accessing the dataset” version2 (Sept 8, 2008)
- Several README files provided in the data directories.

Major information missing is:

- The extrinsic parameters of the sensors, i. e. the position and orientation of all the sensors with respect to a reference system attached to the robot (usually chosen to be centered with the robot odometry) . In the case of the sonar belt used in session0, the lack of extrinsic parameters precludes any sensor validation.
- Description of the different rounds and trajectories performed with their location, starting time, sensors available, etc. From the documentation it is not clear whether the different runs are intended to be used separately or should be used together.
- Description of the settings used for each sensor: acquisition frequency, maximum range, etc.
- Description of the known defects of the dataset such as missing streams, errors detected during the acquisition, etc.

Recovery actions

For all datasets, provide the complete documentation at the same time than the sensor data. This will make dataset validation easier.

Other minor issues that need to be addressed:

- Unify the filenames on all the dataset. Some examples of changed filenames:
    1. ODOMETRY_XYT in session 20080901; ODOMETRY_TXY in the rest.
    2. SICK1 and SICK2 for session 0; SICK_FRONT and SICK_REAR in the rest.
    3. HOKUYO_FRONT and HOKUYO_REAR in session 20080901 – HOKUYO1 and HOKUYO2 in the rest
    4. OMNI for session 20080901 – VSTONE in the rest
    5. SVS1, SVS2 and SVS3 for session 0 – SVS_L, SVS_R and SVS_T in the rest
- Clean up the datasets removing parts of the data streams that are not useful, for example the initial interval before starting robot motion.
- Correct errors in some files:
    1. In session 0 the SICK's files "*.csv" cannot be easily loaded from Matlab because they have variable numbers of columns
    2. In the sessions 0, 1 and 2, the SICK's filenames do not agree with the data:
        - Session 0, SICK1 is rear and SICK2 is front.
        - Session 1 and 2, SICK_FRONT is rear and SICK_REAR is front.
- Document changes in data units
    1. For session0 the Sick readings are in millimeters and have maximum range of 8m; in the rest readings are in meters and maximum range is 80m.
- There are plenty of tools for robot navigation that are established in the community (for instance CARMEN or PLAYER/STAGE). I would be interesting to provide also a tool for converting the .csv formats used in RAWSEEDS datasets into these other major standards. A benefit of this procedure is that one can directly validate the quality of the data, for instance by generating an occupancy grid directly from the odometry and the laser measurements.

4.2. Timing and data loss problems

Summary

There is data loss, from minor to major, in all the datasets.

Detailed Description

The acquisition period for the different sensors suffers from oscillations during the acquisition of each dataset. In some cases several data acquisitions have been lost. In a few cases, like Session1 and Session2–Round1, the failure is fatal for most SLAM algorithms. A summary of the most important problems found per sensor follows.

- IMU: It is the fastest sensor with a period of 8ms, but the information is buffered and acquired by the system every 50ms, giving as a result incorrect timestamps. The corrected timestamps provided in files IMU_STRETCHED have continuous drift. The correct method to recover the timestamps is documented in section 3.1. Even with this correction, all datasets present minor gaps of around 50ms.
- Odometry: It is not correctly synchronized with the rest of the sensors: it runs ahead of time by a value between 80ms and 150ms. In Session1 there are data gaps of almost 0.5 seconds, making it unusable. Odometry is missing is Session2-Round1
- SICK laser: The period is quite stable in Session0 and Session 20080901, but there are data gaps from 1 to 20 seconds in Session1 and Session2.
- Hokuyo laser: The period is quite stable in Session0, Session1 and Session2, but there are data gaps in Session 20080901
- Monocular vision: Period oscillations in Session0 and Session1; gap of 2 seconds missing in Session2; frequent frames lost (up to 4 consecutive frames) in Session 20080901. In Session1, monocular vision is unsynchronized with the rest of sensors by 0.5 seconds.
- Trinocular vision: Very stable in all the datasets, only one frame missing in Session 20080901.
- Panoramic vision: Very stable in Session0 and Session1, and period oscillations in Session20080901 without data loss.

The defects found, and the fact that they appear and disappear from one dataset to the next suggests that the design of the data acquisition software has not taken properly into account the real time requirements of each sensor.

Recovery actions

Deliverable D1.1 describes the robot hardware architecture but it does not describe the design of the data acquisition software. This makes difficult an accurate diagnostic of the origins of the timing and data loss problems. Some generic recommended recovery actions are:

- Document the software architecture used: operating system, structure of processes and threads, priorities, communication channels, etc. Analyze its real-time properties.
- If possible, use a real-time operating system with priority-based preemptive scheduling. For periodic tasks, assign priorities using Rate Monotonic (Burns and Wellings, 2001): higher priority to more frequent tasks. Verify that non critical tasks run at lower priorities to not interfere with the data acquisition tasks.
- Add checkpoints to the software to detect the missing of deadlines and data loss from all sensors. This will avoid performing the complete data acquisition session and finding the problem later, during the dataset validation phase.
- To further reduce the errors in the data acquisition, it would be interesting to build a simple tool for generating and displaying a local occupancy grid map out of the laser readings and the odometry measurements while the robot runs. This would allow us to detect major errors directly while acquiring the data, with obvious benefits.
- If needed, the frequency monocular vision could be reduced to 15Hz, provided that the robot speed is moderate (see example in the validation of Session1) and there are no lost frames.

4.3. Monocular calibration

Summary

The calibration errors in the monocular EYE camera (3.48% error in focal length) are too large and can be reduced. At least a precision of 0.5% should be obtained.

