MultiDrone



3D Drone Localization and Mapping

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3D Drone Localization and Mapping



- Sensors, sources.
- Mapping: create or get 2D and/or 3D maps.
- Semantic mapping: Add semantics to maps.
 - POIs, roads, landing sites.
- Localization: find the 3D location based on sensors.
 - Drone localization.
 - Target localization.
- Simultaneous mapping and localization (SLAM).
- Fusion in drone localization.



3D Drone Localization and Mapping

- Drone localization:
 - Sources, sensors.
 - Mapping.
 - Localization.
 - SLAM.
- Data fusion in drone localization.
- Semantic mapping.





Sources: 2D maps

- Google maps.
- OpenStreetMaps.
- Semantic annotated information:
 - (roads, POIs, landing sites) in KML format in Google Maps.
 - roads in OSM (XML) in case of OpenStreetMaps.
- Google Maps JavaScript API.
- OpenStreetMaps API.





Sources: 3D maps



- Formats:
 - 3D triangle mesh.
 - 3D Octomap.
- Octomap :

Octree in memory: 130 MB Octree file: 50 MB (2 MB .bt) 3D Grid: 649 MB

- The octomap is a fully 3D model representing the 3D environment, where the UAV navigates.
- It provides a volumetric representation of space, namely of the occupied, free and unknown areas.
- It is based on octrees and using probabilistic occupancy estimation.



Geometrical mapping

- Sensors:
 - Velodyne HDL-32E
 - Monocular camera
 - IMU
 - laser altimeter
 - RTK D-GPS
- Processing:
 - Intel NUC NUC6i7KYK2 i7-6770HQ
 - Jetson TX2





Geometrical mapping

- 3D LIDAR.
 - SLAM-like algorithm based on Prediction-Update Recursions
 - Extract from the LIDAR measurements: corner and surface points
 - Prediction: Estimate LIDAR-based odometry from different scans using the ICP algorithm
 - Update: Matching of the LIDAR scan with the estimated map
 - Good estimate of robot 6 DoF pose and geometrical map
- Visual camera
 - Extraction of features using detectors such as SURF, SIFT or ORB
 - Estimation of visual odometry
- Robot odometry:
 - Combination of:
 - LIDAR-based odometry
 - Visual odometry
 - IMU



Geometrical mapping

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Experiments



Repeatibility

Dataset	Mean Error (m)	Median Error (m)	Min Error (m)
1	0,1377	0,1073	0,00098
2	0,1053	0,0769	0,00045
3	0,0847	0,0578	0,00083
4	0,1074	0,0792	0,00078
5	0,1722	0,1560	0,00130







3D localization sensors: GPS

- GPS receivers:
 - Receive position information from GPS satellites and then calculates the device's geographical position (difference from Satellite position). The Global Positioning System (GPS) is a constellation of 27 Earth-orbiting satellites (24 in operation and three extras in case one fails).
- GPS Coordinate system:
 - Longitute varies from 0^0 (Greenwich) to 180^0 East and West.
 - Latitude varies from 0^{0} (Equator) to 90^{0} North or South.
 - Elevation (from a reference ellipsoid that maps sea level).

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3D localization sensors: GPS

- Other Satellite systems (GLONASS (Russia), BeiDou (China), Galileo (EU)).
- RTK-GPS uses measurements of the phase of the signal carrier wave, in addition to the information content of the signal and relies on a single reference station or interpolated virtual station to provide real-time corrections, providing up to cm-level accuracy.



3D localization sensors: IMU

- Inertial Measurement Units (IMU):
 - It measures and reports a body's specific force, angular motion rate and, sometimes, the magnetic field surrounding the body.
 - It uses a combination of accelerometers, gyroscopes and, sometimes, also magnetometers.







3D localization sensors: Laser altimeter



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- It measures the altitude (height) above a fixed level.
- It emits laser pulses which travel to the surface, where they are reflected.
- Part of the reflected radiation returns to the laser altimeter, is detected, and stops a time counter started when the pulse was sent out.
- The distance is then easily calculated by taking the speed of light into consideration.



