Title: PixelLaser: Evaluating Monocular Range-from-Texture

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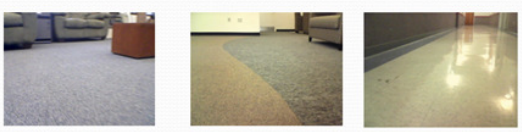
Abstract

Abstracts should clearly state the objective of the work, the results and their significance, and how the paper fits the conference theme. [taken from the TePRA call for abstracts]

Objective of this work: This work extends a TePRA 2009 presentation an estimating range-to-obstacles from monocular vision in three ways: (1) by using a nearest-neighbor texture-matching algorithm that enables straightforward machine learning of groundplane (traversable) texture from non-groundplane (obstacle) texture, (2) reporting the results a rigorous evaluation of the range accuracy obtained through monocular vision alone, and (3) example systems, already deployed, that use monocular ranging including (a) a safe-wandering agent, (b) a localization system using the MCL algorithm, and (c) a mapping system using the publicly available CoreSLAM algorithm. In each of these cases, off-the-shelf algorithms that count on laser scans have been used with our *PixelLaser* scans, as we call them, instead.

Results and their significance: We have published the vision for our *PixelLaser* system in two prior papers: the first at TePRA 2009 and the second at the International Symposium on Visual Computing in 2010 (Koziol et al., 2009; Lesperance, et al. 2010). This paper differs significantly from those two because it will report the accuracy of our monocular-ranging system on several different data sets. Here in Figure 1 we share our charts summarizing those results:

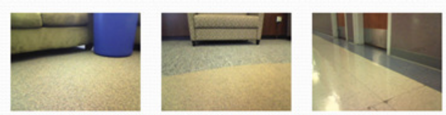


Average Pixel Error per Column (pixels)

	Sprague Lab	Sprague First Floor	Libra Hallways
Multi-resolution	8.86	11.13	14.10
Smooth	3.62	7.99	10.34
Transition Line	2.79	6.08	14.01

Average Distance Error per Column (inches)

	Sprague Lab	Sprague First Floor	Libra Hallways
Multi-resolution	27.34	35.10	55.34
Smooth	17.64	33.01	59.18
Transition Line	19.68	36.45	75.28



Average Pixel Error per Column (pixels)

	Sprague Lab	Sprague First Floor	Libra Hallways
Multi-resolution	9.67	16.24	19.75
Smooth	7.44	5.10	22.11
Transition Line	4.12	4.52	14.27

Average Distance Error per Column (inches)

	Sprague Lab	Sprague First Floor	Libra Hallways
Multi-resolution	12.28	16.05	64.52
Smooth	11.08	9.81	30.15
Transition Line	11.01	8.72	22.78

Figure 1. Average error in pixels and in inches for the scans estimated from single images in three different contexts: Sprague Lab (an indoor office environment), Sprague First Floor (another indoor environment with multiple textures of carpet, and Libra Hallways (specular tile floors with difficult-to-

distinguish molding and traversable texture). The left-hand chart shows values when the robot is moving at 200mm/sec; the right-hand chart shows the results when the robot is stationary.

Note that the best *quantified* range-scan-from-monocular-image results to date have been in (Plagemann et al., 2008), in which they report a ~100cm RMS error in their environment. We match that in the worst of our data sets (fast speed, no horizon control, difficult texture ambiguities) and supersede it in the others. As a result, we feel that our current system offers designers of low-cost autonomous systems a valuable resource to consider as the industry seeks more and more complex autonomy in its products.

To help seed such discussions, we have deployed three prototype systems on iRobot Creates using input only from the built-in webcameras of small netbook computers. No off-board computing was used at all. Figure 2 shows snapshots from our safe-wandering, Monte-Carlo Localization, and Core-SLAM-based systems. We exhibited our physical platform in action at AAAI 2010 in Atlanta in July.