Details

The Matlab camera calibration toolbox (Bouget, 2008) has been used to evaluate the quality of the calibration provided for the monocular EYE camera. Comparing the provided EYE calibration errors with the example given in the toolbox (see the following table), a 3.48% error in focal length seems rather large and could be reduced. Likely sources of error are image capture problems and over-parameterization.

Camera	fc value	fc error	Error %
Toolbox Example	657	0,34	0,05%
Session 1, EYE	198	6,9	3,48%

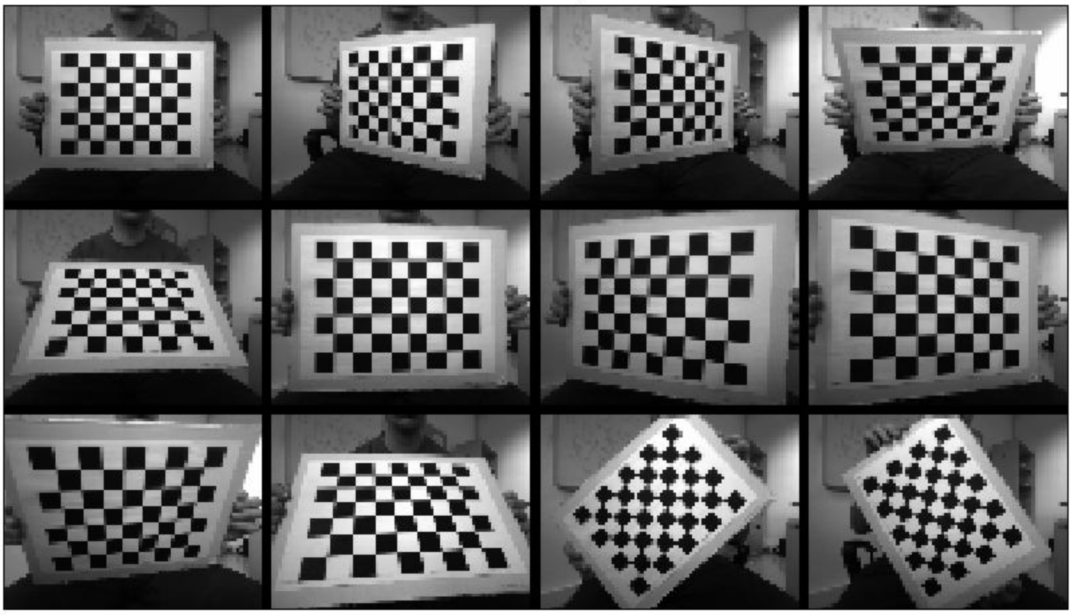
EYE calibration

Recovery actions

1. If the EYE camera lens properties have not been changed, a new calibration sequence following the calibration procedure guidelines below should be taken and the calibration repeated as follows:

   a) Calibration images should be taken under different orientations. The normal of the calibration planar object should not be parallel to the camera optical axis (Zhang, 1999, subsections 3.4 and 5.1). The recommended angle to minimise the calibration error is 45 degrees.

   b) The calibration object should fill the image as much as possible in order to properly capture the distortion model details (some examples can be found in the next figure and also at http://www.vision.caltech.edu/bouguetj/calib_doc/htmls/example.html



Examples of images to be used for monocular calibration

c) The estimated error of some distortion coefficients is larger than the coefficients themselves. This renders the estimation useless; they should be removed from the estimation (see http://www.vision.caltech.edu/bouguetj/calib_doc/htmls/example.html for an explanation).

2. If the EYE camera lens has been modified, auto calibration methods might be used to determine the camera parameters from the already available sequences.
3. Camera location with respect to the robot frame (extrinsic calibration) is not available. This is essential for combining monocular vision with other sensors. A procedure for determining EYE camera with respect to the robot frame has to be defined and used for future datasets.

4.4. Trinocular calibration

Summary

1) Intrinsic calibration parameters of the right camera seems to have large errors due to defects in the calibration process.
2) No extrinsic calibration parameters (relative transformations between cameras) are provided.
3) The recovery of the extrinsic calibration parameters gives low accuracy due to defects in the acquisition of the set of synchronized images provided.

Details

In the following we provide details for one indoor and one outdoor session.

