

OBSTACLES MAPPING BASED ON 3-D
PERCEPTION
FOR MOBILE ROBOT NAVIGATION

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DOCTOR OF PHILOSOPHY

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FOR MOBILE ROBOT NAVIGATION

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for the award of the degree of
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SUPERVISOR'S DECLARATION

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I hereby declare that the work in this thesis is based on my original work except for quotations and citation which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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ABSTRAK

Banyak penyelidik terdahulu telah menawarkan pemetaan dua dimensi untuk navigasi robotik. Walau bagaimanapun, kerana pemetaan dua dimensi hanya dapat mengesan halangan di bidang satah, penyelidik mencari cara lain yang lebih baik untuk mengetahui halangan di kawasan sfera. Kelemahan pemetaan dua dimensi untuk navigasi robot adalah bahawa ia tidak dapat mengesan halangan yang mempunyai perbezaan ketinggian. Penyelidikan ini menawarkan beberapa tahap untuk membina peta tiga dimensi. Tahap pertama adalah mengembangkan robot bergerak sebagai platform ujian. Robot memproyeksikan halangan dengan mengukur jarak menggunakan kamera kedalaman untuk mendapatkan maklumat geometri rintangan dalam bentuk titik klausa yang menunjukkan kedudukan mercu tanda pada koordinat X, Y, dan Z. Tahap kedua menawarkan kaedah menganggarkan peralihan dan putaran robot dengan tepat menggunakan teknik peleburan sensor, yang merupakan gabungan odometri roda, odometri visual, dan odometri inersia. Odometri roda menganggarkan kedudukan robot berdasarkan maklumat mengenai kelajuan putaran roda tanpa dipengaruhi oleh kehadiran cahaya, magnet, atau vektor graviti, tetapi odometri roda mempunyai masalah pengumpulan ralat. Odometri visual melakukan fungsi anggaran berdasarkan gambar visual dengan gabungan kaedah Features from Accelerated Segment Test (FAST) dan singular value decomposition (SVD). Walau bagaimanapun, odometri visual sangat bergantung pada kehadiran cahaya dan tekstur objek, semakin sedikit cahaya dan tekstur objek, semakin tinggi kesalahan estimasi kedudukan. Odometri inersia menggunakan pengukuran Magnetic-Angular-Gravity (MARG) kemudian menggabungkan ketiga-tiga pengukuran melalui kaedah Madgwick untuk menghasilkan nilai anggaran kedudukan yang tepat. Walau bagaimanapun, odometri inersia hanya dapat mengira pergerakan putaran. Kajian ini menawarkan kaedah peleburan berdasarkan Extended Kalman Filter (EKF) untuk menghasilkan output anggaran baru yang menghilangkan kelemahan setiap hasil anggaran (wheel odometry, visual odometry, inertial odometry). Tahap ketiga adalah pembinaan semula peta tiga dimensi berdasarkan anggaran kedudukan robot dan pengukuran kedalaman. Semua masalah ini dikaji dan diselidiki dari perspektif teori-teori melalui analisis matematik. Hasil yang diperoleh disahkan melalui penyelidikan eksperimen. Hasil ujian estimasi kedudukan menggunakan teknik peleburan multi-sensor berdasarkan kaedah EKF selama 120 saat di kawasan 10m x 10m menunjukkan nilai purata ralat peralihan paksi X 7.6cm, ralat peralihan paksi Y 8.5cm, ralat putaran roll 0.678° , ralat putaran pitch 0.491° , dan ralat putaran yaw adalah 0.483° . Hasil visual menunjukkan peta 3-D yang berjaya disusun semula mempunyai keretakan atau tumpang tindih minimum, dan mewakili situasi yang sama dengan kenyataan.

