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ANALYSES OF MARGINALIZED PARTICLE FILTERING BLOCK OF NAVIGATION DATA

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***Abstract*—*The particle filter offers a general numerical tool to approximate the posterior density function for the state in nonlinear and non-Gaussian filtering problems. While the particle filter is fairly easy to implement and tune, its main drawback is that it is quite computer intensive, with the computational complexity increasing quickly with the state dimension. One remedy to this problem is to marginalize out the states appearing linearly in the dynamics. The result is that one Kalman filter is associated with each particle. Filtering block has been developed with the help of which navigation data received from UAV is filtered. UAV motion with camera on board has been conducted and photos have been captured from it. Photos have been processed by OpenSurf method, with the help of which feature points has been detected, filtered and compared with previous image. Result of research shows that with help of comparing of two neighboring images we can reconstruct relief above which UAV flew.*

Index Terms—Particle filter; marginalized particle filter; filtering block; correlation extreme navigation system.

I. INTRODUCTION

Central task of any system of navigation is defining as precisely as possible the coordinates of the UAV. Significant number of algorithms is developed to solve it, based mainly on the famous recursive algorithm for the Kalman filter, and effectively implemented on a digital computer. Nevertheless we still cannot consider this problem finally solved. This is because of many reasons, and one of the most important is the non-linear nature of the motion models and measurement in many practical problems. Nonlinearity occurs for many factors – due to the nonlinear connection of coordinate systems used in the equations of the observed object and the measurer, because of the nonlinear nature of the equations themselves. Nonlinear problems arise in the construction of adaptive systems, implemented by the inclusion of uncertain parameters in the estimated state vector. Extreme simplification of the situation ignoring and nonlinearities may significantly reduce the efficiency of coordinates, altitude and velocities estimation algorithms in the real systems. In practice, non-linear estimation algorithms are applied, but in general, limited to simple options such as extended Kalman filter.

More powerful algorithms exist at the same time but are rarely used because they require large computational cost. However, the rapid growth during the past years of computer technology opportunities enables us to use many of these algorithms in practice. So, marginalized particle filtering algorithm [1] is developed. It is a powerful tool, which successfully solves problem of nonlinearity by separating of linear and nonlinear parts and does not require high computing performance (Fig. 1).

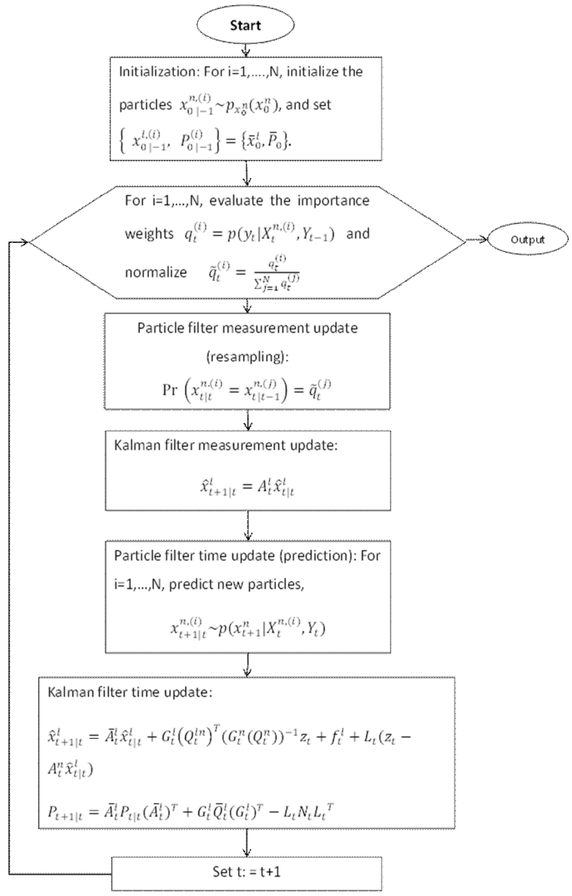

Fig. 1. Marginalized particle filter algorithm

II. Problem Statement

The nonlinear non-Gaussian filtering problem consists of recursively computing the posterior probability density function of the state vector in a general discrete-time state-space model, given the observed measurements. Such a general model can be formulated as