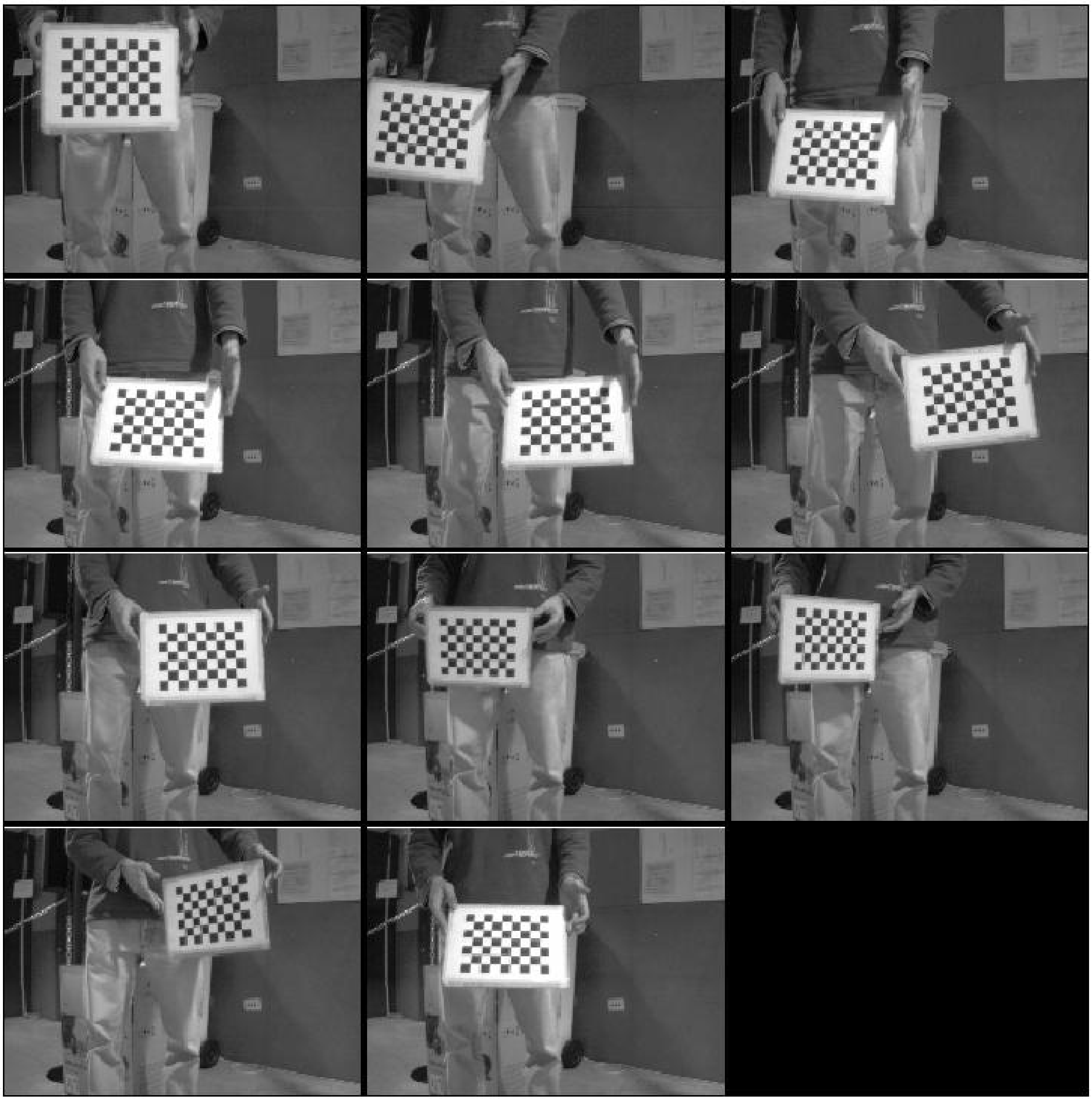
Session 1:

The calibration of the trinocular system for this session can be found in folder \Session1\CALIBRATION\CALIBRATED\TRINOCULAR, in 3 directories corresponding to a different camera: SVS_L, SVS_R and SVS_T for left, right and top images. The images used for the calibration of each camera are not synchronized and thus each set of images is only valid for independent camera calibration. The result of independent camera calibration has low accuracy, specially in the case of the right camera (see table, next).

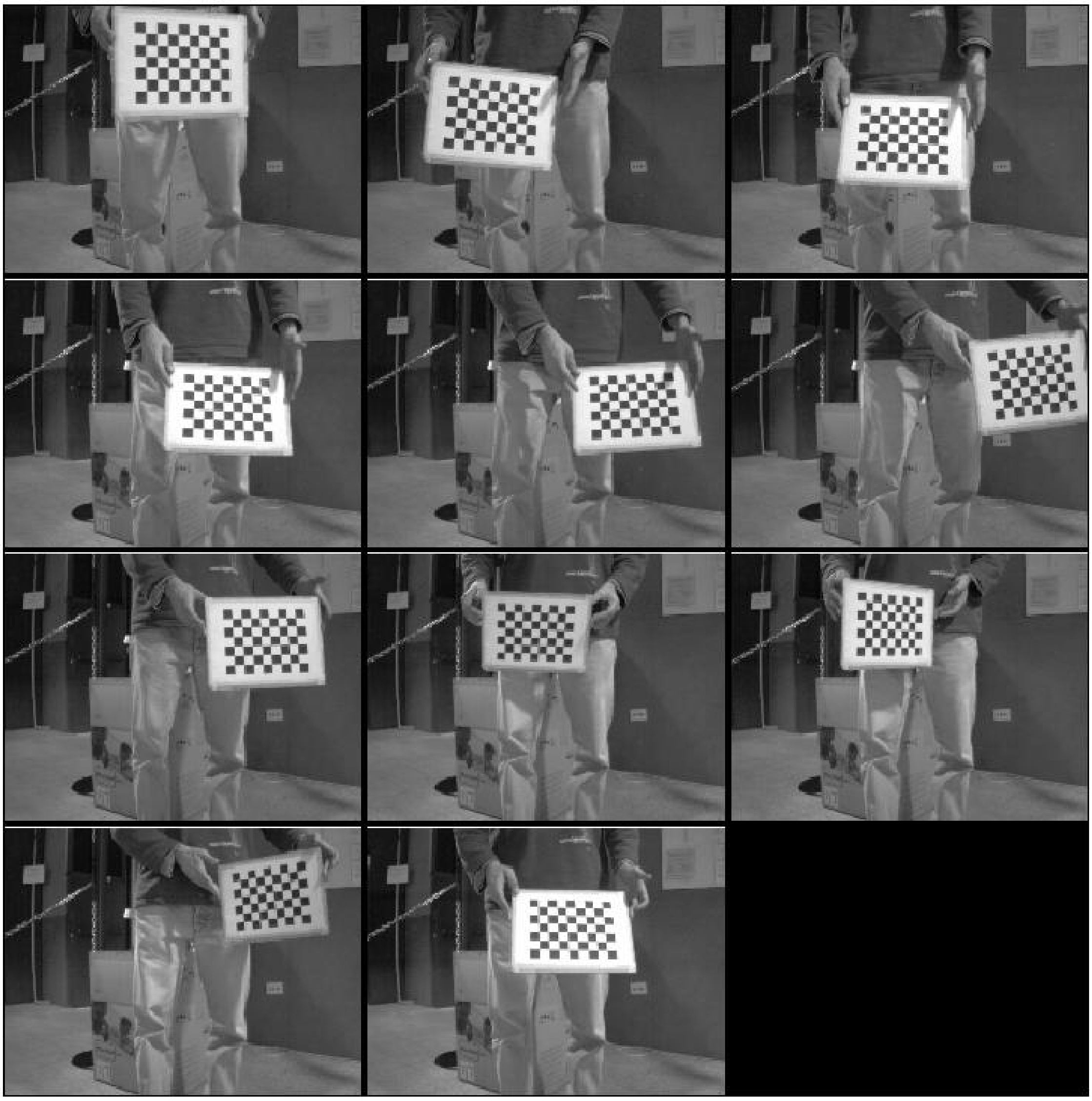
Camera	fc value	fc error	Error %
Toolbox Example	657	0,34	0,05%
Session1, SVS_L	660	2,6	0,39%
Session1, SVS_R	677	14,3	2,11%
Session1, SVS_T	664	4	0,60%