ABSTRACT

Many previous researchers have offered two-dimensional mapping for robotic navigation. However, since two-dimensional mapping is only able to detect the barriers in planar fields, researchers are looking for other better ways to discover the obstacles in the spherical area. The disadvantage of two-dimensional mapping for robot navigation is that it is unable to detect the barriers that have elevation differences. This research offers several steps in order to build a three-dimensional map. The first step is to develop the mobile robot as a test-bed platform. Robot projects the obstacles by measuring the distance uses depth camera to get obstacles geometry information in the form of point-cloud that show the position of landmarks on X, Y, and Z coordinate. The second step offers a method of estimating robot translation and rotation accurately using sensors fusion technique, which is a combination of wheel odometry, visual odometry, and inertial odometry. Wheel odometry estimates the position of the robot based on information on wheel rotation speed without being affected by the presence of light, magnetism, or gravity vectors, but wheel odometry has error accumulation issue. Visual odometry performs estimation functions based on visual images with the combination of Features from Accelerated Segment Test (FAST) and singular value decomposition (SVD) methods. However, visual odometry is very dependent on the presence of light and texture of the object, the less light and texture of the object, the higher the error of position estimation. Inertial odometry uses Magnetic-Angular-Gravity (MARG) measurement then combines the three measurements through the Madgwick method to produce accurate position estimation values. However, inertial odometry is only able to estimate rotational motion. This study offers a fusion method based on the Extended Kalman Filter (EKF) to produce a new estimation output that eliminates the weaknesses of each estimation result (wheel odometry, visual odometry, inertial odometry). The third step is the registration of three-dimensional map based on robot pose estimation and depth measurement. All these issues are examined and investigated from an estimation-theoretic perspective through mathematical analysis. The theories have been validated through experimental investigations. The results of position estimation test using multi-sensor fusion techniques based on the EKF method for 120 seconds in the area of 10m x 10m show the average value of X axis translation error of 7.6cm, Y axis translation error of 8.5cm, roll rotation error of 0.678° , pitch rotation error of 0.491° , and yaw rotation errors are 0.483° . The visual results show a 3-D map which successfully reconstructed has a minimal fracture or overlapping, and represent the same situation as the reality.

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LIST OF SYMBOLS

${}^A T_B$	homogenous transf. representing frame {B} with respect to frame {A}
${}^A \xi_B$	3-D relative pose frame {B} with respect to frame {A}
E	Euclidean distance
K	camera calibration matrix
M	map points
P	world points
R	orthogonal rotation matrix, $R \in SO(2)$ or $SO(3)$
t	translation matrix
T	homogenous transformation, $T \in SO(2)$ or $SO(3)$
u	eigen vector
v	linear velocity
$\sin(\cdot)$	sine of
$\cos(\cdot)$	cosine of
$f(\cdot)$	function of
$h(\cdot)$	function of
$SO(n)$	special orthogonal group, the set of all orientations in n dimensions
$SE(n)$	special Euclidean group (all poses) in n dimensions
\mathbb{R}	set of real numbers
\mathbb{R}^2	the space of all 2-D points
\mathbb{R}^3	the space of all 3-D points
X, Y, Z	cartesian coordinates
ϕ, θ, ψ	roll pitch yaw angles $\in SO(3)$
G_k	the Kalman gain
U_k	control signal
$P_{k k-1}$	current prediction error
S_k	the residual covariance
v_k	measurement noise
w_k	process noise
$X_{k k}$	state vector
$\hat{X}_{k k-1}$	current prediction state
\tilde{Y}_k	the measurement residual
$Z_{k k}$	observations vector
{F}	coordinate frame F
λ	eigen value
θ	robot heading
μ	mean

σ	standard deviation
σ^2	variance
ξ	abstract representation of 3-D cartesian pose
ω	angular velocity
\in	element of

LIST OF ABBREVIATIONS

1-D	one dimensional
2-D	two dimensional
3-D	three dimensional
AHRS	attitude heading & reference system
CMOS	complementary metal oxide semiconductor
COG	center of gravity
COTS	commercially of the shelf
DCM	direct cosine matrix
DMR	differential mobile robot
DO	depth odometry
DOF	degree of freedom
e.g.	example
EKF	extended Kalman filter
Eq.	equation
et al.	and others
Fig.	figure
i.e.	that is
ICP	iterative closest point
IMU	inertial measurement unit
LIDAR	light detection and ranging
LOAM	lidar odometry and mapping
LRF	laser range finder
MARG	magnetic angular rate gravity
MCU	microcontroller unit
MEMS	micro electro-mechanical system
PCA	principal component analysis
PID	proportional integral derivative
PWM	pulse width modulation
RANSAC	random sample consensus
RGB	red green blue
RGB-D	red green blue depth
RMSE	root mean square error
ROS	robot operating system
RTK-GPS	real time kinematic global positioning system
SAD	sum of absolute differences
SLAM	simultaneous localization and mapping
SVD	singular value decomposition
SVO	semi direct visual odometry
TOF	time of flight
TSDF	truncated signed distance function
VO	visual odometry
WO	wheel encoder

