СРАВНЕНИЕ ФУНКЦИЙ СХОДСТВА И ВЫБОРОЧНЫЕ АЛГОРИТМЫ В ФИЛЬТРЕ НА ОСНОВЕ ЧАСТИЦ ДЛЯ ЛОКАЛИЗАЦИИ БЕСПИЛОТНОГО ЛЕТАТЕЛЬНОГО АППАРАТА

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В статье анализируются части фильтра на основе частиц для локализации беспилотного летательного аппарата (БЛА). Локализация осуществляется путем сопоставления изображения с камеры БЛА с ранее известной картой ортофотопланов. Функции сопоставления изображения сравниваются, чтобы выбрать наиболее пригодный коэффициент для рассматриваемого случая. Для вычисления наиболее подходящей плотности вероятностей использовался нормализованный коэффициент корреляции с минимаксной нормализацией. Некоторые выборочные методы отбора проб проанализированы, реализованы и сравнены для случая, когда БЛА достигает запрещенного для GPS места. Метод отбора проб, использующий расстояние Kueller-Leiblach (сокр. KLD) показал наилучшую степень успеха локализации (96%) при низких вычислительных затратах (примерно в 1,7 раза быстрее, чем другие алгоритмы выборки).

Ключевые слова: фильтр частиц, локализация, отбор проб, беспилотный летательный аппарат, сравнение изображений, KLD-выборки.

COMPARISON OF IMAGE SIMILARITY FUNCTIONS AND SAMPLING ALGORITHMS IN VISION-BASED PARTICLE FILTER FOR UAV LOCALIZATION

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This paper analyses parts of a computer vision based particle filter for Unmanned Air Vehicle (abbr. UAV) localization. Localization is done by matching camera image from downward looking camera on a UAV to a previously known orthophoto map. Few image matching functions are compared, to select the best fit matching coefficient for the case. Normalized correlation-coefficient with min-max

normalization was used to calculate the most fit probability density function. Few sampling techniques are reviewed, implemented and compared to achieve UAV localization in a GPS denied environment. Kueller-Leiblach distance (abbr. KLD) sampling technique has shown the best localization success rate (96 %) with lowest computational requirement (about 1,7 times faster than other sampling algorithms).

Keywords: particle filter; localisation; sampling; UAV; image matching; kld-sampling.

INTRODUCTION

GPS signal used for UAV navigation is vulnerable to signal jamming and spoofing [7]. Localization, the process of pose estimation relatively to known map, may solve the problem of navigation without GPS signal. Particle filters have solved localization problem for autonomous robots [10] using laser scanners and panoramic vision [1].

Downward looking camera on a UAV may be used to solve pose estimation problem [5, 8] in combination with visual odometry and sensor data. Similar problem of mobile robot localization was solved using Monte Carlo localization in [12]. Particle filter mixed with wheel odometry approach was used in [4], where a mobile robot used ceiling mosaic and a upward facing camera to localize it‘s position using particle filters. Stereo vision systems have been successfully applied to low/medium size UAVs, but the problem of two cameras is the rigid distance between them, which limits the useful altitude range [3]. Computer vision techniques were demonstrated to be able to solve „kidnapped robot problem“ (or global localization problem) using visual odometry and Extended Kalman-filter based SLAM in [3]. This solution relies on natural landmark seen in the which are used calculate homography, recovering the flight.

VISION-BASED PARTICLE FILTER LOCALIZATION

Motion model is used to estimate aircraft pose according to UAV sensor data. The search space is narrowed down to pseudo-planar movement using only three parameters (see figure 1), where $z_t = \langle x, y, \theta_{yaw} \rangle$ is the aircraft pose on time t and θ_{yaw} is the UAV heading angle. Motion model implementations for movement in planar space can be found in [11]. Template matching technique is used to calculate similarity between image viewed by the camera and cropped image from map on the hypothesized UAV pose. Three popular template matching functions from OpenCV [2] library were adapted to calculate image similarity R between camera image T and cropped map image I , using these formula:

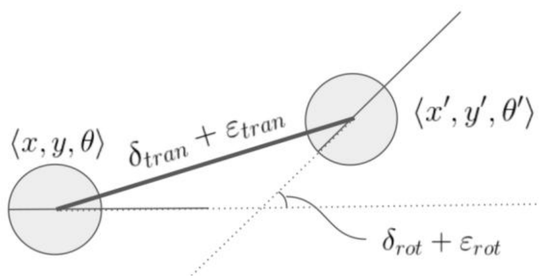


Fig. 1. Simplified planar motion model for UAV on a two-dimensional map

Normalized sum of squared differences (SQDIFF): $R_{SQD} = 1 - \frac{\sum_{x=0}^{w}\sum_{y=0}^{h}(T(x,y)-I(x,y))^2}{\sqrt{\sum_{x=0}^{w}\sum_{y=0}^{h}T(x,y)^2 \cdot \sum_{x=0}^{w}\sum_{y=0}^{h}I(x,y)^2}}$.

