Localization and Rover Home Approach

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***Abstract*— Temporary Abstract**

I. Introduction

II. Problem Statement

III. Algorithm

Agent localization can be broken down into two parts: 1) static initialization, and 2) dynamic refactoring.

Algorithm 1 *Static Initialization*: create reference anchor node based on collective agent position.

Input: x_j : the current agent pose, where $j = \{1, ..., m\}$
Output: x_A: the position of the reference anchor node.

1: **for** $i \in \mathbb{N}\ s.t.\ i < I_{max}$ **do**
2:     **for** $x_k \in X$ where $k = \{1, ..., n\}$ **do**
3:         $(x_{mid}, y_{mid}) = \frac{\sum \frac{x_{k_c}}{2}}{n}$ where $k \neq j$
4: **return** S, V

After initialization, localization aims to improve the percieved location of the agent by correcting the recorded pose by a dynamic x and y offset. These offsets can be model by the equations,

$$\begin{aligned}(x, y) =& w \cdot ((x, y)_c - (x, y)_p) + \\ & u \cdot ((x, y)_g - (x, y)_c) + \\ & v \cdot (cos/sin)(\theta)\end{aligned} \tag{1}$$

where $(x, y)_c$ and $(x, y)_p$ are the current and previously recorded GPS locations, $(x, y)_g$ is the goal agent location and θ is the current heading. The weights applied to the relative change in position w, u, and v can then be model by the piece wise functions,

$$w = \begin{cases} 1 & \mathcal{D}_{\mathcal{A}} < 0.1 \\ e^{-(x,y)} & \text{otherwise} \end{cases} \tag{2}$$

$$u = \begin{cases} 1 & \mathcal{D}_{\mathcal{G}} < 0.05 \\ \frac{1}{1+(x,y)} & \text{otherwise} \end{cases} \tag{3}$$

$$v = \begin{cases} 0 & \frac{d(x,y)}{dt} < 0.01 \\ (\frac{d(x,y)}{dt})^2 & \text{otherwise} \end{cases} \tag{4}$$

such that $\mathcal{D}_{\mathcal{A}}$ is the distance from the anchor node, $\mathcal{D}_{\mathcal{G}}$ is the distance to the goal location, and $\frac{d(x,y)}{dt}$ is the linear velocity of the agent.

IV. Results

Show in

Modeled below is graph of the localization of a single rover. The ideal path can be seen in black, originating at the origin (0,0) and traversing to point (1,3).

- Mean Square Error = 0.964
- R^2 Regression Score = 0.0067

V. Conclusion