REFERENCES

- Achmad, M. S. H., Findari, W. S., Ann, N. Q., Pebrianti, D., & Daud, M. R. (2016). Stereo Camera – based 3D Object Reconstruction Utilizing Semi-Global Matching Algorithm. In *2016 2nd International Conference on Science and Technology-Computer (ICST)* (pp. 1–6).
- Achmad, M. S. H., Murtdza, N. A., Lokman, N. A. A., Daud, M. R., Razali, S., & Pebrianti, D. (2015). Exploration of Unknown Environment with Ackerman Mobile Robot Using Robot Operating System (ROS). *ARPN Journal of Engineering and Applied Sciences*, *10*(23), 17573–17579.
- Agrawal, M., Konolige, K., & Blas, M. R. (2008). CenSurE: Center Surround Extremas for Real-time Feature Detection and Matching. In *Proc. European Conf. Computer Vision* (pp. 102–115).
- Alter, O., Brown, P. O., & Botstein, D. (2000). Singular value decomposition for genome-wide expression data processing and modeling. *Proceedings of the National Academy of Sciences*, *97*(18), 10101–10106. <http://doi.org/10.1073/pnas.97.18.10101>
- Antonelli, G., Chiaverini, S., & Fusco, G. (2005). A calibration method for odometry of mobile robots based on the least-squares technique: Theory and experimental validation. *IEEE Transactions on Robotics*, *21*(5), 994–1004. <http://doi.org/10.1109/TRO.2005.851382>
- Arun, K. S., Huang, T. S., & Blostein, S. D. (1987). Least-Squares Fitting of Two 3-D Point Sets. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *PAMI-9*(5), 698–700. <http://doi.org/10.1109/TPAMI.1987.4767965>
- Aulinas, J., Petillot, Y., Salvi, J., & Lladó, X. (2008). The SLAM problem: A survey. *Frontiers in Artificial Intelligence and Applications*, *184*(1), 363–371. <http://doi.org/10.3233/978-1-58603-925-7-363>
- Bajd, T., Mihelj, M., Lenarcic, J., Stanovnik, A., & Munih, M. (2010). Homogenous Transformation Matrices. In *Robotics* (pp. 9–22). Springer. <http://doi.org/10.1007/978-90-481-3776-3>
- Barbosa, D., Lopes, A., & Araujo, R. E. (2016). Sensor Fusion Algorithm Based on Extended Kalman Filter for Estimation of Ground Vehicle Dynamics. In *42nd Annual Conference of the IEEE Industrial Electronics Society (IECON)* (pp. 1049–1054). IEEE. <http://doi.org/https://doi.org/10.1109/IECON.2016.7793145>
- Barnard, S. T., & Fischler, M. a. (1982). Computational Stereo. *ACM Computing Surveys*, *14*(4), 553–572. <http://doi.org/10.1145/356893.356896>
- Bay, H., Tuytelaars, T., & Van Gool, L. (2006). SURF: Speeded up Robust Features. In *Proc. ECCV* (pp. 404–417). http://doi.org/10.1007/11744023_32

- Bellekens, B., Spruyt, V., Berkvens, R., Penne, R., & Weyn, M. (2015). A Benchmark Survey of Rigid 3D Point Cloud Registration Algorithms. *International Journal of Advances in Intelligent Systems*, 8(1), 118–127.
- Besl, P., & McKay, N. (1992). A Method for Registration of 3-D Shapes. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 14(2), 239–256. <http://doi.org/10.1109/34.121791>
- Borenstein, J., Everett, H. R., & Feng, L. (1996). *Where am I? Sensors and Methods for Mobile Robot Positioning*. University of Michigan. <http://doi.org/10.1017/CBO9781107415324.004>
- Borenstein, J., & Feng, L. (1996). Measurement and Correction of Systematic Odometry Errors in Mobile Robots. *IEEE Transactions on Robotics and Automation*, 12(6), 845–857. <http://doi.org/10.1109/70.544768>
- Boutarel, F., & Nozick, V. (2010). Epipolar Rectification for Autostereoscopic Camera Setup. In *The 8th France-Japan and 6th Europe-Asia Congress on Mechatronics* (pp. 133–136).
- Brown, M. Z., Burschka, D., Hager, G. D., & Member, S. (2003). Advances in Computational Stereo. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25(8), 993–1008.
- Chen, Y., & Medioni, G. (1991). Object Modeling by Registration of Multiple Range Images. In *Proceeding of the 1991 IEEE International Conference on Robotics and Automation* (pp. 2724–2729).
- Copi, I. M., Cohen, C., & Flage, D. E. (2007). *Essentials of Logic (2nd edition)*. Upper Saddle River, NJ: Pearson Education.
- De Berg, M., Cheong, O., Van Kreveld, M., & Overmars, M. (2008). *Computational Geometry: Algorithms and Applications*. *Computational Geometry* (Vol. 17). <http://doi.org/10.2307/3620533>
- Domínguez-Morales, M., Jiménez-Fernández, A., Paz-Vicente, R., Linares-Barranco, A., Jiménez-Moreno, G., Mutto, C. D., ... Sandini, G. (2012). *Current Advancements in Stereo Vision*. (A. Bhatti, Ed.) (1st ed.). InTech. <http://doi.org/10.5772/2611>
- Erdem, A. T., & Ozer, A. (2015). Fusing Inertial Sensor Data in an Extended Kalman Filter for 3D Camera Tracking. *IEEE Transactions on Image Processing*, 24(2), 538–548.
- Fanello, S. R., Rhemann, C., Tankovich, V., Kowdle, A., Escolano, S. O., Kim, D., & Izadi, S. (2016). HyperDepth: Learning Depth from Structured Light Without Matching. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (pp. 5441–5450). <http://doi.org/10.1109/CVPR.2016.587>