Other 3D localization sensors



- Wi-Fi, Bluetooth beckons: measures Receive Signal Strength Indicator (RSSID, ID).
 - Wi-FI localization accuracy: 5 15 meters.
 - Bluetooth: up to 1m.
- Ultra-wideband: Measures (Time Of Flight, ID, timestamp):
 - short-range radio technology, that employs transit time methodology (Time of Flight, ToF). Exact localization requires 3 receivers (trilateration). Each tracked object is equipped with a battery powered tag. Accuracy 10 – 30 cm.



Mapping and localization: sensors



LIDAR sensors



http://eijournal.com/print/articles/understanding-the-benefits-of-lidardata?doing_wp_cron=1517767340.6914100646972656250000

Monocular cameras



https://www.youtube.com/watch?v=8LWZSGNjuF0



LIDAR



- Laser scan sensors provide point clouds resulting from the impact of the laser rays on the scene.
- Thousands of sparse measurements on each frame.
- Frequencies of several Hertz.
- Method categories based on how the higher-level depth features are obtained:
 - Grid (2D) or voxel (3D) methods.
 - Segmentation methods.
 - Invariant feature methods.



Monocular images

- A single monocular image does not convey depth information.
- But it can detect points at any range.





Calibrated monocular image



- The camera detects:
 - Azimuth and elevation angles per pixel, with accuracy ranging from 0.1 to 0.01 degrees.
 - Colour of the reflected or emitted light by the scene point per pixel.
 - Millions of pixels per image.
 - Tens of images per second.



Calibrated monocular image



Victor Blacus (https://commons.wikimedia.org/wiki/File:Amagnetic_theodolite_Hepi tes_1.jpg),

"Amagnetic theodolite Hepites 1",

https://creativecommons.org/licenses/by-sa/3.0/legalcode

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Ángel Miguel Sánchez (https://commons.wikimedia.org/wiki/File:Sta_Maria_Naranco.jpg), "Sta Maria Naranco", modified,

https://creativecommons.org/licenses/by-sa/3.0/es/deed.en



Stereo imaging



- Two cameras in known locations.
- Calibrated cameras.
- Stereo images can create a disparity (depth) map.









3D perception (at least two views)

- Two cameras in known locations.
- Calibrated cameras.
- Known matches.

 $\mathbf{x}_{i_1 j}$

 O^{i_1}

In an ideal world ...

In this real world ...

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 \mathbf{X}_{wj}

 l_2

 O^{i_2}

d



 $\mathbf{x}_{i_1 j}$

 $0^{i_{1}}$

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 $0^{i_{21}}$



Geometrical accuracy depends on parallax angle.



3D Drone Localization and Mapping

- Drone localization
 - Sources, sensors
 - Mapping
 - Localization
 - SLAM
- Data fusion in drone localization
- Semantic mapping



Mapping techniques



- To obtain a map, robots/drones need to take measurements that allow them to perceive their environment.
- Relationship between the inner state of the drone (i.e., 6-DoF pose) and the state of the map (e.g., the position of features in a map).
- Two main approaches:
 - Odometry-based methods.
 - Simultaneous Localization and Mapping (SLAM).



Visual odometry



- The problem of recovering relative camera poses and threedimensional (3-D) structure from a set of camera images (calibrated or noncalibrated) is known in the computer vision community as Structure from Motion (SfM).
- Visual Odometry is a particular case of SFM.
- Focuses on estimating the 3-D motion of the camera sequentially, as a new frame arrives, in real time.









Structure from Motion (SfM)



- Unknown camera location, even not calibrated cameras.
- Unknown feature correspondences across views.
- It is computed, up to scale factor:
 - Location for the cameras.
 - 3D location of the matched points.



Structure from Motion (SfM)

Photo tourism: exploring photo collections in 3D (https://www.youtube.com/watch?v=6eQ-CB8TY2Q)

N Snavely, SM Seitz, R Szeliski. "*Modeling the world from internet photo collections*", International Journal of Computer Vision, 80 (2), 189-210 Hartley, Richard, and Andrew Zisserman. *Multiple View Geometry in Computer Vision*. Cambridge University Press, 2004.