Normalized cross-correlation (CCORR): $R_{CCORR} = \frac{\sum_{x=0}^{w}\sum_{y=0}^{h}(T(x,y)\cdot I(x,y))}{\sqrt{\sum_{x=0}^{w}\sum_{y=0}^{h}T(x,y)^2 \cdot \sum_{x=0}^{w}\sum_{y=0}^{h}I(x,y)^2}}$.

Normalized correlation coefficient (CCOEFF): $R_{CCOEFF} = \frac{\sum_{x=0}^{w}\sum_{y=0}^{h}(T'(x,y)\cdot I'(x,y))}{\sqrt{\sum_{x=0}^{w}\sum_{y=0}^{h}T'(x,y)^2 \cdot \sum_{x=0}^{w}\sum_{y=0}^{h}I'(x,y)^2}}$,

where $T'(x,y) = T(x,y) - \frac{\sum_{x'=0}^{w}\sum_{y'=0}^{h}T(x',y')}{wh}$, $I'(x,y) = I(x,y) - \frac{\sum_{x'=0}^{w}\sum_{y'=0}^{h}I(x',y')}{wh}$

and *w*, *h* image dimensions (width and height).

Particle filter localization (or Monte Carlo localization) is a recursive Bayes filter that estimates the posterior distribution of robot poses conditioned on sensor data [12]. The probability distribution of the a particle is described in the form $p(z_t \mid z_{0:t-1}, m_{1:t-1})$, where z_t is robot pose on time *t* and m_t is sensor data (may be IMU, barometer, wind speed and other data used for dead-reckoning) on time *t*. Probability density function for the particles is obtained by calculating image similarity R with formulas R_{SQD}, R_{CCORR}, R_{CCOEFF}.

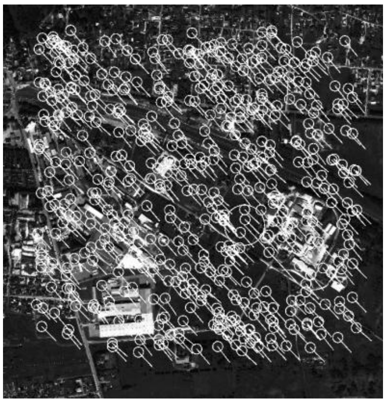
To map the similarity to probability space we use simple min-max normalization $b = \frac{R_j - R_{min}}{R_{max} - R_{min}}$, then we can represent the UAV pose belief as $bel(z_t) = p(z_t \mid z_{0:t-1}, m_{1:t-1}, b_{1:t-1})$. The next iteration of particle filter begins after some time by estimating the UAV motion, capturing new imagery from camera and selecting particles from previous iteration. This part of the particle filter is called sampling.

Sampling is the stage of the Particle Filter when particles are re-sampled according to their belief. Each iteration resamples particles to find the most plausible UAV location over time. Few sampling techniques were selected for comparison – Rejection Sampling [13], Importance Sampling [9] and KLD-Sampling [6].The principle of rejection sampling is to evaluate randomly selected particle to survive with a probability equal to it’s belief. Importance sampling was introduced to deal with higher uncertainty in the measurements. This sampling technique uses weight w_i (calculated by normalising all probabilities) to resample the particles. The higher particle belief is, the larger weight it gets and a particle is more likely to be resampled. KLD-sampling is an extension of the importance sampling. It uses Kueller – Leiblach distance to dynamically calculate required number of particles for the filter without the loss of accuracy.

EXPERIMENTAL RESULTS

Experiments are made in simulated environment where the flight of UAV is simulated in a planar coordinates of the map. Grayscaled map and images are used to speed up image matching procedure. The map is located in a suburb region of Lentvaris, Lithuania. An example search of UAV location is presented in figure 2, where 500 particle are scattered uniformly over an area of a map (fig. 2, *a*) to localize the true UAV pose. Images of a hypothesized location are cropped out of the map, re-scaled and simulate real flight imaging conditions by adding noise. To compare the image matching coefficients, we generate a set of 500 particle hypothesis and calculate image matching with the image of the ground truth location to preview the calculated coefficients.

The effectiveness of sampling algorithm is measured by percentage of successful convergences to the ground truth pose (best particle is not further from ground truth then 15 meters/50 pixels) after 50 iterations. 100 start locations are randomly selected and each sampling algorithm is evaluated using same starting conditions – 350 particles are uniformly distributed in a radius of 250 meter (833 in pixels) of ground truth position (worst case GPS accuracy is 156 meters). Image size of 400×400 was selected to be cropped out of the map, imitating a flight at around 100 meter altitude.