SVS trinocular calibration

The stereo calibration was executed using the synchronized sequence that appears in folder \Session1\CALIBRATION\RAW for the left and right cameras, selecting 11 synchronized pairs, shown in the next two figures.



Calibration images from Session1 (left)



Calibration images from Session1 (Right)

The final result is rather poor (see the following table).

Camera	fc value	fc error	Error %
Toolbox Example	657	0,34	0,05%
Session1, SVS_L	663	11,12	1,67%
Session1, SVS_R	654	9,4	1,44%

Stereo Calibration

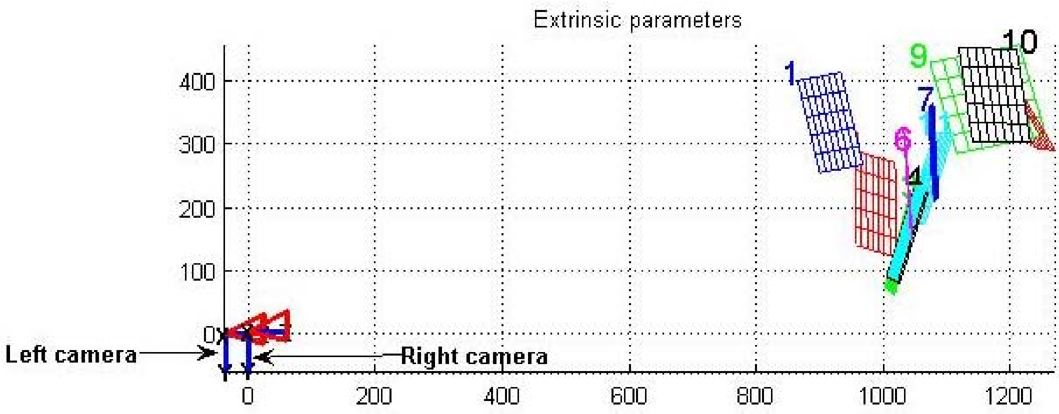
Extrinsic stereo calibration was carried out running the stereo_gui.m program of the MATLAB toolbox to obtain the relative transformations between left and right cameras (see table, next). The results are extremely poor, with an error of 2.59% in the baseline.

Camera	T value	T error	Error %
X position	178.7880	4.6390	2.59%
Y position	-7.8106	9.2592	--
Z position	41.2150	25.5010	--

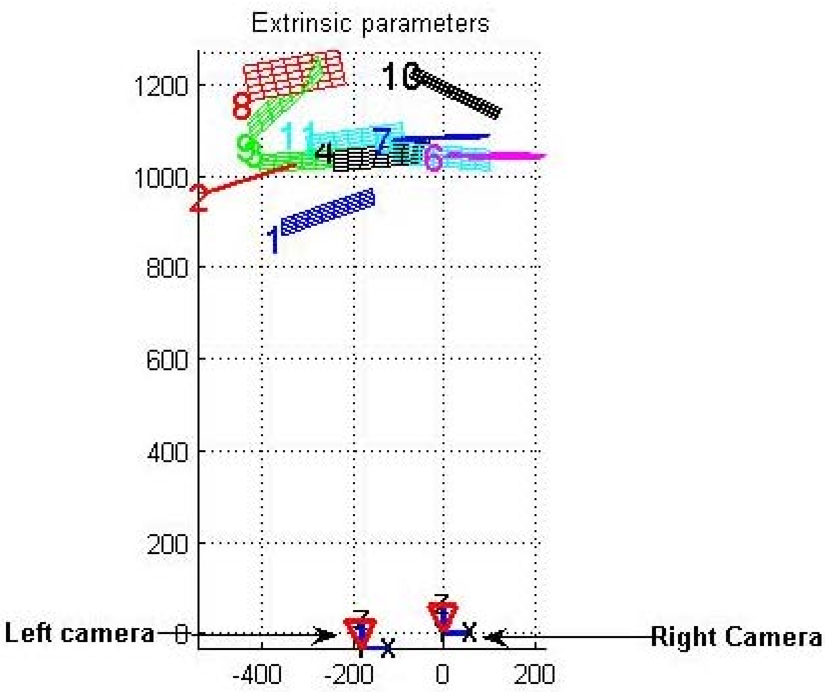
Camera	Om value	Om error	Error %
X component	0.0081	0.0164	--
Y component	-0.0287	0.0337	--
Z component	-0.0293	0.0052	--

Extrinsic stereo calibration

The 3D reconstruction resulting from this calibration can be seen in the two following figures. The pattern appears too far from the cameras, with too small changes in orientation.