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- Robot/drone estimates its inner state using sensors that incrementally measure the motion and update the map.
- The map is built with each new measurement using the information of the sensor and the position of the robot/drone.
- The odometry and the mapping problems are separated, and only the second depends on the first one, which can lead to significant odometry drifts that affect the quality of the robot/drone localization and hence, the map estimation.





- Usually fast, efficient, simple to implement methods.
- Accurate enough if the proposed sensor does not induce drifts, due to noise or non-linearities.





- LOAM:
 - An odometry estimation and mapping method that calculates the trajectory of the laser using, high-level features based on the properties of rotatory lasers.
 - Identifies both corner and surface points, as features, and generates a map that contains both of them separately.







- SVO:
 - Stands for Semi-Direct Visual Odometry.
 - Generates a five-level pyramid representation of the incoming frame: data association is first established through an iterative direct image alignment, scheme starting from the highest pyramid level up till the third.



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6 DoF localization

- Multi-sensor MCL for real-time 6DoF localization:
 - MCL Prediction: LIDAR odometry
 - Update of particles X, Y, Yaw: LIDAR point-clouds + camera features
 - Update of particles Z, pitch, roll: altimeter + IMU
 - MCL Update using the consistency of LIDAR point clouds with the map
- SLAM-based localization
 - SLAM that uses a previous map
 - Rely on previous maps but at the same time incorporates map changes







6 DoF localization

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Localization



- Not an easy task.
- Unconstrained nature of robot/drone movements → use of high-fidelity algorithms and sensors that do not reply on them.
- Many methods used for Mapping, are also used for Localization.
- Localization methods can be used as an alternative, in case of GPS failure, when installed.


The "kidnapped" problem



- When a robot is to be localized in an environment, two different cases are possible:
 - Its initial position is known (with a respect to global map).
 - The "kidnapped problem":
 - Solution \rightarrow The AMCL algorithm.





- Probabilistic localization system for a moving robot.
- Implements the adaptive Monte Carlo localization approach, i.e., a particle filter to track the pose of a robot against a known map.





- Stages:
 - Starts with a distribution of particle over the configuration space.
 - When a robot moves, it shifts the particle to predict its new state after the movement (Prediction Stage).
 - When the robot perceives its environment, the particles are updated using a Bayesian estimation that relies on how well the actual sensed measurements correlate with the predicted state (Update Stage).





https://www.mathworks.com/help/search.html?qdoc=amcl&submitsearch=

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https://www.mathworks.com/help/search.html?qdoc=amcl&submitsearch=





https://www.mathworks.com/help/search.html?qdoc=amcl&submitsearch=

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Methods for mapping based on SLAM



- Robot/drone uses the map in order to update the robot inner state.
- Both the robot/drone and the map share information and are updated altogether.



Methods for mapping based on SLAM



- New measurements can have an impact on the state of the map, but can also be used to improve the accuracy of the state of the robot/drone.
- Most mapping problems are solved using SLAM approaches, due to their superiority in producing better solutions with lowquality sensors.



Visual SLAM

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https://youtu.be/sr9H3ZsZCzc





Visual SLAM





- From the sole input of the video stream:
 - Simultaneous estimation of the camera motion and the 3D scene.
 - Real-time at frame rate.
 - Sequential processing.
 - The field of view of the camera \ll than the map size.
- Pivotal piece of information in automated scene interaction:
 - Sensor/robot pose with respect to the scene.
 - Localization for robots, cars, drones, autonomous navigation.
 - AR/VR user/sensor positional tracking.



SLAM methods



- LSD SLAM:
 - Uses a randomly initialized scene depth from the first viewpoint that is later refined through measurements across subsequent frames. This method does not suffer from the degeneracies of geometry methods.
- HECTOR SLAM:
 - A grid-based SLAM method that employs gradient-based optimization algorithms to watch each scan with the overall map. It is widely used for 2D mapping.



