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Research Experiences for Teachers and Young Scholars in Advanced Self-Powered Systems of Integrated Sensors and Technologies (ASSIST)

Merging Autonomous Execution and Human Intuition

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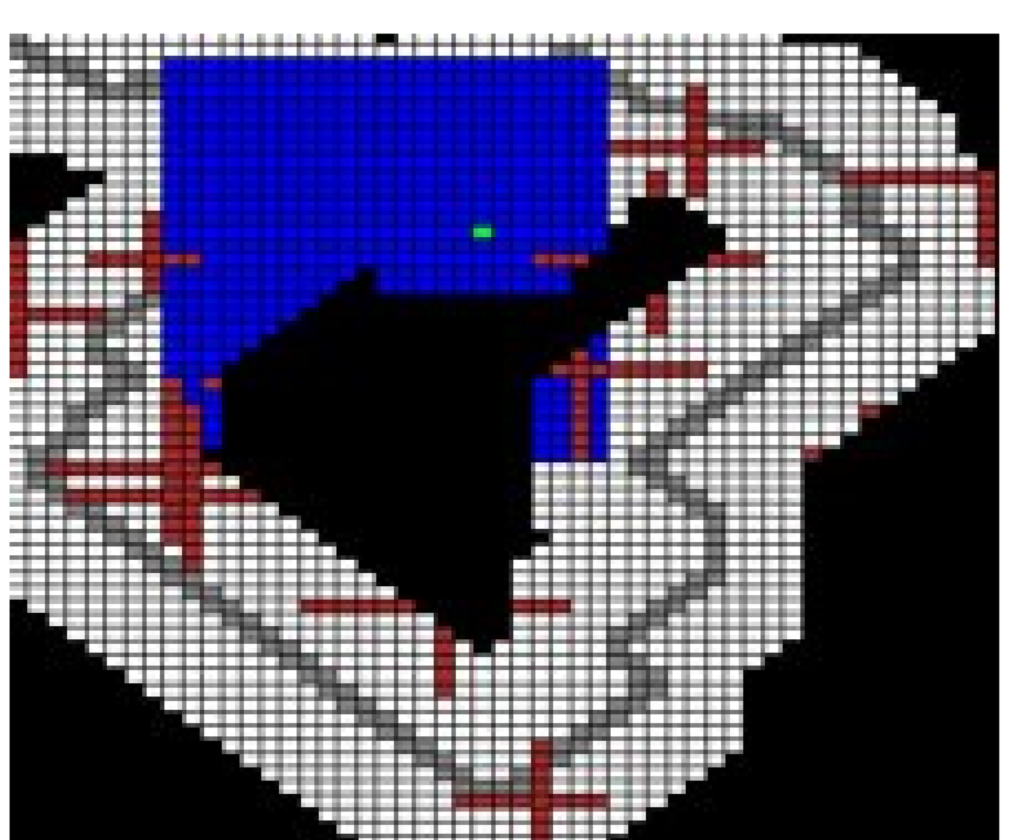
Overview

With autonomous machines, namely, self-driving vehicles, on the rise, I wanted to see if autonomous execution was as fool-proof as they say. Is present-day autonomy as efficient as it could be?

Methods

I used a simulator to test the efficiency of a fully autonomous machine, a machine somewhat controlled by an outside source(me), and a machine completely controlled by me. The machines were tasked with finding the shortest path to the objective without going over obstacles. Using ticks (movements that the machines made) as a measurement of time, I measured how fast each machine found the objective. I also used the amount of obstacles each machine hit as a measurement of failure. I developed the simulator and machines using the knowledge I acquired during a four-week JavaScript course.



Snapshot of a section of the grid. The black cells are unexplored, the white cells are unobstructed, the gray cells represent the path taken, the red cells represent trees, blue cells represent bodies of water, and the green cell represents the machine. The objective is not found yet, and is likely in an unexplored area.

Findings and Results

The results from each machine were varied. The completely autonomous machine was efficient, but often crossed over obstacles. The machine controlled by me didn't hit any obstacles, but perhaps wasn't as efficient as the completely autonomous machine. The machine that was both autonomous and controlled by an outside source consistently performed more efficiently than the other two. This machine also didn't hit any obstacles.

Completely autonomous

	Map 1	Map 2	Map 3	Map 4	Map 5	Map 6	Map 7	Map 8	Map 9
Ticks	623	1822	659	1346	1377	770	529	878	543
OC	2	3	4	2	2	3	2	3	2

Human assisted autonomy

	Map 1	Map 2	Map 3	Map 4	Map 5	Map 6	Map 7	Map 8	Map 9
Ticks	410	184	503	536	310	509	378	763	496
OC	0	0	0	0	0	0	0	0	0

Not autonomous

	Map 1	Map 2	Map 3	Map 4	Map 5	Map 6	Map 7	Map 8	Map 9
Ticks	872	710	959	1112	723	935	451	745	579
OC	0	0	0	0	0	0	0	0	0

Information recorded from the grid. OC stands for obstacles crossed. Each column represents the amount of ticks, used as a measurement of time, and the amount of obstacles crossed, used as a measurement of failure.

Conclusion

To summarize, the machine that was partly controlled by me, and partly autonomous was consistently the most efficient and crossed the least obstacles of all of the machines. Using this information, one can infer that autonomous machines would perform optimally with an outside influence.

Implications

Using the previous findings, one can infer that autonomy is not foolproof. In fact, the optimal system would be a healthy balance between autonomous execution and human intuition. Machines, when compared to humans, are much better at performing tedious tasks that humans get bored of quickly. Humans, however, are much better at performing tasks that require a deeper understanding of a situation.

Future Research

Future research will most likely include where we can implement this mixture of autonomous execution and human influence.

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