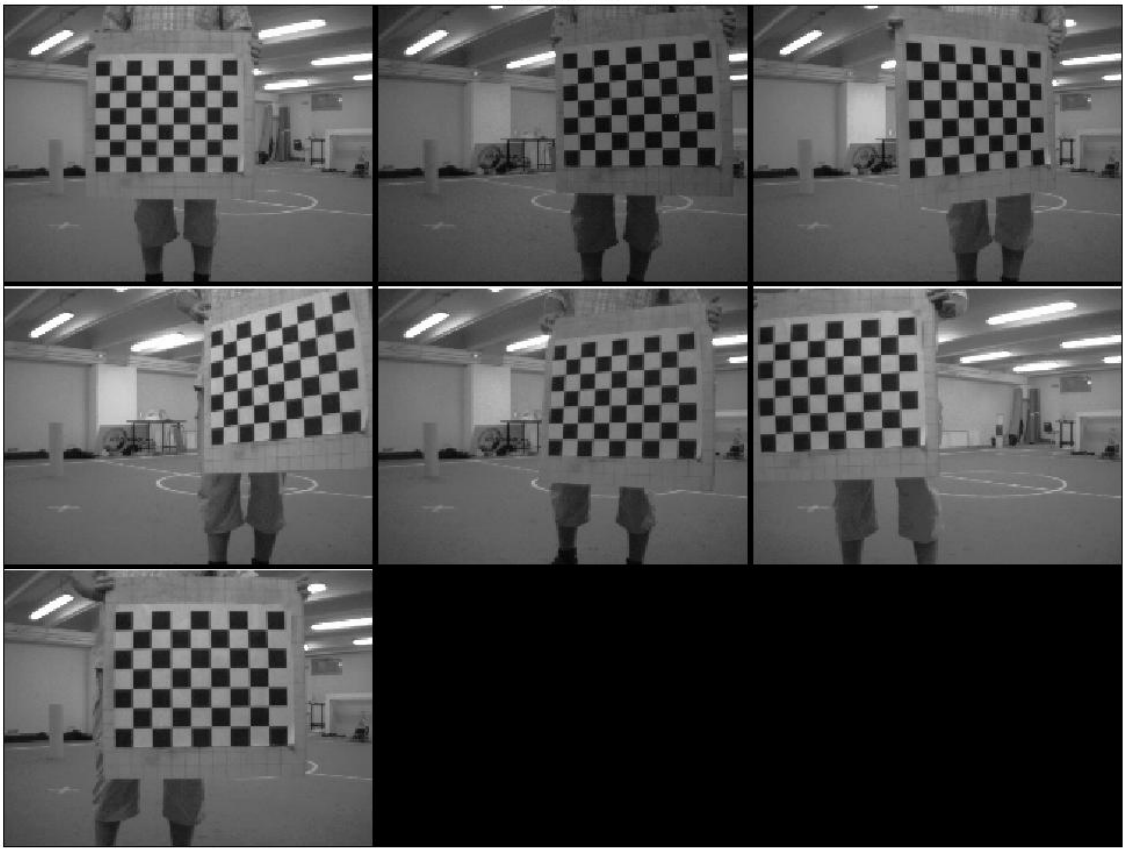
Extrinsic calibration of Session1 (lateral view)



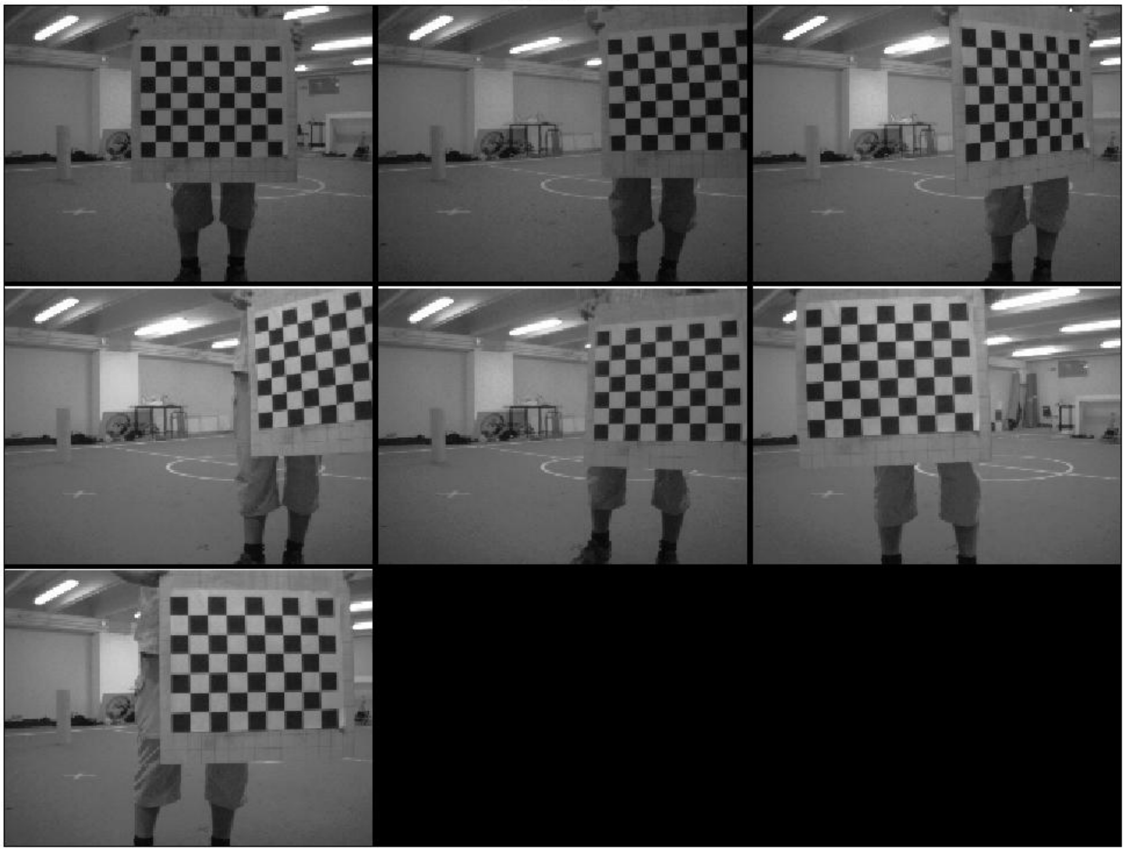
Extrinsic calibration of Session1 (top view)