$$x_{t+1} = f(x_t, w_t), \qquad y_t = h(x_t, e_t).$$

Here, y_t is the measurement at time t, x_t is the state variable, w_t is the process noise, e_t is the measurement noise, and f, h are two arbitrary nonlinear functions. The two noise densities p_{w_t} and p_{e_t} are independent and are assumed to be known.

The posterior density $p(x_t \mid Y_t)$ where $Y_t = \{y_i\}_{i=0}^{t}$ is given by the following general measurement recursion:

$$p(x_t|Y_t) = \frac{p(y_t \mid x_t)\, p(x_t \mid Y_{t-1})}{p(y_t \mid Y_{t-1})},$$

$$p(y_t|Y_{t-1}) = \int p(y_t \mid x_t)\, p(x_t \mid Y_{t-1})\, dx_t,$$

and the following time recursion:

$$p(x_t|Y_t) = \int p(x_{t+1} \mid x_t)\, p(x_t \mid Y_t)\, dx_t,$$

initiated by $p(x_0|Y_{-1}) = p(x_0)$. For linear Gaussian models, the integrals can be solved analytically with a finite dimensional representation. This leads to the Kalman filter recursions, where the mean and the covariance matrix of the state are propagated. More generally, no finite dimensional representation of the posterior density exists. Thus, several numerical approximations of the integrals have been proposed. A recent important contribution is to use simulation based methods from mathematical statistics, sequential Monte Carlo methods, commonly referred to as particle filters [2].

Integrated navigation is used as a motivation and application example. Briefly, the integrated navigation system in them Swedish fighter aircraft Gripen consists of an inertial navigation system (INS), a terrain-aided positioning (TAP) system and an integration filter. This filter fuses the information from INS with the information from TAP [3], [4]. Terrain-aided positioning is currently based on a point-mass filter, where it is also demonstrated that the performance is quite good, close to the Cramér–Rao lower bound. Field tests conducted by the Swedish air force have confirmed the good precision. Alternatives based on the extended Kalman filter have been investigated but have been shown to be inferior particularly in the transient phase (the EKF requires the gradient of the terrain profile, which is unambiguous only very locally). The point-mass filter is likely to be changed to a marginalized particle filter in the future for Gripen. TAP and INS are the primary sensors. Secondary sensors (GPS and so on) are used only when available and reliable. The current terrain-aided positioning filter has three states (horizontal position and heading), while the integrated navigation system estimates the accelerometer and gyroscope errors and some other states. The integration filter is currently based on a Kalman filter with 27 states, taking INS and TAP as primary input signals.

The Kalman filter that is used for integrated navigation requires Gaussian variables. However, TAP gives a multi-modal un-symmetric distribution in the Kalman filter measurement equation and it has to be approximated with a Gaussian distribution before being used in the Kalman filter. This results in severe performance degradation in many cases, and is a common cause for filter divergence and system reinitialization.

The appealing new strategy is to merge the two state vectors into one, and solve integrated navigation and terrain-aided positioning in one filter. This filter should include all 27 states, which effectively would prevent application of the particle filter. However, the state equation is almost linear, and only three states enter the measurement equation nonlinearly, namely horizontal position and heading. Once linearization (and the use of EKF) is absolutely ruled out, marginalization would be the only way to overcome the computational complexity. More generally, as soon as there is a linear sub-structure available in the general model this can be utilized in order to obtain better estimates and possibly reduces the computational demand. The basic idea is to partition the state vector as

$$x_t = \begin{bmatrix} x_t^l \\ x_t^n \end{bmatrix},$$

where x_t^l denotes the state variable with conditionally linear dynamics and x_t^n denotes the nonlinear state variable.