ORB-SLAM



- Among top performers in sparse features VSLAM.
- Robust, real-time, large scale operation.
- Able to operate in general scenes.
- Prototypical VLSAM system ready to use.



ORB-SLAM

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D. Gálvez-López, R. Mur-Artal, J.M.M Montiel, J.D. Tardós
Source code (released under dual GPLv3/ commercial) ORB-SLAM: https://github.com/raulmur/ORB_SLAM (Monocular. ROS integrated) ORB-SLAM2: https://github.com/raulmur/ORB_SLAM2 (Monocular, Stereo, RGB-D. ROS optional)
R. Mur-Artal, J. M. M. Montiel and J. D. Tardós, "ORB-SLAM: A Versatile and Accurate Monocular SLAM System", IEEE Transactions on Robotics, 1(5), 1147-1163, 2015
IEEE Transactions on Robotics, 2016, King-Sun Fu Memorial Best Paper Award

R. Mur-Artal, J. D. Tardós, "Orb-slam2: An open-source slam system for monocular, stereo, and rgb-d cameras", IEEE Transactions on Robotics, 33(5), 1255-1262, 2017

R. Mur-Artal, J. D. Tardós, "Visual-inertial monocular SLAM with map reuse", IEEE Robotics and Automation Letters, 2(2), 796-803, 2017

D. Gálvez-López, J. D. Tardos, "*Bags of binary words for fast place recognition in image sequences*", IEEE Transactions on Robotics, 28(5), 1188-1197, 2012



MultiDrone Frame / keyframe Local Map. Bundle • Full Adjustment: KeyFrames and map points. • Frames: • Only camera pose is computed.

G. Klein and D. Murray . Parallel tracking and mapping for small AR workspaces. (ISMAR), November 2007







ORB-SLAM system overview

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TRACKING





ORB-SLAM system overview



- Full system including all stages of a typical VSLAM:
 - Tracking at frame rate.
 - Mapping, subframe rate.
 - Loop closing.
 - Relocation.
 - FAST corner + ORB descriptor.
 - Binary descriptor.
 - Fast to compute and compare.





ORB-SLAM system overview

- Same feature all stages.
- Survival of the fittest policy for points and key-frames management.
- Three thread architecture.
- All stages end up providing an accurate initial guess to non-linear re-project $\underset{\mathbf{T}_{iw}, \mathbf{X}_{wj}}{\operatorname{argmin}} \sum_{i,j} \rho\left(\|\mathbf{x}_{ij} \pi_i (\mathbf{T}_{iw}, \mathbf{X}_{wj})\|^2 \right)$



Features

- Repeatability.
- Accuracy.
- Invariance:
 - Illumination
 - Position
 - In-plane rotation
 - Viewpoint
 - Scale.
- Efficiency.



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Features







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2000

Popular features for visual SLAM

Detector	Descriptor	Rotation Invariant	Scale Invariant	Accuracy	Relocation & Loops	Efficiency
Harris	Patch	×	×	$\checkmark \checkmark \checkmark$	×	$\checkmark \checkmark \checkmark$
Shi-Tomasi	Patch	×	×	$\checkmark \checkmark \checkmark$	×	$\checkmark \checkmark \checkmark$
SIFT	SIFT	$\checkmark \checkmark \checkmark$	$\checkmark \checkmark \checkmark$	$\checkmark\checkmark$	$\checkmark \checkmark \checkmark$	\checkmark
SURF	SURF	$\checkmark \checkmark \checkmark$	$\checkmark \checkmark \checkmark$	$\checkmark\checkmark$	$\checkmark \checkmark \checkmark$	$\checkmark\checkmark$
FAST multi	BRIEF	×	$\checkmark\checkmark$	$\checkmark \checkmark \checkmark$	\checkmark	$\checkmark \checkmark \checkmark$
FAST multi	ORB	$\checkmark \checkmark \checkmark$	$\checkmark\checkmark$	$\checkmark \checkmark \checkmark$	$\checkmark\checkmark$	$\checkmark \checkmark \checkmark$



Popular features for visual SLAM



- ORB: Oriented FAST and Rotated Brief.
- 256-bit binary descriptor.
- Fast to extract and match (Hamming distance).
- Good for tracking, relocation and Loop detection.
- Multi-scale detection at same point appears on several scales.