Session 20080109:

Despite that in this case the pattern is larger in size for calibration, it still shows the same orientation deficiencies (see the next two figures).



Calibration images session 20080901 (left). It should be right image



Calibration images session 20080901 (right). It should be left image

This results again in large calibration errors (see the following table).

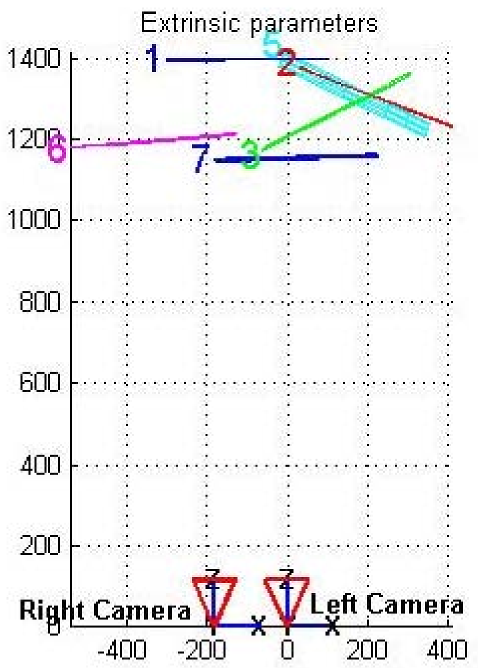
	fc value	fc error	Error %
Session1, SVS_L	694,14	12,80	1,84%
Session1, SVS_R	686,82	11,82	1,72%

Camera	T value	T error	Error %
X position	181,370	1,436	0,79%
Y position	0,2525	1,255	--
Z position	-2,7995	8,979	--

Camera	Om value	Om error	Error %
X component	0,0005	0,0053	--
Y component	0,0057	0,0119	--
Z component	-0,0050	0,0008	--

Calibration results for session20080109

In addition, from the calibration images in \Session20080109\CALIBRATION\CALIBRATED\TRINOCULAR and the sequence in \Session20080109 \CALIBRATION\RAW, it seems that left and right images are interchanged (SVS_L should be SVS_R and vice versa). This can be seen in the 3D reconstruction (see figure next).



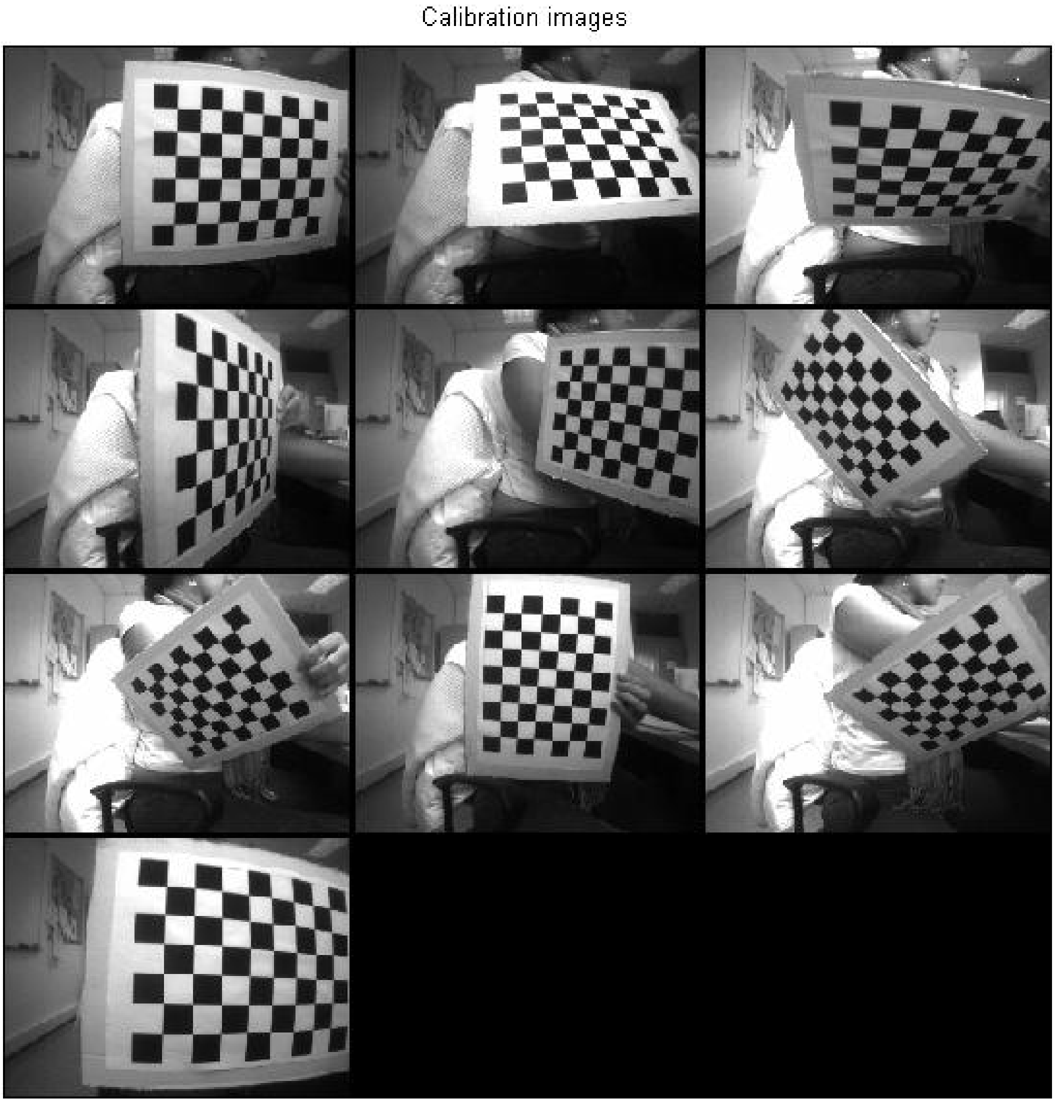
Extrinsic calibration for Session 20080901 (top view)

