UAV NAVIGATION ON THE BASIS OF THE FEATURE POINTS DETECTION ON UNDERLYING SURFACE

Ivan A. Konovalenko
Moscow Institute of Physics and Technology
141700, 9, Institutskiy per., Dolgoprudny,
Moscow Region, Russia;
Institute for Information
Transmission Problems, RAS
127994, 19, Bolshoy Karetny per.,
Moscow, Russia
E-mail: konovalenko@iitp.ru

Alexander B. Miller
Institute for Information
Transmission Problems, RAS
127994, 19, Bolshoy Karetny per.,
Moscow, Russia
E-mail: amiller@iitp.ru

Boris M. Miller
Institute for Information
Transmission Problems, RAS
127994, 19, Bolshoy Karetny per.,
Moscow, Russia
E-mail: bmiller@iitp.ru

Dmitry P. Nikolaev
Institute for Information
Transmission Problems, RAS
127994, 19, Bolshoy Karetny per.,
Moscow, Russia
E-mail: dimonstr@iitp.ru

KEYWORDS

UAV, visual odometry, projective geometry, video stream, feature points, Kalman filter, control.

ABSTRACT

This work relates to the intelligent systems tracking such as UAV's (unmanned aviation vehicle) navigation in GPS-denied environment. Generally it considers the tracking of the UAV path on the basis of bearing-only observations including azimuth and elevation angles. It is assumed that UAV's cameras are able to capture the angular position of reference points and to measure the directional angles of the sight line. Such measurements involve the real position of UAV in implicit form, and therefore some of nonlinear filters such as Extended Kalman filter (EKF) or others must be used in order to implement these measurements for UAV control. Meanwhile, there is well-known method of pseudomeasurements which reduces the estimation problem to the linear settings, though these method has a bias. Recently it was shown that the application of the modified filter based on the pseudomeasurements approach provides the reliable UAV control on the basis of the observation of reference points nominated before the flight. This approach uses the known coordinates of reference points and then applies the optimal linear Kalman type filter. The principal difference with the usage of location of reference points nominated in advance is that here we use the observed reference points detected on-line during the flight. This approach permits to reduce the necessary on-board memory up to reasonable size. In this article the modified pseudomeasurement method without bias for estimation of the UAV position has been suggested. On the basis of this estimation the control algorithm which provides the tracking of reference path in case of external perturbation and the angles measurements errors has been developed. Another principal novelty of this work is the usage of RANSAC approach to detection of reference landmarks which used further for estimation of the UAV position.

INTRODUCTION

Modern UAV's navigation systems use the standard elements of INS (inertial navigation system) along with GPS, which permit to correct the bias and improve the UAV localization which is necessary for resolving mapping issues, targeting and reconnaissance tasks (Osborn and Bar-Shalom, 2013). The performing of these tasks in autonomous flights needs so-called *data fusion* which is a difficult task especially for small UAVs which are implemented usually at low altitude, and therefore have relatively high level of the barometric altitude sensor errors. There are systematic errors which are inherent in GPS usage at low altitude, and they are also rather important and for this reason special approaches such as robust nonlinear (Nemra et al., 2008), (Nemra and Aouf, 2010) or adaptive (Ding et al., 2010) filtering are necessary. An alternative to the GPS is the usage of various complementary measurement systems such as opto-electronic cameras and passive radio- or ultrasonic locators which give direction-finding (or bearing-only) observations.

Optical absolute positioning

In our approach some aerospace maps of the terrain under the planned flight path are loaded into UAV control system memory. For this purpose the technology of feature points (Lowe and David, 1999) has been used. As a result one can detect current location and orientation without time-error accumulation. These methods are invariable

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to deformations of that predetermined maps which may be caused by change of height, aspect ratio, luminance, weather conditions, etc. Also from the previous plane surveying some new constructions could have been built or the landscape could have been partly changed. For these reasons some special recognition system is needed to detect special points like specific buildings, cross of the roads, tops of mountains and so on. The principal difficulties inherent in detecting of such special objects are the different scale and aspect angles of observed and stored images which leads to the necessity of huge templates library in the memory of UAV control system. Here one can avoid these difficulties using another approach based on observation of so-called feature (Konovalenko and Kuznetsova, 2015) points which are the scale and the aspect angle invariant. This technology appeared first in (Guan and Bai, 2012). Another contribution of our work is the usage of modified unbiased pseudo measurements filter for bearing only observations of some reference points with known terrain coordinates.