- Fiolka, T., Stückler, J., Klein, D. A., Schulz, D., & Behnke, S. (2012). SURE: Surface Entropy for Distinctive 3D Features. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (Vol. 7463 LNAI, pp. 74–93). http://doi.org/10.1007/978-3-642-32732-2_5
- Fitzgibbon, A. W. (2001). Robust Registration of 2D and 3D Point Sets. In *Proceedings of the British Machine Vision Conference 2001* (p. 43.1-43.10). <http://doi.org/10.5244/C.15.43>
- Foix, S., & Aleny, G. (2011). Lock-in Time-of-Flight (ToF) Cameras: A Survey. *IEEE Sensors Journal*, 11(3), 1–11.
- Forster, C., Zhang, Z., Gassner, M., Werlberger, M., & Scaramuzza, D. (2016). SVO: Semi-Direct Visual Odometry for Monocular and Multi-Camera Systems. *IEEE Transactions on Robotics*, PP(99), 1–18. http://doi.org/10.0/Linux-x86_64
- Forstner, W. (1986). A Feature Based Correspondence Algorithm for Image Matching. *Int. Arch. of Photogrammetry*, 26(3), 150–166.
- Francis, S. L. X., Anavatti, S. G., Garratt, M., & Shim, H. (2015). A ToF-camera as a 3D Vision Sensor for Autonomous Mobile Robotics. *International Journal of Advanced Robotic Systems*, 12(11), 1–15. <http://doi.org/10.5772/61348>
- Garcia, F., Aouada, D., Solignac, T., Mirbach, B., & Ottersten, B. (2013). Real-time depth enhancement by fusion for RGB-D cameras. *IET Computer Vision*, 7(October), 335–345. <http://doi.org/10.1049/iet-cvi.2012.0289>
- Garcia, M. a., & Solanas, A. (2004). 3D simultaneous localization and modeling from stereo vision. *IEEE International Conference on Robotics and Automation (ICRA)*, 1(April), 847–853. <http://doi.org/10.1109/ROBOT.2004.1307255>
- Gavin, H. P. (2016). *The Levenberg-Marquardt Method for Nonlinear Least Squares Curve-Fitting Problems*. Department of Civil and Environmental Engineering, Duke University.
- Gräfe, G. (2008). Kinematic 3D Laser Scanning for Road or Railway Construction Surveys. In *1st International Conference on Machine Control & Guidance 2008* (pp. 1–10).
- Greenspan, M. A., Godin, G., & Talbot, J. (2000). Acceleration of binning nearest neighbor methods. In *Proceedings of Vision Interface 2000* (Vol. NRC 44167, pp. 337–344).
- Grimson, W. E. L. (1991). *Object Recognition by Computer*. The MIT Press.
- Harris, C. G., & Pike, J. M. (1987). 3D Positional Integration from Image Sequences. In *Proceedings of the Alvey Vision Conference 1987* (pp. 233–236). <http://doi.org/10.5244/C.1.32>