These calibration problems result in the trinocular system being unusable for SLAM at this point.

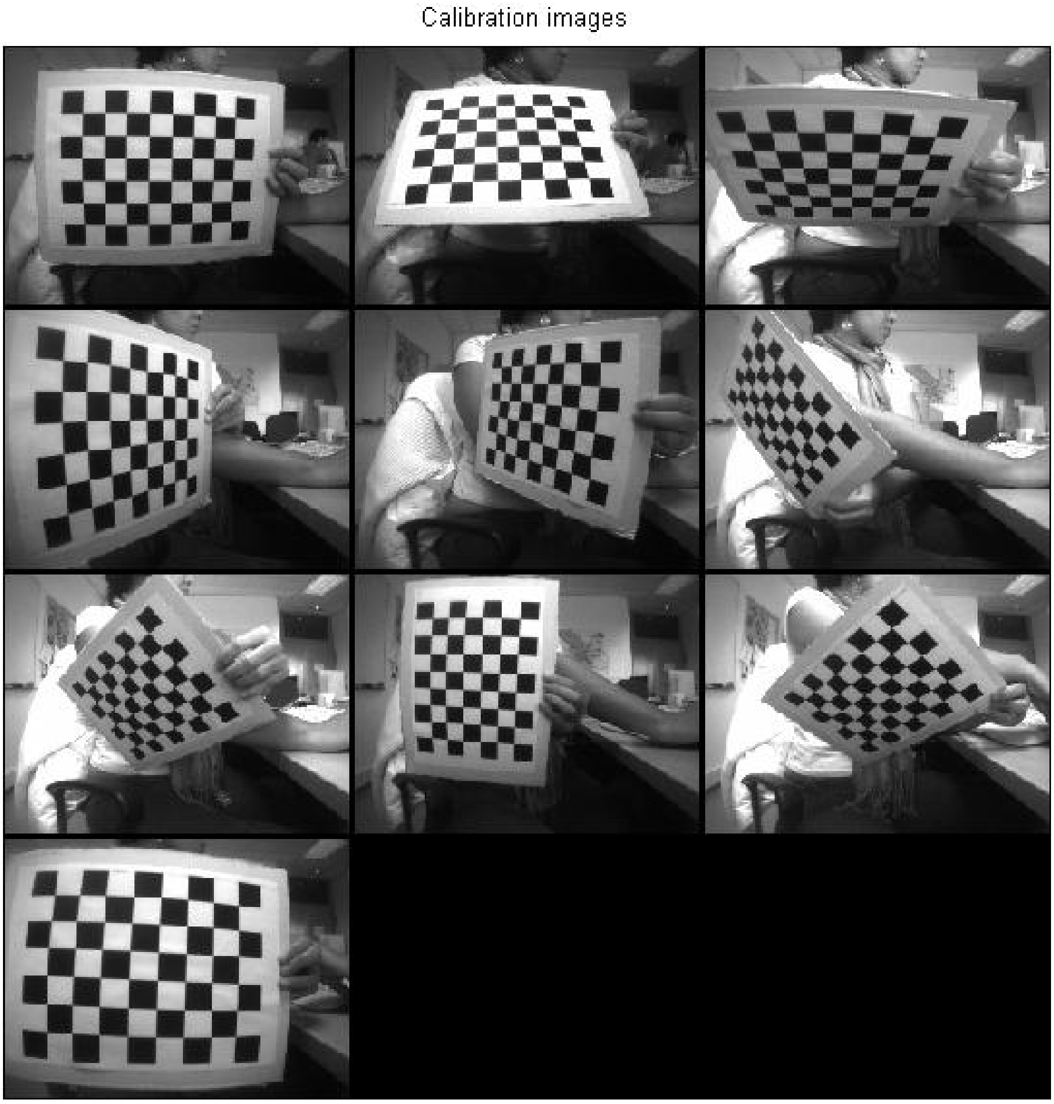
Recovery actions

1) If the stereo system has not been altered, the intrinsic camera parameters can be estimated from a set of new synchronized stereo calibration images, following the recommendations mentioned before.

   As an example, we have calibrated a Bumblebee stereo system using groups of images seen in the next two figures.