In order to evaluate the performance of suggested algorithms we use the computer simulation of the UAV flight and corresponding video sequence simulation obtained by video camera on its board. Simulation program is written in MATLAB. The types of detected feature points are: ASIFT, OpenCV (Python). Feature points in this model are used in real conditions because the modelled images captured by on-board camera and the images known from previously loaded maps were transformed projectively according to the flight model and obtained from different cameras' careers.

Kalman filter

In order to get the metric data from visual observations one needs first to make observations from different positions (*i.e. triangulation*) and then to use the nonlinear filtering. However, all nonlinear filters either have unknown bias (Belfadel et al., 2013) or very difficult for on-board implementation like the Bayesian type estimation (Bishop et al., 2010), (Jauffet et al., 2011). Approaches for the position estimations based on bearing-only observations had been analyzed long ago especially for submarine applications (Lin et al., 2002) and nowadays for UAV applications (Osborn and Bar-Shalom, 2013), (Zhang and Bar-Shalom, 2011).

Comparison of different nonlinear filters for bearing-only observations in the issue of the ground-based object localization (Miller et al., 2013) shows that EKF (extended Kalman filter), unscented Kalman filter, particle filter and pseudomeasurement filter give almost the same level of accuracy, while the pseudomeasurement filter is usually more stable and simple for on-board implementation. This observation is in accordance with rather old results (Lin et al., 2002), where all these filters were compared in the issue of moving objects localization. It have been mentioned that all these filters have bias which makes their use in data fusion issues rather problematic (Aidala and Nardone, 1982). The principle demand to such filters in data fusion is the non-biased estimate with known mean square characterization of the error. Among the variety of possible filters only the pseudomeasurement filter can be modified to satisfy the data fusion demands. The idea of such nonlinear filtering has been developed by V. S. Pugachev and I. Sinitsyn in the form of so-called conditionally-optimal filtering (Pugachev and Sinitsyn, 1987), which provides the non-biased estimation within the class of linear filters with the minimum mean squared error. In this paper we use such filter for the UAV position estimation and give the algorithm for the path planning along with the reference trajectory under external perturbations and noisy measurements.

RANDOM SAMPLE CONSENSUS FOR HOMOGRAPHY

The principal issue in comparison of observed and template images is that they are related by some unknown projective transformation. Generally this transformation is known up to some level of accuracy which is determined by the UAV attitude/position errors. In order to find the correspondence between the cloud of feature points on observed and template images one needs to identify this transformation. So the task is to find a projective transformation (generally the homography matrix H) between two images. To solve this problem the technology of feature points and RANdom SAmple Consensus (RANSAC) (Zuliani et al., 2005) method had been used.

Let $r = \begin{vmatrix} x \\ y \end{vmatrix}$ are the coordinates of feature points in the original plane, $r' = \begin{vmatrix} x' \\ y' \end{vmatrix}$ are the coordinates of feature points in the target plane, and projective transformation has the form

$$h(r) = \begin{vmatrix} \frac{h_{11}x+h_{12}y+h_{13}}{h_{31}x+h_{32}y+h_{33}} \\ \frac{h_{21}x+h_{22}y+h_{23}}{h_{31}x+h_{32}y+h_{33}} \end{vmatrix},$$

where coefficients $h_{i,j}$ depend on the aspect angle and the height of the flight.

Threshold t is a maximum allowed reprojection error which permits to treat a point pair as an inlier. That is, if

$$||r' - h(r)||_2 < t$$

the pair $(r^{'}, r)$ is treated as inlier.