- Pixel surrounded by consecutive pixels all brighter/darker than *p*.
- Much faster than other detectors.



Binary descriptors: rBRIEF

- Computed around a FAST corner.
- Has orientation.





 $p \triangleq interest point \ C \triangleq intensity centroid$

Hamming distance 5

Hamming distance 51

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Rublee, E., Rabaud, V., Konolige, K., & Bradski, G. ORB: an efficient alternative to SIFT or SURF, ICCV 2011



Camera tracking



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- Map assumed perfectly estimated.
- ORB point detection in the image.
- Camera assumed close to its last pose, predicted by motion model.
- Map back-projected in the image.
- Putative matches ORB similarity.
- Camera pose optimization T_{iw} fixing all map points X_{wj}.

$$\operatorname{argmin}_{\mathbf{T}_{wi}} \sum_{j} \rho \left(\|\mathbf{x}_{ij} - \pi_i \left(\mathbf{T}_{iw}, \mathbf{X}_{wj}\right)\|^2 \right)$$



Place recognition: Relocation / Loop closing



- Relocation:
 - During SLAM, tracking can be lost (occlusions, low texture, quick motions, etc.):
 - Re-acquire camera pose and continue.









Place recognition: Relocation / Loop closing

- Loop closing to avoid map duplication:
 - Loop detection.
 - Loop correction: correct accumulated drift.



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Why is place recognition difficult





Likely algorithm answer: YES

TRUE POSITIVE

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YES



Why is place recognition difficult





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Likely algorithm answer:





Why is place recognition difficult





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Likely algorithm answer:

YES

NO



Perceptual aliasing is common in indoor scenarios



False positives





Scene 1430







 $\boldsymbol{\bigotimes}$

 \checkmark

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Scene 637

Scene 1244





False positives



- False positives may ruin the map.
- You must add robustness in the SLAM back-end:
 - Rigidity.
 - Repeated detection.







DBoW2 Database of Keyframes



 Direct index Image 1

 Node 3
 Node 4

 f_{1,65}
 f_{1,10}, f_{1,32}

Direct index speeds up putative matches between recovered keyframes and the query image

Inverse index fast recovery of keyframes with similar vector of words to the query

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 731667 (MULTIDRONE) D. Gálvez-López, J.D. Tardós, "Bags of Binary Words for Fast Place Recognition in Image Sequences", IEEE Transactions on Robotics, 28(5), 1188-1197, 2012.



Relocation



- Per new frame:
 - Most similar keyframe from database:
 - Inverse index, efficient search.
 - Score considers covisible keyframes, spatial consistency.
 - Putative matches:
 - ORB query \rightarrow ORB keyframe \rightarrow 3D map points.
 - Direct index to avoid brute force search for matches.
 - RANSAC + PnP + guided search to compute camera pose.






most similar keyframe

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Relocation

	Initial Map		Relocalization			
System	KFs	RMSE (cm)	Recall (%)	RMSE (cm)	Max. Error (cm)	
	<i>fr2_x</i>	yz. 2769 fi	ames to re	elocalize		
PTAM	37	0.19	34.9	0.26	1.52	
ORB-SLAM	24	0.19	78.4	0.38	1.67	
fr	3_walki	ing_xyz. 85	59 frames	to relocali	ze	
PTAM	34	0.83	0.0	-	-	
ORB-SLAM	31	0.82	77.9	1.32	4.95	



Challenging relocation in fr3_walking_xyz

Relocation in fr2 xyz. Map created 30 seconds of the sequence, 2769 frames

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Loop closure detection and MultiDrone correction