Using Bayes' theorem we can then marginalize out the linear state variables and estimate them using the Kalman filter, which is the optimal filter for this case. The nonlinear state variables are estimated using the particle filter. This technique is sometimes referred to as Rao-Blackwellization. The variance of the estimates obtained from the standard particle filter can be decreased by exploiting linear substructures in the model. The corresponding variables are marginalized out and estimated using an optimal linear filter. This is the main idea behind the marginalized particle filter.

Speeded Up Robust Features (SURF) is a local feature detector and descriptor that can be used for tasks such as object recognition or registration or classification or 3D reconstruction. It is partly inspired by the scale-invariant feature transform (SIFT) descriptor. The standard version of SURF is several times faster than SIFT and claimed by its authors to be more robust against different image transformations than SIFT.

To detect interest points, SURF uses an integer approximation of the determinant of Hessian blob detector, which can be computed with 3 integer operations using a precomputed integral image. Its feature descriptor is based on the sum of the Haar wavelet response around the point of interest. These can also be computed with the aid of the integral image.

The SIFT approach uses cascaded filters to detect scale-invariant characteristic points, where the difference of Gaussians (DoG) is calculated on rescaled images progressively. In SURF, square-shaped filters are used as an approximation of Gaussian smoothing. Filtering the image with a square is much faster if the integral image is used, which is defined as:

$$S(x,y)=\sum_{i=0}^{x}\sum_{j=0}^{y} I(i,j).$$

The sum of the original image within a rectangle can be evaluated quickly using the integral image, requiring four evaluations at the corners of the rectangle.

Speeded Up Robust Features uses a blob detector based on the Hessian matrix to find points of interest. The determinant of the Hessian matrix is used as a measure of local change around the point and points are chosen where this determinant is maximal. In contrast to the Hessian–Laplacian detector by Mikolajzyk and Schmid, SURF also uses the determinant of the Hessian for selecting the scale, as it is done by Lindeberg. Given a point $p = (x, y)$ in an image I, the Hessian matrix $\mathbf{H}(p, \sigma)$ at given point and scale σ, is defined as follows:

$$\mathbf{H}(\rho,\sigma)=\begin{pmatrix} L_{xx}(p,\sigma) & L_{xy}(p,\sigma) \\ L_{xy}(p,\sigma) & L_{yy}(p,\sigma) \end{pmatrix}.$$

where $L_{xx}(p,\sigma)$ etc. are the second-order derivatives of the grayscale image.

The box filter of size 9×9 is an approximation of a Gaussian with $\sigma = 1.2$ and represents the lowest level (highest spatial resolution) for blob-response maps.

Consider the example of a system consisting of one or two cameras and three-dimensional space of a point M. Some space forms the point M on the projected images m_1 and m_2. If you know the internal and external characteristics of the stereo system, you can restore the position of the point M in the three-dimensional space. Determination of compliance between the projections m_1 and m_2 for all pixels a stereo pair of images is a key task stereophotogrammetry, as well as one of the most studied problems in computer vision. The value of $d = x_2 – x_1$ is the parallax of the projection of the point M on the stereo pair images. This value is also called the disparity. An ordered set of values for all pixels' parallax stereo pair is called disparity map, stereo correspondence or depth map. In the prior art stereo correspondence problem finding it may have different names, such as "the establishment of pixel correspondences on stereo pairs", "identification of corresponding pixels' stereo image", "identification of pixels' stereo" and others (Fig. 2).