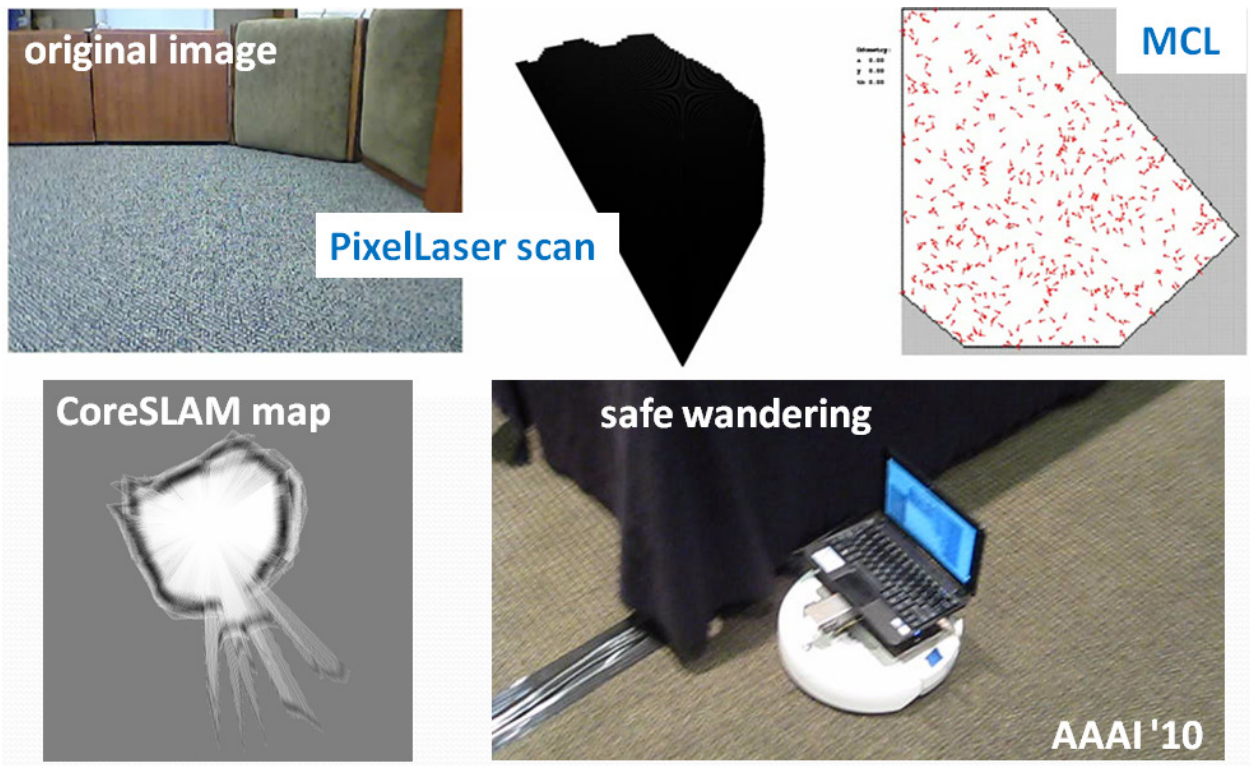


Figure 2. (Top) A raw image appears at left, its image-based *PixelLaser* scan in the middle, and an ongoing estimation of the robot's position within the particle filter of an MCL implementation. (Bottom) At left is a CoreSLAM-based map created with *PixelLaser* scans used as a drop-in replacement for laser scans; at right is a snapshot of an extended safe-wandering run of the platform at AAAI '10's robot exhibition.

Fit with the conference theme: This work provides, to the authors' best knowledge, state-of-the-art accuracy results for estimating range scans from monocular input. Starting from the ~100cm root-mean squared error reported in Plagemann, et al. (ICRA, 2008), we demonstrate that better accuracy results can be obtained with a simpler system by using extended patches of texture within a machine-learning nearest neighbors framework. The primary limitation of such systems is the estimation of the horizon within the input image: this provides engineers and system-builders an opportunity to improve our results even further by removing through careful design the factor that contributed most to errors remaining in our software system.

References

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(Koziol, et al. 2009) Z. Koziol, (HMC '10), S. Lakhani, (HMC '11), A. Paine, (HMC '11) and Z. Dodds, ***A vision for spatial-reasoning commodity robots***. Proceedings, IEEE Int. Conf. on Technologies for Practical Robot Applications (TePRA '09), Woburn, MA, Nov. 9-10, 2009.

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