Brief Report

Indoor Localization Method Based on WiFi and Depth Camera

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1. Introduction

Indoor localization approaches typically rely on already available maps. Architectural floor plans are readily available for most buildings, and some approaches use these floor plans for localization. However, architectural floor plans only represent the basic architectural structures of buildings. The lack of knowledge of a target environment causes pose ambiguities in localization.

To solve the problem of pose ambiguities, we propose an indoor global localization approach based on WiFi and a depth camera. Our approach estimates a coarse position using a WiFi signal model and narrows down the hypothesis to a fine position by using wall-like virtual measurements extracted from the depth data. The results show that the combination of the WiFi signal model and the virtual measurements improves the localization in terms of convergence speed and accuracy.

2. Localization Approach

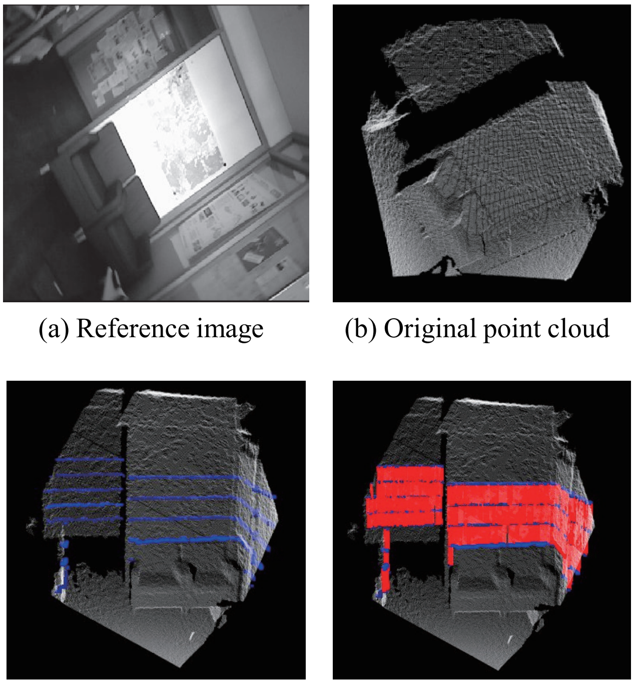
We employ a particle filter (PF)(1) for localization. The PF recursively estimates the position of the target as follows:

$$p(x_t \mid z_{1:t}, u_{0:t-1}) \propto p(z_t \mid x_t) \int_{\hat{x}} p(x_t \mid \hat{x}, u_{t-1}) \, p(\hat{x} \mid z_{1:t-1}, u_{0:t-2}) d\hat{x}, \quad (1)$$

where $u_{0:t-1}$ is the motion command executed by the robot and $z_{1:t}$ is the observations. The motion model $p(x_t \mid \hat{x}, u_{t-1})$ denotes the probability of the robot's state x_t, given that it executes u_{t-1} in the state $\hat{x}$. The observation model $p(z_t \mid x_t)$ denotes the likelihood of the observation. The major differences between vanilla PF and our localization method are the initialization of particles by using the WiFi signal model, and the weight calculation by using wall-like virtual measurements extracted from the depth data. This brief paper focuses on the initialization and virtual measurements.

A widely used approach for the initialization of particles is to generate initial particles uniformly throughout the environment. However, this initialization method cannot solve the ambiguities of particles. To reduce the ambiguities of initial particles, our method utilizes WiFi signal models of the Gaussian Process (GP)(2) for initialization. By using the GP based WiFi signal model,(3) the method uniquely localizes a target. In section 3, we show typical results of our initialization.

After initializing particles, our method calculates the weight of particles by using wall-like features. A major approach for extraction of wall-like features is RANSAC (Random Sample Consensus) based plane extraction, which is implemented in the PCL (Point Cloud library).(4) However, the RANSAC based plane extraction approach with a dense point cloud requires high computational cost. We propose a difference extraction approach for wall-like features with low computational cost. First, our approach corrects the attitude of the raw point cloud by using an inertial measurement unit (**Figs. 1** (b) and (c)). Then, the method extracts horizontal scans at different heights (blue lines in Fig. 1 (c)). Finally, the method connects the scans above and below if the vertical gradient is below a threshold (red lines in Fig. 1 (d)). We project these points onto the 2D plane of the floor plan for weight calculation. This simple procedure extracts rich wall-like features with low computational cost.