MultiDrone Loop closure detection and correction in •

- **VSLAM** Monocular trajectory exploratory
- drifts:

london

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- Translation
- Orientation
- Scale
- Predict-match-update loop fails rome
 - Duplicated map
 - Loop detection by place radridi recognition
 - Computation relative to camera pose

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Loop closure detection and MultiDrone correction

- Iondon zaragoza 12120012 δ δ ň rome П П nadrid ranada
- Monocular VSLAM exploratory trajectory drifts:
 - Translation
 - Orientation
 - Scale
 - Predict-match-update loop fails
 - Duplicated map
 - Loop detection by recognition
 - Computation relative to camera pose
 - Pose graph cameras correction
 - Map correction

H. Strasdat, J.M.M. Montiel and A.J. Davison, "Scale Drift-Aware Large Scale Monocular SLAM", RSS, 2010.

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place

london

rome

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Experimental results - KITTI

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Geiger, A., Lenz, P., Stiller, C., & Urtasun, R., "Vision meets robotics: The KITTI dataset", The International Journal of Robotics Research, 32(11), 1231-

1237, 2013. (https://youtu.be/8DISRmsO2YQ?t=52s) This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 731667 (MULTIDRONE)



Experimental results - KITTI

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		ORE	3-SLAM	+ Global l	BA (20 its.)
Sequence	Dimension (m×m)	KFs	RMSE (m)	RMSE (m)	Time BA (s)
KITTI 00	564 imes 496	1391	6.68	5.33	24.83
KITTI 01	1157×1827	Х	Х	Х	Х
KITTI 02	599 imes 946	1801	21.75	21.28	30.07
KITTI 03	471×199	250	1.59	1.51	4.88
KITTI 04	0.5 imes 394	108	1.79	1.62	1.58
KITTI 05	479×426	820	8.23	4.85	15.20
KITTI 06	23×457	373	14.68	12.34	7.78
KITTI 07	191×209	351	3.36	2.26	6.28
KITTI 08	808×391	1473	46.58	46.68	25.60
KITTI 09	465×568	653	7.62	6.62	11.33
KITTI 10	671×177	411	8.68	8.80	7.64

- Error $\approx 1\%$ of trajectory length
- Pose graph quite close full BA

Raúl Mur-Artal, J. M. M. Montiel and Juan D. Tardós, "ORB-SLAM: A Versatile and Accurate Monocular SLAM System", IEEE Trans. on Robotics, 31(5),

1147-1163, 2015. This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 731667 (MULTIDRONE)



EuRoc monocular maps

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Michael, et al. "The EuRoC micro aerial vehicle datasets", The International Journal of Robotics Research, 35(10), 1157-1163, 2016.

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EuRoc monocular + IMU

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https://youtu.be/rdR5OR8egGI



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EuRoc monocular + IMU

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 TABLE I

 Keyframe Trajectory Accuracy in EuRoc Dataset (Raw Ground-Truth)

			Visual-Inertia	I ORB-SLAM			Monocular C	ORB-SLAM
		No Full BA			Full BA		No Full BA	Full BA
	RMSE (m)	Scale Error (%)	RMSE(m) GT scale*	RMSE (m)	Scale Error (%)	RMSE (m) GT scale*	RMSE(m) GT scale*	RMSE(m) GT scale*
V1_01_easy	0.027	0.9	0.019	0.023	0.8	0.016	0.015	0.015
V1_02_medium	0.028	0.8	0.024	0.027	1.0	0.019	0.020	0.020
V1_03_difficult	X	X	X	X	X	X	X	X
V2_01_easy	0.032	0.2	0.031	0.018	0.2	0.017	0.021	0.015
V2_02_medium	0.041	1.4	0.026	0.024	0.8	0.017	0.018	0.017
V2_03_difficult	0.074	0.7	0.073	0.047	0.6	0.045	X	X
MH_01_easy	0.075	0.5	0.072	0.068	0.3	0.068	0.071	0.070
MH_02_easy	0.084	0.8	0.078	0.073	0.4	0.072	0.067	0.066
MH_03_medium	0.087	1.5	0.067	0.071	0.1	0.071	0.071	0.071
MH_04_difficult	0.217	3.4	0.081	0.087	0.9	0.066	0.082	0.081
MH_05_difficult	0.082	0.5	0.077	0.060	0.2	0.060	0.060	0.060

*GT scale: the estimated trajectory is scaled so that it perfectly matches the scale of the ground-truth. These columns are included for comparison purposes but do not represent the output of a real system, but the output of an *ideal* system that could estimate the true scale.