- Hartley, R., & Zisserman, A. (2004). Multiple View Geometry in Computer Vision. *2nd Ed. Cambridge U.K.*, 1–673.
- He, Y., Liang, B., Zou, Y., He, J., & Yang, J. (2017). Depth Errors Analysis and Correction for Time-of-Flight (ToF) Cameras. *Sensors*, *17*(1), 92. <http://doi.org/10.3390/s17010092>
- Heikkila, J., & Silven, O. (1997). A Four-step Camera Calibration Procedure with Implicit Image Correction. In *Proceedings - IEEE Computer Society Conference on Computer Vision and Pattern Recognition* (pp. 1106–1112).
- Hongdong Li, & Hartley, R. (2006). Five-Point Motion Estimation Made Easy. In *18th International Conference on Pattern Recognition (ICPR'06)* (Vol. 1, pp. 630–633). IEEE. <http://doi.org/10.1109/ICPR.2006.579>
- Howard, A. (2008). Real-time Stereo Visual Odometry for Autonomous Ground Vehicles. In *2008 IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 3946–3952). IEEE. <http://doi.org/10.1109/IROS.2008.4651147>
- Huang, A., & Bachrach, A. (2011). Visual odometry and mapping for autonomous flight using an RGB-D camera. In H. I. Christensen & O. Khatib (Eds.), *Springer Tracts in Advanced Robotics* (100th ed., pp. 1–16). Springer. http://doi.org/https://doi.org/10.1007/978-3-319-29363-9_14
- Ibbotson, M. R., Hung, Y. S., Meffin, H., Boeddeker, N., & Srinivasan, M. V. (2017). Neural basis of forward flight control and landing in honeybees. *Scientific Reports*, *7*(1), 1–15. <http://doi.org/10.1038/s41598-017-14954-0>
- Izadi, S., Davison, A., Fitzgibbon, A., Kim, D., Hilliges, O., Molyneaux, D., ... Freeman, D. (2011). KinectFusion. In *Proceedings of the 24th annual ACM symposium on User interface software and technology - UIST '11* (pp. 559–568). New York, New York, USA: ACM Press. <http://doi.org/10.1145/2047196.2047270>
- Jiang, X., & Bunke, H. (1999). Edge Detection in Range Images Based on Scan Line Approximation. *Computer Vision and Image Understanding*, *73*(2), 183–199. <http://doi.org/10.1006/cviu.1998.0715>
- Jiaolong, Y., Hongdong, L., Campbell, D., & Jia, Y. (2015). Go-ICP: A Globally Optimal Solution to 3D ICP Point-Set Registration. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, *38*(11), 2241–2254. <http://doi.org/10.1109/TPAMI.2015.2513405>
- Jung, C., & Chung, W. (2011). Calibration of Kinematic Parameters for Two Wheel Differential Mobile Robots by Using Experimental Heading Errors. *Journal of Mechanical Science and Technology*, *8*(6), 134–142. <http://doi.org/10.1007/s12206-011-0334-y>
- Jung, J., Yoon, S., Ju, S., & Heo, J. (2015). Development of kinematic 3D laser scanning system for indoor mapping and as-built BIM using constrained SLAM. *Sensors (Switzerland)*, *15*(10), 26430–26456. <http://doi.org/10.3390/s151026430>

- Kahlmann, T., Remondino, F., & Ingensand, H. (2005). Calibration for Increased Accuracy of The Range Imaging Camera Swissranger. In *ISPRS Commission V Symposium "Image Engineering and Vision Metrology"* (pp. 136–141).
- Kalman, R. E. (1960). A New Approach to Linear Filtering and Prediction Problems. *Journal of Basic Engineering*, 82(1), 35. <http://doi.org/10.1115/1.3662552>
- King, A. D. (1998). Inertial Navigation - Forty Years of Evolution. *GEC REVIEW*, 13(3), 140–149.
- Klein, G., & Murray, D. (2007). Parallel Tracking and Mapping for Small AR Workspaces. In *2007 6th IEEE and ACM International Symposium on Mixed and Augmented Reality* (pp. 1–10). IEEE. <http://doi.org/10.1109/ISMAR.2007.4538852>
- Koninckx, T. P., & Van Gool, L. (2006). Real-time Range Acquisition by Adaptive Structured Light. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 28(3), 432–445. <http://doi.org/10.1109/TPAMI.2006.62>
- Lachat, E., Macher, H., Mittet, M., Landes, T., & Grussenmeyer, P. (2015). FIRST EXPERIENCES WITH KINECT V2 SENSOR FOR CLOSE RANGE 3D MODELLING. In *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* (Vol. XL-5/W4, pp. 93–100). <http://doi.org/10.5194/isprsarchives-XL-5-W4-93-2015>
- Lamon, P. (2008). *3D-Position Tracking and Control for All-Terrain Robots*. (B. Siciliano, O. Khatib, & F. Groen, Eds.) *Springer Tracts in Advanced Robotics* (Vol. 43). Springer.
- Laskar, Z. (2016). *Robust Loop Closures in 3D Mapping Systems*.
- Lazaros, N., Sirakoulis, G. C., & Gasteratos, A. (2008). Review of Stereo Vision Algorithms: From Software to Hardware. *International Journal of Optomechatronics*, 2(December), 435–462. <http://doi.org/10.1080/15599610802438680>
- Low, K.-L. (2004). *Linear Least-squares Optimization for Point-to-plane ICP Surface Registration*. Technical Report TR04-004, Department of Computer Science, University of North Carolina at Chapel Hill. Retrieved from https://www.iscs.nus.edu.sg/~lowkl/publications/lowk_point-to-plane_icp_techrep.pdf
- Lowe, D. G. (2004). Distinctive image features from scale invariant keypoints. *Intl. Journal of Computer Vision*, 60, 1–28. <http://doi.org/http://dx.doi.org/10.1023/B:VISI.0000029664.99615.94>
- Madgwick, S. O. H. (2010). *An efficient orientation filter for inertial and inertial/magnetic sensor arrays*. Retrieved from http://sharenet-wii-motion-trac.googlecode.com/files/An_efficient_orientation_filter_for_inertial_and_inertial_magnetic_sensor_arrays.pdf
- Madgwick, S. O. H., Harrison, A. J. L., & Vaidyanathan, R. (2011). Estimation of IMU and MARG orientation using a gradient descent algorithm. In *2011 IEEE*