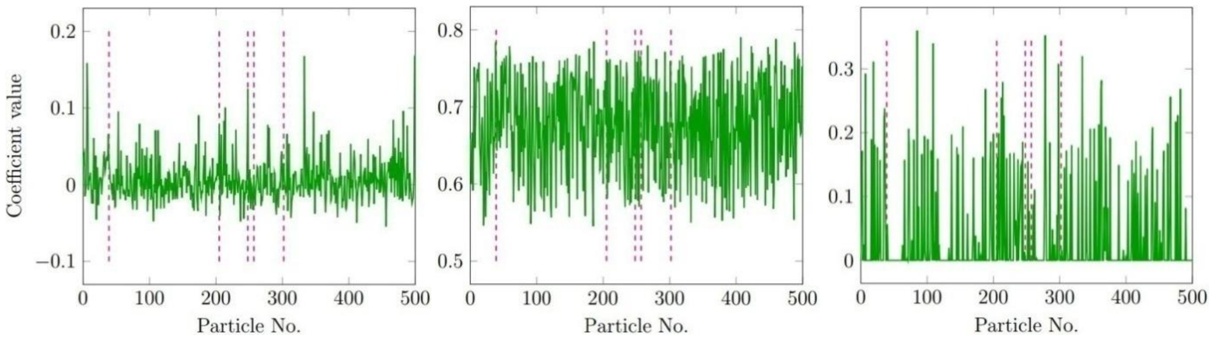
a: Initial search

b: Particles at final location

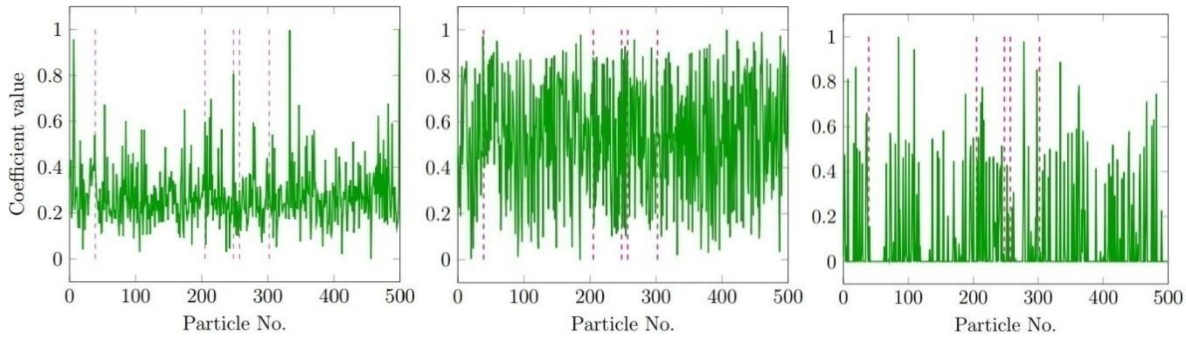
Fig. 2. Hypothesized UAV locations on the known map

COMPARISON OF IMAGE MATCHING FUNCTIONS

CCORR function (see fig. 3, *b* and 3, *e*) does not distinguish any poses from the common, there are many peak values which will survive during localization and it may take considerable time to filter out the final pose. SQDIFF function (see fig. 3, *c* and 3, *f*) contains a lot of zero values, which will certainly be omitted during sampling. This causes a very early pose convergation. Particle Filter requires some iterations to collect enough evidence over time to select a proper pose. Meanwhile, CCOEFF (see fig. 3, *a* and 3, *d*) has few high probability particles and others are in a low probability zone. This allows ensure survival of the very probable locations, but other locations are still left for consideration with lower probability. The dashed vertical lines marks 5 nearest to ground truth particles. Correlation coefficient (CCOEFF) with min-max normalization will be used for experiments in the next section.



a CCOEFF *b* CCORR *c* SQDIFF



d min-max CCOEFF *e* min-max CCORR *f* min-max SQDIFF

Fig. 3. Image similarity coefficients

SAMPLING ALGORITHM COMPARISON

Table shows the experimental results of the algorithm comparison. Ending particle count is the average particle count at the last iteration of the algorithm. Rejection and importance sampling algorithms has fixed particle counts and the KLD-sampling particle count is variable over time. Average time is calculated by adding up execution time of each 100 flight starting point tests. Experiments were concluded on a Intel i5-4200M processor with 3,1 GHz operating frequency. The average duration is the same for rejection and importance sampling, but KLD is faster with the similar, but slightly better success rate. KLD sampling uses more than 3 times less particles after 50 iterations.

Comparison of sampling algorithms

Sampling	End particle count	Average duration, s	Successful localization
Rejection	350	235	87 %
Importance	350	234	94 %
KLD	83.8	131	96 %

CONCLUSIONS AND FUTURE WORK

Comparison of image matching functions and sampling algorithms used in Particle Filter localization was presented in this paper. Image matching function - correlation coefficient (after min-max normalization) was identified to be most fit for particle belief representation. KLD sampling technique has proved to be as accurate as other sampling techniques, but by adapting particle count reduces computational load when it is not necessary. KLD sampling technique has shown to be at least 1,7x times faster than other sampling techniques with comparable localization success rate. The experiments with KLD sampling is planned with real life flight imagery and UAV sensor data. Localized pose with GPS location and other vision based localization techniques.

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