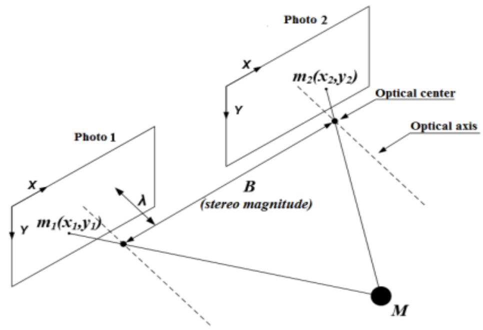

Fig. 2. The model of formation of a stereo pair of images

The main practical goal of the search pixel correspondences on stereo pairs – obtaining a three-dimensional model of the projection space, embodied in the two pictures. For the model of the formation of a stereo pair of images, presented in the introduction, the equality:

$$Z=f-\frac{f\,B}{x_2-x_1}=f-\frac{f\,B}{d},$$

where f is camera focal length; B is stereo magnitude (the distance between photo points); $d = x_2 – x_1$ is the difference in the ordinate corresponding pixels in the images of the stereo pair, Z is the distance from the shooting plane to the point of the space M. It should be noted that the difference between the projected coordinate d must be converted into the same units as the focal length and the stereo, for example, in the subway. Knowing the physical size and its resolution photo matrices, you can calculate the size of one pixel ρ_C in meters, which is then used to convert the pixel values of the disparity in meters. Thus, when the parameters of the optical system (f, B, ρ_C) are known the task of restoring the relief is reduced to the establishment of pixel correspondences according to the mentioned relationship [5].

III. PROBLEM SOLUTION

In this work motion of UAV which was flying above one of the Kyiv region was performed. Camera was fixed to UAV and after flight execution we have got a full flight video as well as navigation log with such parameters as latitude, longitude, GPS altitude, velocity, ground speed, acceleration, angular acceleration, barometric altitude, roll, pitch, yaw. Figure 3 shows the flight path of UAV.

Fig. 3. Flight path of UAV

We have chosen a segment of the whole trajectory with constant height and velocity (Fig. 4).

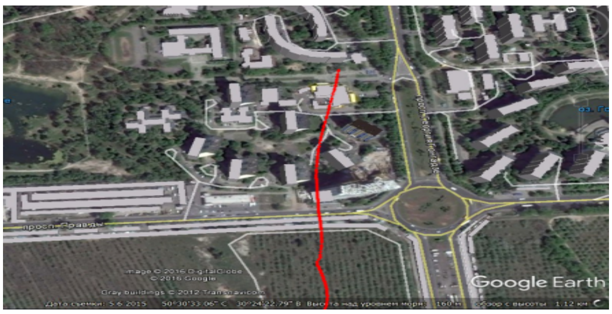

Fig. 4. Chosen segment of trajectory

The task is to compute the height as well as data about relief of the ground UAV flies over with the help of comparing images captured from video using SURF method. There was only 1 camera on board so we had to compare two frames, which are chosen with some constant time interval in order to use stereo pair technique of image depth obtaining.

So we have selected 10 pairs of images with 1 sec interval. Following figure represents two photos, which was computed.

With the help of SURF method 12125 feature points were detected. All points are shown in Fig. 5.

Fig. 5. Pair of compared images

Feature points were found on both photos and in the following figures we can see how points were tracked from frame to frame (Figs 6 and 7).

