Entropy-weighted Particle Filter-based Vehicle Localization using Vertical and Road Intensity Information

Hyungjin Kim[1], Bingbing Liu[2], Chi Yuan Goh[2], Serin Lee[2], *Senior Member, IEEE*, and Hyun Myung[1], *Senior Member, IEEE*

***Abstract*— This paper proposes a robust vehicle localization method based on a prior point cloud in urban area. Since the prior point cloud has many changed aspects of environment due to outdated data, the proposed method estimates vehicle pose using a particle filter by considering the reliability of extracted features from the prior map. In this paper, multi-layer vertical and road intensity information are utilized as the extracted features. The proposed method is demonstrated by an autonomous vehicle in Singapore.**

I. INTRODUCTION

A vehicle localization based on a prior point cloud is important in urban area. This paper proposes a robust localization method by considering reliabilities of various features extracted from the prior point cloud.

II. THE PROPOSED METHOD

The proposed method uses a modified weight update part in a conventional particle filter as shown in Algorithm 1. While the weights of each feature are summed up in the conventional method, the proposed method employs weighted sum according to entropies of particles. The entropy values are calculated by distributions of particles' feature weight values. In Algorithm 1, $x^{[k]}$,$w^{[k]}$,u_t, z_t, and m denote the k-th particle, its weight, control input, measurement at time t, and a map, respectively. The **measurement** function is ${}^{(r,v)}w_t^{[k]} = \exp\left\{-\frac{1}{2}\cdot \text{corr}\left(m^{(r,v)}, x_t^{[k]}, z_t^{(r,v)}\right)+1\right\}$, where corr() function denotes the Pearson product-moment correlation coefficient, and the entropies of weights are calculated as $H(W_t^{(r,v)}) = -\frac{1}{N}\sum_{k=1}^{N} {}^{(r,v)}w_t^{[k]} \log {}^{(r,v)}w_t^{[k]}$. The entropy values apply to the gains of weighted sum.

This paper is a short summary of the letter "Robust Vehicle Localization using Entropy-weighted Particle Filter-based Data Fusion of Vertical and Road Intensity Information for a Large Scale Urban Area," accepted February, 3, 2017 in RA-L.

*This work was supported by the Industrial Convergence Core Technology Development Program(No. 10063172, Development of robot intelligence technology for mobility with learning capability toward robust and seamless indoor and outdoor autonomous navigation) funded by the Ministry of Trade, industry & Energy (MOTIE), Korea; and also supported in part by the Technology Innovation Program, 10045252, Development of robot task intelligence technology, funded by the MOTIE, Korea.

[1]Hyungjin Kim and Hyun Myung are with the Urban Robotics Laboratory, Korea Advanced Institute of Science and Technology (KAIST) Daejeon, 34141, South Korea {hjkim86, hmyung}@kaist.ac.kr

[2]Bingbing Liu, Chi Yuan Goh, and Serin Lee are with Department of Autonomous Vehicle, Institute for Infocomm Research, A*star, 138632, Singapore {bliu, gohcy, serin-lee}@i2r.a-star.edu.sg

Algorithm 1 The proposed localization method:

Initialization:
  $x_0^{[k]} \leftarrow p(x_0)$, $k = 1, \ldots, N$
  $w_0^{[k]} \leftarrow 1/N$, $k = 1, \ldots, N$
Iterations:
  for $k = 1$ to N **do**
    $x_t^{[k]} =$ **motion_model**$(u_t, x_{t-1}^{[k]})$
    ${}^{(r,v)}w_t^{[k]} =$ **measurement**$(z_t^{(r,v)}, x_t^{[k]}, m^{(r,v)})$
  end for
  Normalization step s.t. $\sum_{k=1}^{N} {}^{(r,v)}w_t^{[k]} = 1$
  $H(W_t^{(r,v)}) = -\sum_{k=1}^{N} {}^{(r,v)}w_t^{[t]} \log {}^{(r,v)}w_t^{*,[t]}$
  for $k = 1$ to N **do**
    Conventional method :
      $\tilde{w}_t^{[k]} = {}^{r}w_t^{[k]} + \sum_{i=1}^{n} {}^{v_i}w_t^{[k]}$
    The proposed method :
      $\tilde{w}_t^{[k]} = (1 - H(W_t^r))\cdot {}^{r}w_t^{[k]}$
      $+ \sum_{i=1}^{n}(1 - H(W_t^{v_i}))\cdot {}^{v_i}w_t^{[k]}$
    $w_t^{[k]} \propto w_{t-1}^{[t]} \cdot \tilde{w}_t^{[k]}$
  end for
  Normalization step s.t. $\sum_{k=1}^{N} w_t^{[k]} = 1$
  $N_{eff} = \left[\sum_{k=1}^{N}\left(w_t^{[k]}\right)^2\right]^{-1}$
  if $N_{eff} \leq \eta_{eff}$ **then**
    $\left[x_t^{[k]}, w_t^{[k]}\right] =$ **Resampling**$(x_t^{[k]}, w_t^{[k]})$
  end if

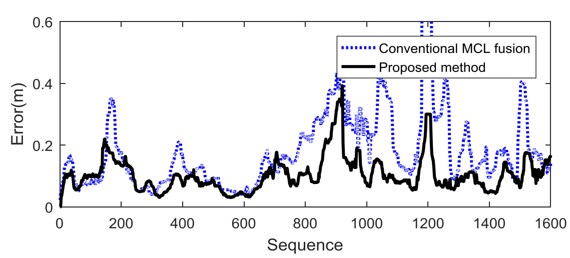

Fig. 1. The distance errors for the proposed and conventional method.

III. RESULTS AND CONCLUSIONS

The proposed method is applied to an autonomous vehicle equipped with 32-channel LiDAR (Velodyne 32E), IMU (KVH-1775), and wheel odometry. The comparison results of the proposed method and the conventional method are shown in Fig. 1 and the mean errors for x, y, and θ are 0.125 m, 0.129 m, and 0.195 degree, respectively.