Mur-Artal, R., & Tardós, J. D. "Visual-inertial monocular SLAM with map reuse", IEEE Robotics and Automation Letters, 2(2), 796-803, 2017.



EuRoc monocular + IMU







Comparison with state of the art Direct Stereo + IMU visual odometry Usenko, Vladyslav, et al. "*Direct visual-inertial odometry with stereo cameras*", Robotics and Automation (ICRA), 2016

No drift because of the map - Smaller error variance

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SLAM in dynamic scenes









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3D Drone Localization and Mapping

- Drone localization
 - Sources, sensors
 - Mapping
 - Localization
 - SLAM
- Data fusion in drone localization
- Semantic mapping





- The main idea of improving accuracy on localization and mapping in Multidrone is to exploit the synergies between different sensors such as:
 - RTK GPS.
 - 3D LIDAR.
 - Monocular camera pointing downwards.
 - Laser altimeter.
 - Inertial Measurements Units (IMU).





- INPUT: measurements from multiple sensors.
- OUTPUT: 3D geometrical map (X_m) and the 3D drone pose estimation (X_r) .







- Accomplish 3D Geometrical Mapping through SLAM:
 - Estimate robot's odometry through measurements.
 - Odometry estimation will be used in Prediction Stage of SLAM filter.
 - The Update Stage of SLAM filter will use the measurements of laser altimeter to update the robot location estimation and will integrate the LIDAR features and the images from the monocular visual images in order to create and update the 3D geometrical map.





- INPUT: measurements from multiple sensors + 3D geometrical map.
- OUTPUT: 3D drone pose estimation (X_r) .







- Accomplish 3D pose estimation through AMCL-based scheme.
 - Prediction Stage: The particles of the Particle Filter are predicted using:
 - the robot odometry estimates, computed by integrating GPS measurements.
 - X-Y odometry obtained from the visual images.
 - Z odometry obtained from laser altimeter, corrected with the drone orientation provided by the IMU.





 Update Stage: The particles are updated considering the RTK GPS measurements and the fitting of the 3D LIDAR with the preloaded 3D geometrical map obtained in pre-production.



3D Drone Localization and Mapping

- Drone localization
 - Sources, sensors
 - Mapping
 - Localization
 - SLAM
- Data fusion in drone localization
- Semantic mapping



Semantic Map Annotation types (navigation/logistics)

Туре	Static/dynamic	Who	How	Geometric entity type
Regular takeoff and landing sites	Static	Supervisor	Manually	Point
No flight zones	Static	Supervisor	Manually or imported from a file, if available	Polygon (2D coordinates, longitude- latitude)
Potential emergency landing sites	Static	Supervisor	Manually	Polygon
Crowd gathering areas	Dynamic, during production	Visual Semantic annotator, Semantic map manager	Automatically	Polygon (2D coordinates, longitude- latitude)
Points of interest	Static		Manually	Point

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Semantic information structure



- Static semantic information:
 - Roads, POIs, no-flight zones, private areas.
- Dynamic semantic information:
 - Crowd locations.
- KML format.



Semantic Map Annotation types (static: navigation/logistics)



 Static annotations are stored in KML file available from a ROS service in ROS node Semantic Map Manager:

<?xml version="1.0" encoding="UTF-8"?> <kml xmlns="http://www.opengis.net/kml/2.2"> <Document> <name>KML STRUCTURE</name> <Folder> <name>Annotations</name> <Placemark> <name>1 </name> <address>1.1</address> <description> Landing Site/Regular Takeoff Site (re-charging/ relay stations)</description> <Point> <coordinates>

22.9662323,40.6832416,0

</coordinates>

</Point>

</Placemark>

.... </kml>



Semantic 3D Map Annotation



- Dynamic annotations derived through drone video analysis are projected on the 3D map.
- 3D scene models: 3D Mesh or Octomap.
- Assumes that we know the camera extrinsic and intrinsic parameters.