- International Conference on Rehabilitation Robotics* (pp. 1–7). IEEE. <http://doi.org/10.1109/ICORR.2011.5975346>
- Mahony, R., Hamel, T., & Pflimlin, J. (2008). Nonlinear Complementary Filters on the Special Orthogonal Group. *IEEE Trans. on Automatic Control*, 53(5), 1203–1218.
- Marden, S., & Guivant, J. (2012). Improving the Performance of ICP for Real-Time Applications using an Approximate Nearest Neighbour Search. In *Proceedings of Australasian Conference on Robotics and Automation* (pp. 1–6).
- May, S., Surmann, H., & Birlinghoven, S. (2006). 3D Time-of-Flight Cameras for Mobile Robotics. In *Proceeding of the IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 790–795).
- Mei, C., Sibley, G., Cummins, M., Newman, P., & Reid, I. (2009). A Constant-Time Efficient Stereo SLAM System. In *Proceedings of the British Machine Vision Conference 2009* (p. 54.1-54.11). <http://doi.org/10.5244/C.23.54>
- Milstein, A. (2008). Occupancy Grid Maps for Localization and Mapping. In *Motion Planning* (pp. 381–408).
- Moravec, H. P. (1980). *Obstacle Avoidance and Navigation in The Real World by a Seeing Robot Rover*. Ph.D. dissertation, Stanford University, Stanford, CA. Retrieved from https://www.ri.cmu.edu/publication_view.html?pub_id=22
- Müller, M., Surmann, H., Pervözl, K., & May, S. (2006). The accuracy of 6D SLAM using the AIS 3D laser scanner. In *IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems* (pp. 389–394). <http://doi.org/10.1109/MFI.2006.265647>
- Munaro, M., Rusu, R. B., & Menegatti, E. (2016). 3D robot perception with Point Cloud Library. *Robotics and Autonomous Systems*, 78, 97–99. <http://doi.org/10.1016/j.robot.2015.12.008>
- Mur-Artal, R., & Tardos, J. D. (2016). *ORB-SLAM2: an Open-Source SLAM System for Monocular, Stereo and RGB-D Cameras*. *arXiv:1610.06475*. Retrieved from <http://arxiv.org/abs/1610.06475>
- Nefti-Meziani, S., Manzoor, U., Davis, S., & Pupala, S. K. (2015). 3D perception from binocular vision for a low cost humanoid robot NAO. *Robotics and Autonomous Systems*, 68, 129–139. <http://doi.org/10.1016/j.robot.2014.12.016>
- Nistér, D. (2004). An Efficient Solution to the Five-point Relative Pose Problem. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 26(6), 756–770. <http://doi.org/10.1109/TPAMI.2004.17>

- Nister, D., Naroditsky, O., & Bergen, J. (2004). Visual odometry. In *Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), 2004.* (Vol. 1, pp. 652–659). <http://doi.org/10.1109/CVPR.2004.1315094>
- Nordin, P. (2012). *Mobile Robot Traversability Mapping For Outdoor Navigation.*
- Nüchter, A. (2008). Parallel and Cached Scan Matching for Robotic 3D Mapping. *Journal of Computing and Information Technology*, 51–65. <http://doi.org/10.2498/cit.1001174>
- Nüchter, A. (2009). *3D Robotic Mapping. Springer Tracts in Advanced Robotics* (Vol. 52). Berlin, Heidelberg: Springer Berlin Heidelberg. <http://doi.org/10.1007/978-3-540-89884-9>
- Nüchter, A., Lingemann, K., & Hertzberg, J. (2007). Cached k-d Tree Search for ICP Algorithms. In *3DIM 2007 - Proceedings 6th International Conference on 3-D Digital Imaging and Modeling* (pp. 419–426). <http://doi.org/10.1109/3DIM.2007.15>
- Núñez, P., Vázquez-Martín, R., & Bandera, A. (2011). Visual Odometry Based on Structural Matching of Local Invariant Features Using Stereo Camera Sensor. *Sensors*, 11(12), 7262–7284. <http://doi.org/10.3390/s110707262>
- Nyqvist, H. E., Skoglund, M. A., Hendeby, G., & Gustafsson, F. (2015). Pose Estimation Using Monocular Vision and Inertial Sensors Aided with Ultra Wide Band. In *2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN)* (p. 10 pp.). <http://doi.org/10.1109/IPIN.2015.7346940>
- Orts-Escalano, S., Morell, V., Garcia-Rodriguez, J., & Cazorla, M. (2013). Point Cloud Data Filtering and Down sampling Using Growing Neural Gas. In *Proceedings of the International Joint Conference on Neural Networks.* <http://doi.org/10.1109/IJCNN.2013.6706719>
- Pennington, K. S., Will, P. M., & Shelton, G. L. (1970). Grid Coding: A Technique for Extraction of Differences from Scenes. *Optics Communications*, 2(3), 113–119.
- Prakhya, S. M., Bingbing, L., Weisi, L., & Qayyum, U. (2015). Sparse Depth Odometry: 3D keypoint based pose estimation from dense depth data. In *2015 IEEE International Conference on Robotics and Automation (ICRA)* (Vol. June, pp. 4216–4223). IEEE. <http://doi.org/10.1109/ICRA.2015.7139780>
- Rocchini, C., Cignoni, P., Montani, C., Pingi, P., & Scopigno, R. (2001). A low cost 3D scanner based on structured light. *Computer Graphics Forum*, 20(3), 299–308. <http://doi.org/10.1111/1467-8659.00522>
- Rosten, E., & Drummond, T. (2006). Machine Learning for High-speed Corner Detection. In *Proc. European Conf. Computer Vision* (Vol. 1, pp. 430–443). http://doi.org/10.1007/11744023_34