The method finds and returns the projective transformation between the source and the destination planes so that the back-projection error:

$$\sum_{i=1}^{n} ||r_i' - h(r_i)||_2$$

is minimized over set of original three points chosen for determining the transformation $h(r)$.

If not all of the points' pairs fit the rigid projective transformation (that is, there are some outliers) this estimate will be poor. In this case one can use RANSAC. It tries many different random subsets of the corresponding point pairs (of four pairs each) and by using this subset estimates the homography matrix and the explicit formula, and thereby gives the possibility to compute the quality/goodness of the computed homography (which is the number of inliers for RANSAC). The best subset is then used to produce the estimate of the homography matrix and the mask of inliers/outliers.

The computed homography matrix is refined further (using inliers only) with the Levenberg-Marquardt method (Mor, 1978) for stronger decrease of re-projection error.

The RANSAC method can handle practically any ratio of outliers but it needs a threshold to distinguish inliers from outliers. Homography matrix is determined up to a scale. Thus, it is normalized so that $h_{33} = 1$.

CREATION OF A REFERENCE POINT

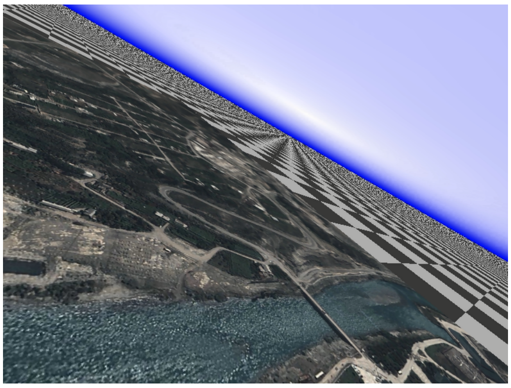

Figure 1: Modeling of frames received by on-board video camera

Figure 1 shows a modelled frame received by on-board video camera. It corresponds to left slot of figure 4. Chess colouring surface corresponds to null data.

At the figure 2 above there is frame I_1 obtained by the camera and below is the map I_2 which is stored in UAV's memory. So one can obtain an estimate of projective transformation between them, that is $I_2 = h(I_1)$. The modified pseudomesurement Kalman filter, which will be used further, requires knowledge of certain reference point on the image I_1, a point with known coordinates. Since projective transformation retains direct lines the point of quadrangle's diagonals' intersection B is projectively invariant. That's why an original point of diagonals' intersection of stored map is chosen as a reference point $A = h^{-1}(B)$.

FILTERING PROBLEM STATEMENT

The problem of the bearing-only filtering is considered to determine the coordinates of UAV which could observe some objects with precisely known coordinates. Of course one can take into account coordinates' errors, but we will do it in further works.

Assumptions:

- The UAV has the standard set of INS devices, which enables to perform the flight with some degree of accuracy which, however, is not enough for the mission completion.
- The UAV control system determines the bearings on the observed reference points with known coordinates. These points determined with the aid of RANSAC algorithm.

Figure 2: Creation of a reference point

- The UAV motion is defined by two angles, namely: $\theta(t)$ (the angle between the projection of velocity to the plane $y0x$ and the axis OX) and $\gamma(t)$ (the angle between the the vector of velocity and the plane $y0x$). We assume the reference motion has the constant linear velocity and varying altitude.

Model of the UAV motion

The model of the UAV motion is described by equation (1) corresponding to so called navigation control level which is important for the path planning in the case of GPS denied environment. This level of simplification is common for navigation control. See (Miller and Miller, 2014a)–(Miller, 2015) and references wherein. We assume 3D UAV motion described by coordinates $(X(t_k), Y(t_k), Z(t_k))$ at times $t_k = k\Delta t, \quad k = 1, 2, \ldots.$. These coordinates satisfy the following equations:

$$\begin{pmatrix} X(t_{k+1}) \\ Y(t_{k+1}) \\ Z(t_{k+1}) \end{pmatrix} = \begin{pmatrix} X(t_k) \\ Y(t_k) \\ Z(t_k) \end{pmatrix} + V\Delta t \begin{pmatrix} \cos\gamma(t_k)\cos\theta(t_k) \\ \cos\gamma(t_k)\sin\theta(t_k) \\ \sin\gamma(t_k) \end{pmatrix} + \begin{pmatrix} W_k^x \\ W_k^y \\ W_k^z \end{pmatrix} \tag{1}$$

where (W_k^x, W_k^y, W_k^z) are uncorrelated random perturbations acting along axis (OX, OY, OZ), having zero means and variances $(\sigma_x^2, \sigma_y^2, \sigma_z^2)$, correspondingly. The controls $\theta(t_k)$ and $\gamma(t_k)$ are the angles between projection of velocity vector on the the plane $y0x$ and the axis OX, and between vector of velocity and the axis OX, correspondingly (see figure 3), these angles define the nominal UAV motion.

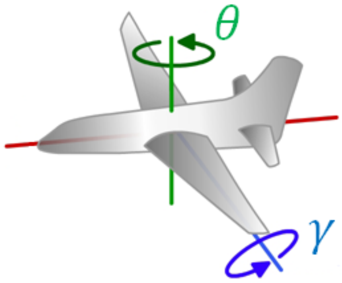

Figure 3: UAV's rotation angles

Measurements

Assume that (X_i, Y_i, Z_i) are the coordinates of i - th reference point and $(\phi_i(t_k), \lambda_i(t_k)$ are the bearing angles on that point. At moment t_k these angles satisfy the relations:

$$\frac{Y_i - Y(t_k)}{X_i - X(t_k)} I_i(t_k) = \tan\phi_i(t_k) + \varepsilon'_k$$

$$\frac{Z_i - Z(t_k)}{\sqrt{(X_i - X(t_k))^2 + (Y_i - Y(t_k))^2}} I_i(t_k) = \tan\lambda_i(t_k) + \varepsilon''_k, \quad (2)$$

where one can assume that $\varepsilon'_k \sim \mathcal{WN}(0, \sigma_1^2)$, $\varepsilon''_k \sim \mathcal{WN}(0, \sigma_2^2)$ are uncorrelated random variables with zero means and variances σ_1^2, σ_2^2, defined as errors in measurement of tangents of angles $\phi_i(t_k), \lambda_i(t_k)$, and forming the white noise sequences.

MODIFIED METHOD OF PSEUDOMEASUREMENTS

Linear measurements model

The idea of the pseudomeasurement method is to separate in (2) the observable and non observable values, which gives the following measurement vector (Miller and Miller, 2014a), (Miller and Miller, 2014b):

$$m_k = \begin{pmatrix} m'_k \\ m''_k \end{pmatrix}$$

$$= \begin{pmatrix} Y(t_k)\cos\phi_i(t_k) - X(t_k)\sin\phi_i(t_k) \\ +\varepsilon'_k(X_i - X(t_k))\cos\phi_i(t_k) \\ \\ Z(t_k)\sin\phi_i(t_k)\cos\lambda_i(t_k) - Y(t_k)\sin\lambda_i(t_k) \\ +\varepsilon''_k(Y_i - Y(t_k))\cos\lambda_i(t_k) \end{pmatrix}. \quad (3)$$

Thereby we obtain the system (3) of linear measurement equations, though the noise variance depends on unobservable coordinates. By using V. S. Pugachev method (Pugachev and Sinitsyn, 1987) one can obtain the unbiased estimation and the variance evaluation with the aid of prediction-correction filter (Miller and Pankov, 2007),(Miller and Miller, 2014a), (Miller and Miller, 2014b).