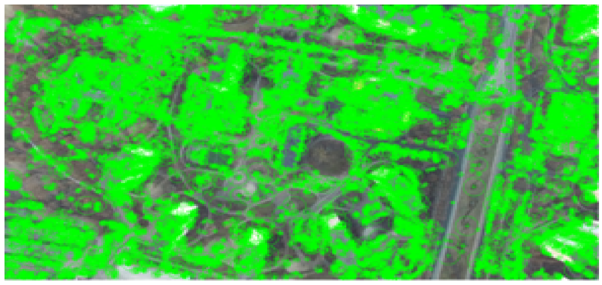

Fig. 6. Feature points

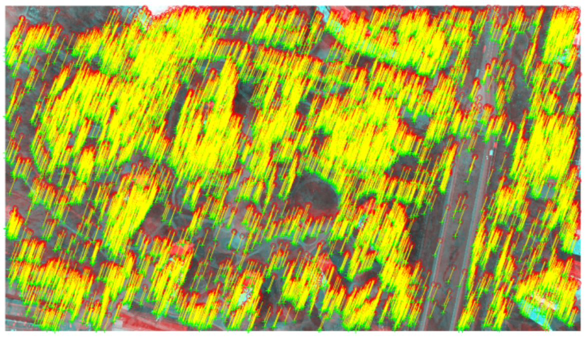

Fig. 7. Tracked feature points

Now it is possible to reconstruct relief of flyover point as well as to obtain height. In following figure we can see reconstructed 3D terrain with shown positions of camera (Fig. 8).

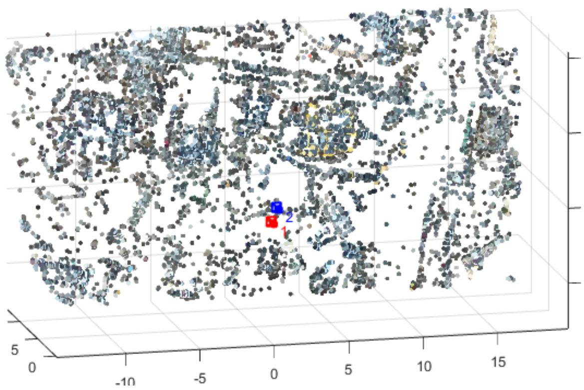

Fig. 8. Reconstructed relief

Figure 9 shows the heights of 50 random points on image.

Fig. 9. Height of 50 random points

From the last it is clear that UAV is flying on average height ~360 m. Also we can see that if point lies on building the height value differs a lot from average. It is natural, because algorithm defines distance to points not only on the ground, but on the buildings as well.

In order to verify if height determination is true we used GPS altitude from navigation log. It shows altitude above sea level, so we just subtracted ground elevation (in this region ground elevation equals 160 m) from GPS altitude and received height. Figure 10 shows the graphs of height calculated by program and height obtained from navigation log.

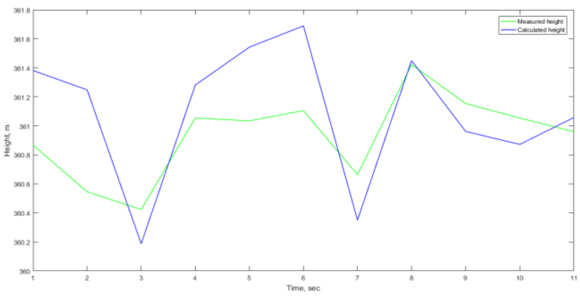

Fig. 10. Measured and calculated heights

In Fig. 11 it is clearly seen that height calculated by program has to be filtered. So we applied marginalized particle filtering algorithm. During particle filtering a priori data was taken from satellite and calculated data from stereoscopic measurements. Particle filtering gave us level of reliability to each new calculated value. As a result more accurate value of height has been obtained.

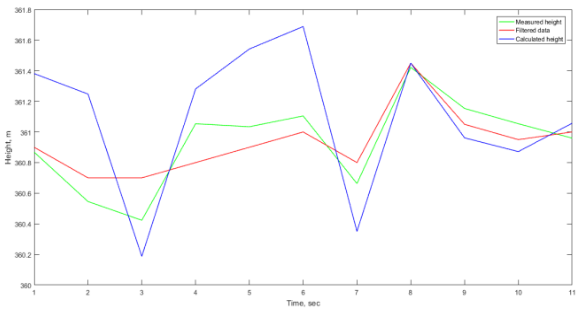

Fig. 11. Filtered height

As we can see in Fig. 10 filtered value of height is more close to measured one and we can say that marginalized particle filter works well. The difference in error between true and filtered heights is represented in Fig. 12.