- Rublee, E., & Bradski, G. (2011). ORB - an efficient alternative to SIFT or SURF. <http://doi.org/10.1109/ICCV.2011.6126544>
- Rusinkiewicz, S., & Levoy, M. (2001). Efficient variants of the ICP algorithm. In *Proceedings Third International Conference on 3-D Digital Imaging and Modeling* (pp. 145–152). IEEE Comput. Soc. <http://doi.org/10.1109/IM.2001.924423>
- Rusu, R. B. (2010). Semantic 3D Object Maps for Everyday Manipulation in Human Living Environments. *KI - Künstliche Intelligenz*, 24(4), 345–348. <http://doi.org/10.1007/s13218-010-0059-6>
- Rusu, R. B., Blodow, N., & Beetz, M. (2009). Fast Point Feature Histograms (FPFH) for 3D registration. In *2009 IEEE International Conference on Robotics and Automation* (pp. 3212–3217). IEEE. <http://doi.org/10.1109/ROBOT.2009.5152473>
- Rusu, R. B., Marton, Z. C., Blodow, N., Dolha, M., & Beetz, M. (2008). Towards 3D Point cloud based object maps for household environments. *Robotics and Autonomous Systems*, 56(11), 927–941. <http://doi.org/10.1016/j.robot.2008.08.005>
- Saidi, K. S., Brien, J. B. O., Lytle, A. M., Meyer, J., Guillot, A., Yoshida, K., ... Nolfi, S. (2008). *Springer Handbook of Robotics*. (B. Siciliano & O. Khatib, Eds.). Springer International Publishing. <http://doi.org/10.1007/978-3-540-30301-5>
- Scaramuzza, D. (2011). 1-Point-RANSAC Structure from Motion for Vehicle-Mounted Cameras by Exploiting Non-holonomic Constraints. *International Journal of Computer Vision*, 95(1), 74–85. <http://doi.org/10.1007/s11263-011-0441-3>
- Scaramuzza, D., & Fraundorfer, F. (2011). Visual odometry: Part I: The First 30 Years and Fundamental. *IEEE Robotics and Automation Magazine*, 18(4), 80–92. <http://doi.org/10.1109/MRA.2012.2182810>
- Scaramuzza, D., & Fraundorfer, F. (2012). Visual odometry: Part II: Matching, robustness, optimization, and applications. *IEEE Robotics & Automation Magazine*, 19(1), 78–90. <http://doi.org/10.1109/MRA.2011.943233>
- Scharstein, D., & Szeliski, R. (2002). A Taxonomy and Evaluation of Dense Two-Frame Stereo Correspondence Algorithms. *International Journal of Computer Vision*, 47(1), 7–42. <http://doi.org/10.1023/A:1014573219977>
- Sequeira, V., Gonçalves, J. G. M., & Ribeiro, M. I. (1995). 3D environment modelling using laser range sensing. *Robotics and Autonomous Systems*, 16(1), 81–91. [http://doi.org/10.1016/0921-8890\(95\)00036-F](http://doi.org/10.1016/0921-8890(95)00036-F)
- Shi, J., & Tomasi, C. (1994). Good Features to Track. In *Proc. CVPR* (pp. 593–600). <http://doi.org/10.1109/ICCVW.2013.40>
- Siegwart, R., & Nourbakhsh, I. R. (2004). *Introduction to Autonomous Mobile Robots*. (R. C. Arkin, Ed.) *Robotica* (Vol. 23). The MIT Press.