Projection of crowd location onto the 3D map







MultiDrone

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Projection onto the map



- Based on raycasting.
- Leads to polygonal areas (more specifically their boundaries):
 - Geo-localized on the map and
 - Exported in KML (Keyhole Markup Language) format.
- Requires the camera/gimbal parameters.



Projection onto the map



- Octomap: a fully 3D model representing the 3D environment where the UAV navigates.
 - It provides a volumetric representation of space namely of the occupied, free and unknown areas.
 - It is based on octrees and uses probabili. Octree in memory: 130 MB Octree file: 50 MB (2 MB.bt) 3D Grid: 649 MB



 INPUT: a 2D heatmap where each pixel value represents the crowd existence probability for this location on the image/frame.







- Heatmap thresholding
 - Only image locations with high probabilities of crowd existence are retained.
- Conversion of the image into binary where groups of adjacent pixels with value 1 (white) represent 2D regions occupied by crowd.



crowd detection heatmap crowd thresholded regions



- Contour detection on the thresholded crowd image applying a contour following algorithm:
 - a new binary image indicating the boundaries (white pixels) of the aforementioned crowd regions is produced.

crowd thresholded regions

crowd regions boundaries





- This contour image lies on the focal plane of the drone camera.
- Camera parameters needed:
 - a) the location of the center of projection (COP) in the 3D world (derived from the drone location);
 - b) the camera orientation (derived from the gimbal state);
 - c) the distance of the focal plane from the COP (the camera focal length).







- Ray casting by traversing the points (pixels) of the regions' boundaries in a counter clock wise manner:
 - cast a ray from each of the boundary contour points towards the voxels of the octomap:
 - finding the occupied octomap voxel hit by each ray, leads to the evaluation of the X,Y, Z terrain coordinates each of the contours' points is projected on, as the octomap is geo-referenced.
 - 2D boundary contour points are traversed sequentially, so are the points of the 3D boundary contour (polyline).





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- If needed, the polylines are simplified maintaining their shape:
 - Ramer-Douglas-Peucker algorithm:
 - takes a curve composed of line segments
 - finds a similar one with fewer points.
- Store the polygonal lines found on the octomap by the ray casting in a KML file.



KML structure

<Placemark> <name>LinearRing0</name> <description>Crowded location 1 < /description><styleUrl>#msn_ylw pushpin</styleUrl> <Polygon> <extrude>1</extrude> <tessellate>1</tessellate><altitudeMode>clampToGround</altitudeMode> <outerBoundaryIs> <LinearRing> <coordinates> 42, 42.3776, 24.6386 42, 42.3612, 24.674 42, 42.2788, 24.674 42, 42.2822, 24.6386 . . . </coordinates> </LinearRing> </outerBoundaryIs>

</Polygon>

</Placemark>

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Semantic Octomap Annotation

MultiDrone



Output:

ROS topic for the crowd zones with PolygonStamped message

geometry_msgs/PolygonStamped.msg

#This represents a Polygon with reference coordinate frame and timestamp Header header

Polygon polygon

geometry_msgs/Polygon.msg

#A specification of a polygon where the first and last points are assumed to be connected *Point32[] points*

Use: to avoid overflying crowds during mission planning/execution.


Semantic map updating and uploading



- Dynamic Annotations (Annotated Polygons):
 - are being updated by the Map Projector;
 - are uploaded to the interested nodes and
 - will be provided as a ROS topic by the Semantic Map Manager node.
- Static Annotations:
 - will be provided as a service by the Semantic Map Manager node to be requested by the interested nodes as a KML file structure;
 - created during pre-production and not changing during production.







Thank you very much for your attention!

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