Good calibration example (left camera)



Good calibration example (right camera)

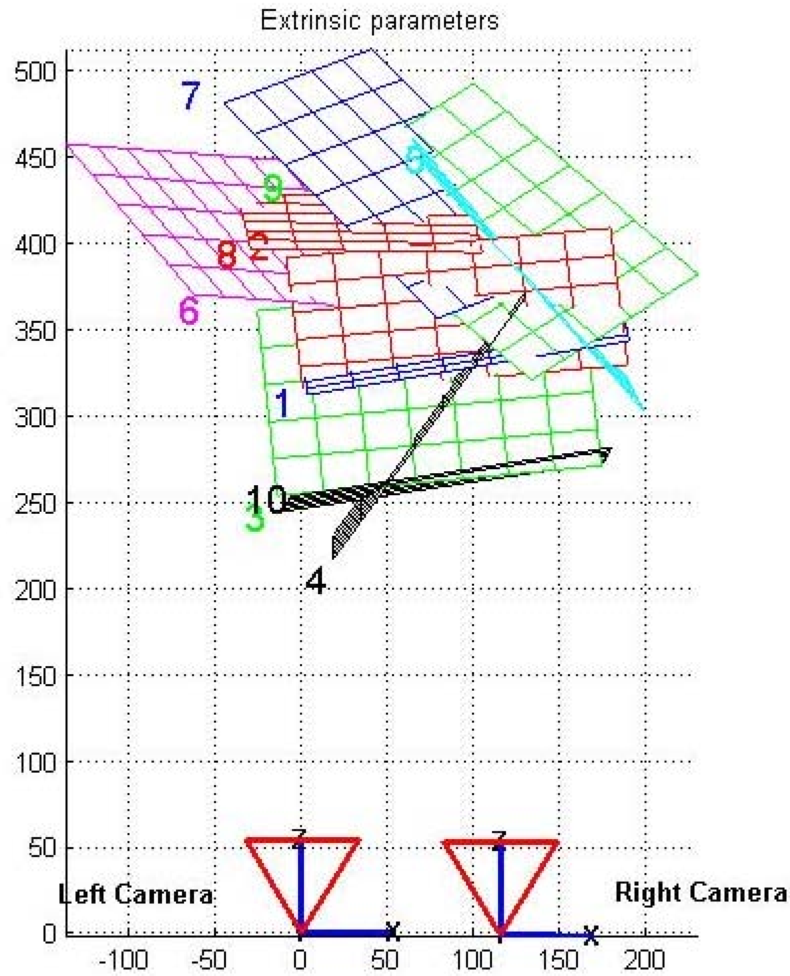
The results of running the stereo_gui.m program can be seen in the following table and the two following figures.

Camera	fc value	fc error	Error %
Toolbox Example	657	0,34	0,05%
Bumblebee, Left	523.22	1.9	0,36%
Bumblebee, Right	522.15	1.8	0,34%

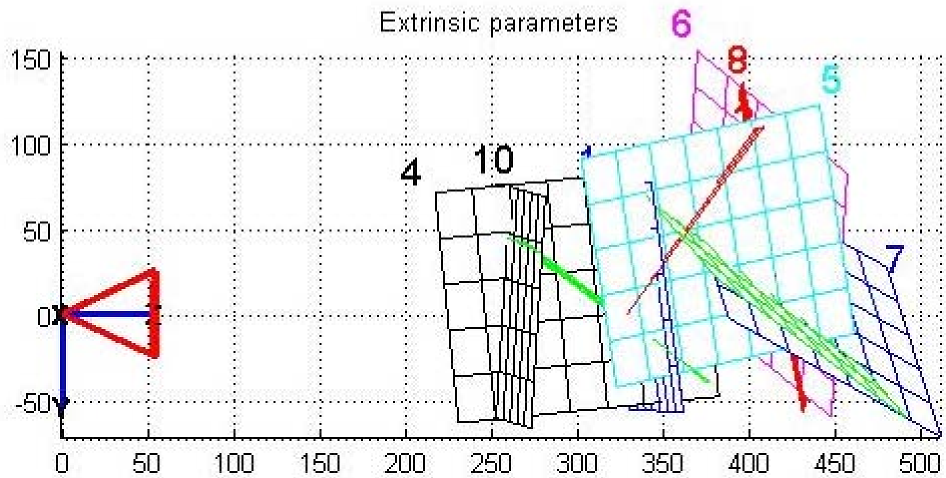
Camera	T value	T error	Error %
X position	-115.68	0.30	0.26%
Y position	0.24	0.24	--
Z position	0.48	1.48	--

Camera	Om value	Om error	Error %
X component	0.0045	0.0076	--
Y component	-0.0081	0.0113	--
Z component	-0.0013	0.0011	--

Calibration parameters for the Bumblebee system



Good calibration example (top view)



Good calibration example (lateral view)

2) If the stereo system has been altered, the following should be tried:

   a) Redo intrinsic calibration of the cameras (their intrinsic values are not likely to have been altered).

   b) Compute the relative camera location using a photogrammetric reconstruction. That is:

      i. select a trinocular view in the dataset where both close and distant object are detected in the thee images

      ii. compute corresponding points across the 3 views and, given the intrinsic calibration, compute the extrinsic calibration by bundle adjustment.

      iii. recover scale from a known environment distance such as a door or window frame length/width.

   c) The precision of the resulting calibration should be verified as explained before.

3) If this does not work:

   a) Calibration should be redone

   b) A new dataset should be obtained.

5. References

- J.Y. Bouget, "Camera Calibration Toolbox for Matlab", available at http://www.vision.caltech.edu/bouguetj/calib_doc/ , 2008
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