- Sprickerhof, J., Nüchter, A., Lingemann, K., & Hertzberg, J. (2011). A heuristic loop closing technique for large-scale 6d slam. *Automatika: Journal for Control, Measurement, Electronics, Computing and Communications*, 52(3), 199–222. Retrieved from http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:A+Heuristic+Loop+Closing+Technique+for+Large-Scale+6D+SLAM#5%5Cnhttp://hrcak.srce.hr/index.php?show=clanak&id_clanak_jezik=112984
- Steder, B., Rusu, R. B., Konolige, K., & Burgard, W. (2010). NARF: 3D Range Image Features for Object Recognition. In *Workshop on Defining and Solving Realistic Perception Problems in Personal Robotics at the IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS)* (pp. 1–2). Retrieved from <http://ais.informatik.uni-freiburg.de/publications/papers/steder10iros.pdf>
- Surmann, H., Lingemann, K., Nüchter, A., & Hertzberg, J. (2001). A 3D laser range finder for autonomous mobile robots. In *Proceedings of the 32nd ISR (International Symposium on Robotics)* (Vol. 19, pp. 153–158).
- Surmann, H., Nuchter, A., & Hertzberg, J. (2003). An autonomous mobile robot with a 3D laser range finder for 3D exploration and digitalization of indoor environments. *Robotics and Autonomous Systems*, 45(3–4), 181–198. <http://doi.org/10.1016/j.robot.2003.09.004>
- Taubin, G., Moreno, D., & Lanman, D. (2014). 3D Scanning for Personal 3D Printing: Build Your Own Desktop 3D Scanner. In *ACM Siggraph* (p. 27). <http://doi.org/10.1145/2619195.2656314>
- Thrun, S., Burgard, W., & Fox, D. (2005). *Probabilistic Robotics*. Cambridge: MIT Press.
- Triggs, B., McLauchlan, P. F., Hartley, R. I., & Fitzgibbon, A. W. (2000). Bundle Adjustment — A Modern Synthesis. In *Proceedings International Workshop Vision Algorithms: Theory and Practice (ICCV'99)* (pp. 298–372). http://doi.org/10.1007/3-540-44480-7_21
- Valenti, R. G., Dryanovski, I., & Xiao, J. (2015). Keeping a Good Attitude: A Quaternion-based Orientation Filter for IMUs and MARGs. *Sensors (Switzerland)*, 15(8), 19302–19330. <http://doi.org/10.3390/s150819302>
- Vinet, L., & Zhedanov, A. (2011). A “missing” family of classical orthogonal polynomials. *Journal of Physics A: Mathematical and Theoretical*, 44(8), 85201. <http://doi.org/10.1088/1751-8113/44/8/085201>
- Wall, M. E., Rechtsteiner, A., & Rocha, L. M. (2003). Singular Value Decomposition and Principal Component Analysis. In *A Practical Approach to Microarray Data Analysis* (pp. 91–109). http://doi.org/10.1007/0-306-47815-3_5

- Whelan, T., Johannsson, H., Kaess, M., Leonard, J. J., & McDonald, J. (2013). Robust real-time visual odometry for dense RGB-D mapping. In *2013 IEEE International Conference on Robotics and Automation* (pp. 5724–5731). IEEE. <http://doi.org/10.1109/ICRA.2013.6631400>
- Will, P. M., & Pennington, K. S. (1971). Grid Coding: A Preprocessing Technique for Robot and Machine Vision. *Artificial Intelligence*, 2(3–4), 319–329. [http://doi.org/10.1016/0004-3702\(71\)90015-4](http://doi.org/10.1016/0004-3702(71)90015-4)
- Wulf, O., & Wagner, B. (2003). Fast 3D scanning methods for laser measurement systems. In *Proceedings of the International Conference on Control Systems and Computer Science* (pp. 312–317). <http://doi.org/10.1117/12.900763>
- Xu, W., Deng, L., & Zheng, Q. (2012). Using stereo vision to construct 3-D surface models. *IEEE Potentials*, 31(2), 31–37.
- Yadav, N., & Bleakley, C. (2011). Two stage Kalman Filtering for Position Estimation Using Dual Inertial Measurement Units. In *2011 IEEE SENSORS Proceedings* (pp. 1433–1436). <http://doi.org/10.1109/ICSENS.2011.6127064>
- Yambor, W. S., Draper, B. A., & Beveridges, J. R. (2002). Analyzing PCS-based Face Recognition Algorithms: Eigenvector Selection and Distance Measures. *Empirical Evaluation Methods in Computer Vision*, 1–14. <http://doi.org/10.1.1.324.518>
- Zhang, J., & Singh, S. (2017). Low-drift and real-time lidar odometry and mapping. *Autonomous Robots*, 41(2), 401–416. <http://doi.org/10.1007/s10514-016-9548-2>
- Zhou, C., Du, Y., & Tang, Y. (2011). A High-Precision Calibration Method for Stereo Vision System. In A. Bhatti (Ed.), *Advances in Theory and Applications of Stereo Vision* (pp. 113–128). InTech.