Prediction-correction estimation

Assume that at the moment t_k we have unbiased estimation $\hat{X}(t_k), \hat{Y}(t_k), \hat{Z}(t_k)$ such that

$$E(\hat{X}(t_k), \hat{Y}(t_k), \hat{Z}(t_k)) = (X(t_k), Y(t_k), Z(t_k)) \quad (4)$$

with the following matrix of the mean-square errors

$$\hat{P}(t_k) = \begin{pmatrix} \hat{P}^{xx}(t_k) & \hat{P}^{xy}(t_k) & \hat{P}^{xz}(t_k) \\ \hat{P}^{xy}(t_k) & \hat{P}^{yy}(t_k) & \hat{P}^{yz}(t_k) \\ \hat{P}^{xz}(t_k) & \hat{P}^{yz}(t_k) & \hat{P}^{zz}(t_k) \end{pmatrix} \quad (5)$$

Problem 1: Get the estimation of the UAV position at time t_{k+1} on the basis of previous estimations $\hat{X}(t_k), \hat{Y}(t_k), \hat{Z}(t_k), \hat{P}(t_k)$, observations $\phi_i(t_{k+1})$, $\lambda_i(t_{k+1})$, known position of i-th observable reference point (X_i, Y_i, Z_i), and known parameters of the motion equations (1) in the interval $[t_k, t_{k+1}]$. In other words one needs to find the unbiased estimations of $(\hat{X}(t_{k+1}), \hat{Y}(t_{k+1}), \hat{Z}(t_{k+1})$ and the matrix $\hat{P}(t_{k+1}))$ on the basis m_k and the motion parameters. These estimates must satisfy (6),(5).

Prediction

The prediction is obtained by assuming that at the moment t_{k+1} the values of $\phi_i(t_{k+1})$ and $\lambda_i(t_{k+1})$ could have been measured

$$\begin{pmatrix} \tilde{X}(t_{k+1}) \\ \tilde{Y}(t_{k+1}) \\ \tilde{Z}(t_{k+1}) \end{pmatrix} = \begin{pmatrix} \hat{X}(t_k) \\ \hat{Y}(t_k) \\ \hat{Z}(t_k) \end{pmatrix}$$

$$+V\Delta t \begin{pmatrix} \cos\gamma(t_k)\cos\theta(t_k) \\ \cos\gamma(t_k)\sin\theta(t_k) \\ \sin\gamma(t_k) \end{pmatrix}$$

$$\tilde{m}_{k+1} = \begin{pmatrix} \tilde{m}'_{k+1} \\ \tilde{m}''_{k+1} \end{pmatrix}$$

$$= \begin{pmatrix} \tilde{Y}(t_{k+1})\cos\phi_i(t_{k+1}) \\ -\tilde{X}(t_{k+1})\sin\phi_i(t_{k+1}) \\ \\ \tilde{Z}(t_{k+1})\sin\phi_i(t_{k+1})\cos\lambda_i(t_{k+1}) \\ -\tilde{Y}(t_{k+1})\sin\lambda_i(t_{k+1}) \end{pmatrix}.$$

Correction

After getting m_{k+1} (more precisely the tangents of angles $\phi_i(t_{k+1})$ and $\lambda_i(t_{k+1})$) one can obtain the estimate of the UAV position at the time t_{k+1}. Therefore, the solution of Problem 1 has a form:

$$\begin{pmatrix} \hat{X}(t_{k+1}) \\ \hat{Y}(t_{k+1}) \\ \hat{Z}(t_{k+1}) \end{pmatrix} = \begin{pmatrix} \tilde{X}(t_{k+1}) \\ \tilde{Y}(t_{k+1}) \\ \tilde{Z}(t_{k+1}) \end{pmatrix}$$

$$+ \begin{pmatrix} \tilde{P}^{xm}(t_{k+1}) \\ \tilde{P}^{ym}(t_{k+1}) \\ \tilde{P}^{zm}(t_{k+1}) \end{pmatrix} (\tilde{P}^{mm}(t_{k+1}))^{-1}(m_{k+1} - \tilde{m}_{k+1}) \tag{6}$$

and the matrix of the mean square errors is equal:

$$\hat{P}(t_{k+1}) = \tilde{P}(t_{k+1})$$

$$- \begin{pmatrix} \tilde{P}^{xm}(t_{k+1}) \\ \tilde{P}^{ym}(t_{k+1}) \\ \tilde{P}^{zm}(t_{k+1}) \end{pmatrix} (\tilde{P}^{mm}(t_{k+1}))^{-1} \begin{pmatrix} \tilde{P}^{xm}(t_{k+1}) \\ \tilde{P}^{ym}(t_{k+1}) \\ \tilde{P}^{zm}(t_{k+1}) \end{pmatrix}^T . \tag{7}$$