(a) Reference image (b) Original point cloud

(c) Transformed cloud by IMU data and extracted virtual lines (blue line) (d) Accepted virtual measurements (red)

Fig. 1 Extraction procedure of wall-like features.

3. Experiments

Figure 2 shows a typical localization result in an ambiguous environment. In this experiment, a target with a mobile phone and a depth camera moved from room A to room B. The color of the dots expresses the time transition of the particles. The red dots depict particles after the fast steps and the blue dots depict particles of the last steps. Without the WiFi signal model (Fig. 2 top), particles are dispersed in many areas that have similar shape compared to room A and could not localize uniquely. With the WiFi signal model (Fig. 2 bottom), the initial particles converged around the true position in room A and localize the target correctly.

4. Conclusion

This brief report introduced a combination localization method using a WiFi signal model and wall-like virtual measurements. WiFi information is useful for quick convergence of particles in an ambiguous environment. Our approach is most useful during global localization, especially when a target is

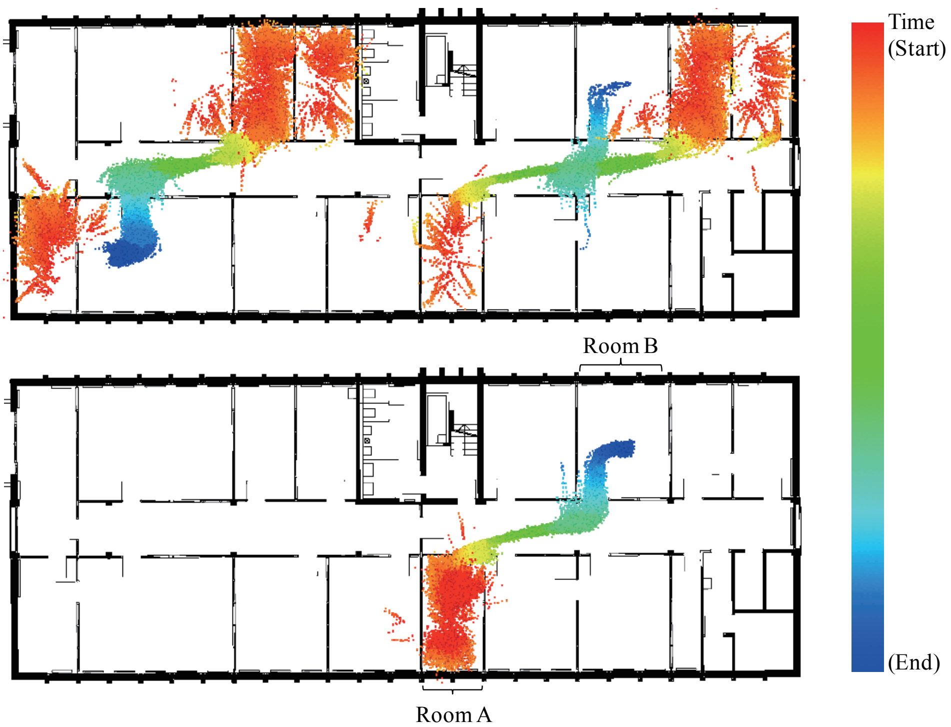


Fig. 2 Trajectories of particles in the ambiguous environment. Localization result with uniform initialization (top). Localization result with WiFi based initialization (bottom). The color of the particles depicts the time transition. Our method uniquely localizes the target. The target moved from room A to room B.

not supposed to move much. Given that a smart phone with a depth camera will soon be available to the public,(5) our method enables us to localize ourselves quickly and accurately in indoor environments.

References

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