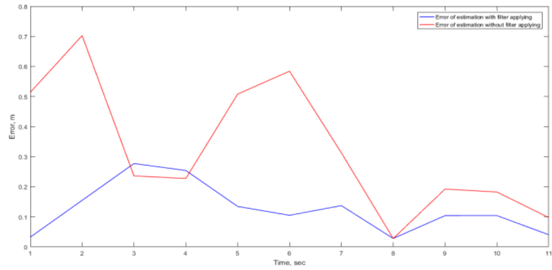

Fig. 12. Errors of estimation

It is obvious that error of estimation with filter applying is significantly less than error of estimation without filter applying.

IV. CONCLUSIONS

In this work marginalized particle filtering block has been realized on practice by filtering data received from video which was recorded from UAV flying under one of the Kyiv regions. Height of UAV was defined by comparing two images taken with 1 sec interval simulating stereo pair technique with the help of SURF method. The relief UAV was flying above was reconstructed as well. Errors of estimation were also computed by comparing calculated height and height received from navigation log.

Program has been developed and researched in Matlab programming language. Program was successfully tested; results of program execution can be considered as reliable. Block can be implemented in unmanned vehicles development.

REFERENCES

[1] Thomas Schön, Fredrik Gustafsson, and Per-Johan Nordlund, "Marginalized Particle Filters for Mixed Linear/Nonlinear State-Space Models," *IEEE Transactions on signal processing*, vol. 53, no. 7, July 2005, pp. 2279–2289.

[2] Sebastian Thrun, Dieter Fox, and Wolfram Burgard, *Probabilistic Robotics*, 1999-2000, 477 p.

[3] Francisco José Curado Mendes Teixeira, *Terrain-Aided Navigation and Geophysical Navigation of Autonomous Underwater Vehicles*, 2007, 131 p.

[4] M. P. Mukhina and I. V. Seden, "Analysis of modern correlation extreme navigation systems," *Electronics and Control Systems*, Kyiv, no. 1(39), pp. 95–101, 2014.

[5] *Modern information technologies in problems of navigation and targeting maneuverable unmanned aerial vehicles*. Edited by M. N Krasilshikov and G. G Sebryakov, Moscow, Fizmatlit, 2009, 556 p. (In Russian).

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М. П. Мухіна, А. П. Примак. Аналіз блока роздільної точкової фільтрації навігаційних даних
Запропоновано розроблений блок фільтрації навігаційних даних безпілотного літального апарата. Під час руху апарату були отримані знімки рельєфу місцевості камерою безпілотного літального апарата. Захоплені зображення були оброблені SURF методом. Результат обробки дозволив виявити відфільтровані характерні точки і порівняти з попереднім зображенням. Таким чином, в ході роботи було зроблено висновок, що за допомогою порівняння двох сусідніх зображень є можливість реконструювати рельєф, над яким пролетів безпілотний літальний апарат, оцінити висоту та провести точкову фільтрацію із розділення вектору стану.
Ключові слова: точковий фільтр; роздільний точковий фільтр; блок фільтрації; кореляційно-екстремальна навігаційна система.

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М. П. Мухина, А. П. Примак. Анализ блока разделенной точечной фильтрации навигационных данных
Предложен разработанный блок фильтрации навигационных данных беспилотного летательного аппарата. В ходе движения аппарата были получены снимки рельефа местности камерой беспилотного летательного аппарата. Данные захваченные изображения были обработаны SURF методом. Результат обработки позволил обнаружить отфильтрованные характерные точки и сравнить с предыдущим изображением. Таким образом, в ходе работы был сделан вывод, что с помощью сравнения двух соседних изображений есть возможность реконструировать рельеф, над которым пролетел беспилотный летательный аппарат, оценить высоту и провести точечную фильтрацию с разделением вектора состояния.
Ключевые слова: точечный фильтр; разделенный фильтр; блок фильтрации; корреляционно-экстремальная навигационная система.

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