Remark 1: The estimates obtained by (6), (7) are unbiased (Miller and Pankov, 2007),(Pugachev and Sinitsyn, 1987) and give the best linear estimates, they are kept constant until measurement at the time $t_{k+1} > t_k$ and they must be updated by formulas (6), (7) at that moment. Of course, these estimates are not equal to the conditional expectations, but they are projections on the set of preceding measurements $m_1, ..., m_k$, therefore, they are orthogonal to the linear space $\mathcal{L}\{m_1, ..., m_k\}$.

CONTROL OF UAV

The problem of the optimal control for system (1) is stochastic one with incomplete information and doesn't have the explicit solution. However, for practical reasons one can simplify it if to consider the locally optimal control. Here we discuss two problems:

Problem 2: Find the locally optimal controls $\gamma(t_k)$ and $\theta(t_k)$ at constant velocity V aimed to keep the motion of UAV along the reference trajectory.

Problem 3: Find the locally optimal controls $\gamma(t_k), \theta(t_k), V(t_k)$ aimed to keep the motion of UAV along the reference trajectory.

Solution of Problem 2

Assuming that we have some reference trajectory $(X_{nom}(t_k), Y_{nom}(t_k), Z_{nom}(t_k))$ we obtain locally optimal controls $\gamma_c(t_k)$ and $\theta_c(t_k)$ on the basis of current estimates $(\hat{X}, \hat{Y}, \hat{Z})$ in order to minimize the deviation from the reference path at the next time moment t_{k+1} (Miller and Miller, 2014a), (Miller and Miller, 2014b):

where

$$\begin{pmatrix} \Delta X(t_k) \\ \Delta Y(t_k) \\ \Delta Z(t_k) \end{pmatrix} = \begin{pmatrix} X_{nom}(t_k) \\ Y_{nom}(t_k) \\ Z_{nom}(t_k) \end{pmatrix} - \begin{pmatrix} \hat{X}(t_k) \\ \hat{Y}(t_k) \\ \hat{Z}(t_k) \end{pmatrix}$$

Solution of Problem 3

We determine velocity $V(t_k)$ and angles $\gamma_c(t_k)$,$\theta_c(t_k)$ on the basis of the current estimates $(\hat{X}, \hat{Y}, \hat{Z})$ in order to minimize the deviation from the reference path on the next step, so the solution of the Problem 3 has a form (Amelin and Miller, 2013), (Miller, 2015):

$$\begin{aligned} &V(t_k) \\ &= \cos\gamma_c(t_k)\cos\theta_c(t_k)\left(\frac{\Delta X(t_k)}{\Delta t} + V\cos\gamma(t_k)\cos\theta(t_k)\right) \\ &+ \cos\gamma_c(t_k)\sin\theta_c(t_k)\left(\frac{\Delta Y(t_k)}{\Delta t} + V\cos\gamma(t_k)\sin\theta(t_k)\right) \\ &+ \sin\gamma_c(t_k)\left(\frac{\Delta Z(t_k)}{\Delta t} + V\sin\gamma(t_k)\right). \end{aligned} \tag{17}$$

While angular controls remain the same as above (15), (16).

SIMULATIONS

At the Fig. 4 there is one of UAV's flight simulation time-step. In the upper left slot there is a modelled frame received by on-board camera. In the upper right slot there is an aerospace map from UAV's memory. Between these two images there are matchings in the form of green line segments. These matchings have been received with the help of feature points method. One can see that they connect the same objects on Earth. In the lower left slot there is a scheme of flight, view of Earth from above. Blue quadrangles signify maps' edges, which are kept in memory; blue dots mean nominal (desired) trajectory; black dots mean real UAV's location (it is affected by noise and control), red signs mean estimate of UAV's own position. The aim of control is to lead the red trajectory to blue ones (squares mean estimates of position, when a reference point has been found, otherwise there are dots). In total, one can see, how control brings red dot's trajectory back to blue ones, however in fact UAV is located on the black trajectory and the upper left slot is being modelled from that very point. On the bottom right slot is the frame received from the on-board camera, but it was projectively converted as if it was map from a UAV's memory. The old map's image is replaced by the new one. One can see, that on both right slots there is one and the same terrain in different survey condition, that visually proves validity of algorithm.

CONCLUSIONS

The usage of this sub-optimal filter provides the good quality of the UAV trajectory estimation. The angular and velocity controls permit to realize the good tracking in the area of bearing-only measurement. However, we do not aim to demonstrate the possibility of good control on the basis of bearing-only observation. Of course, this type of observations must be used with other measurement systems and our results really open the way to the data fusion. The principal reason for this is that we obtain the unbiased UAV position estimate with known mean square

$$\tan\theta_c(t_k) = \frac{\Delta Y(t_k) + V\Delta t\cos\gamma(t_k)\sin\theta(t_k)}{\Delta X(t_k) + V\Delta t\cos\gamma(t_k)\cos\theta(t_k)} \tag{15}$$

and

$$\tan\gamma_c(t_k) = \frac{\Delta Z(t_k) + V\Delta t\sin\gamma(t_k)}{\cos\theta_c(t_k)(\Delta X(t_k) + V\Delta t\cos\gamma(t_k)\cos\theta(t_k)) + \sin\theta_c(t_k)(\Delta Y(t_k) + V\Delta t\cos\gamma(t_k)\sin\theta(t_k))}. \tag{16}$$

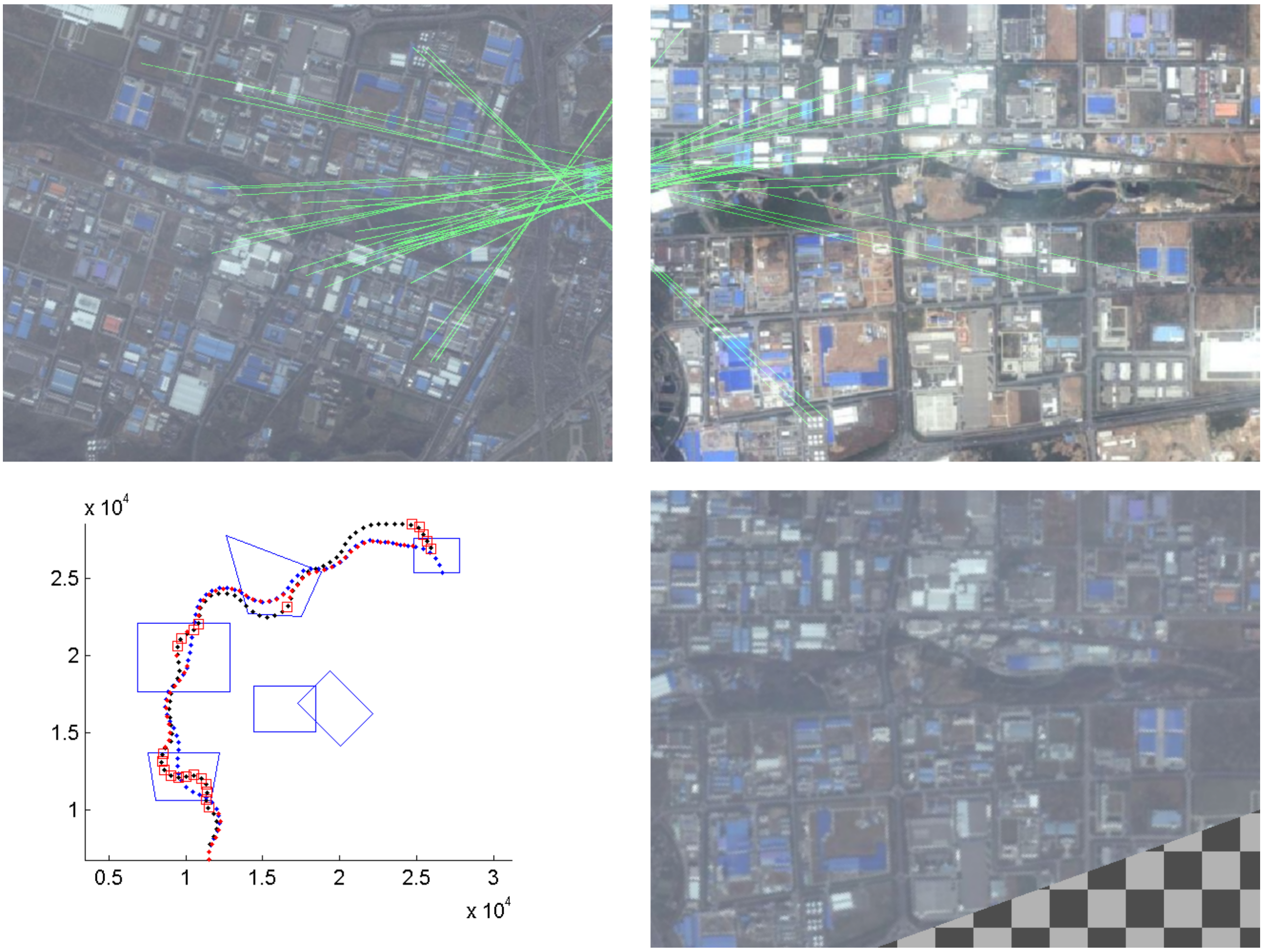

Figure 4: Illustration of the simulation

error. Only both of these properties permit to make the data fusion in an optimal way.

However, another important result had been demonstrated. The usage of the feature points, that are invariant to the scale and the aspect angle, permits to create on-line navigation system based on the observation of underlying surface without the recognition of in advance specified objects. This is the principal advantage of the algorithm, which is extremely important for performance of long-term autonomous UAV missions in dangerous environment.

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AUTHOR BIOGRAPHIES

IVAN A. KONOVALENKO was born in Karasuk, Russia. He studied at the Moscow Institute of Physics and Technology (State University), where he obtained his Master degree in 2014. Since 2014 he is a PhD Student and a Junior Researcher in the Vision Systems Lab. at the Institute for Information Transmission Problems, RAS. His e-mail address is konovalenko@iitp.ru.

ALEAXANDER B. MILLER was born in Krasnogorsk, Russia and went to the Moscow Institute of Physics and Technology (State University), where he obtained his degree in 2008. In 2012 he obtained PhD in the Institute for Information Transmission Problems RAS where he is working till now in the Laboratory of Image Analysis and Processing. His e-mail address is: amiller@iitp.ru and his Web-page can be found at http://iitp.ru/en/users/449.htm.

BORIS M. MILLER was born in Igevsk, Russia, graduated from Moscow Institute of Physics and Technology (State University) in 1974. He obtained PhD in 1978 and doctor of sciences (mathematics) in 1991. Now he is a principal research fellow in IITP RAS, professor. His e-mail address is: bmiller@iitp.ru.

DMITRY P. NIKOLAEV was born in Moscow, Russia. He studied physics, obtained his Master degree in 2000 and Ph.D. degree in 2004 from Moscow State University. Since 2007 he is a head of the Vision Systems Lab. at the Institute for Information Transmission Problems, RAS. His research activities are in the areas of computer vision with primary application to color image understanding. His e-mail address is dimonstr@iitp.ru.