UAV navigation on the basis of video sequences registered by onboard camera *

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Abstract

In recent years navigation on the basis of computation of the camera path and the distance to obstacles with the aid of field of image motion velocities (i.e. optical flow, OF) became highly demanded particularly in the area of relatively small and even micro unmanned aerial vehicles (UAV). Video sequences captured by onboard camera gives the possibility of the OF calculation with the aid of relatively simple algorithms, like Lucas-Kanade. The complete OF is the linear function of linear and angular velocities of the UAV which provides an additional means for the navigation parameters estimation. Such UAV navigation approach presumes that on-board camera gives the video sequence of the underlying surface images providing the information about the UAV evolutions. Navigation parameters are extracted on the basis of exact formulas for OF which gives the description of the observation process for estimation based on Kalman filtering. One can expect the high accuracy of the estimated parameters (linear and angular velocities) because their number is substantially less than the number of measurements (practically the number of the camera pixels).

1. Introduction

Development in optoelectronic devices and the systems of the data transmission leads to usage of optical devices in UAV remote control. In the case of remote control the characteristics of such devices must be coordinated with the properties of the human vision. But during the autonomous flight, when the optical systems work together with on-board computer servicing for objects recognition and their position determination, demands to these devices become different. The function of the optoelectronic system (OES) and on-board computer is the determining of the camera motion as well as observable objects [1] with the aid of their images analysis. There are two approaches in the OES usage. The first one is the extraction and determining of the motion of some specific features of the objects by analogy of the human vision, in this case the metrics of such measurements may be easily implemented in the navigation system. The second one is non metrical analysis by analogy of the insects and birds vision [2]. However, recently it appears the possibility to use so-called optical flow (OF) which contains the information about the camera evolution in the implicit form [3]. The OF may be used for UAVs landing-docking [4], [5], in tracking of various communication lines [6], and even for manoeuvring control [7]. The problem of the image motion is very urgent in the analysis and optimization of OES for air and space observation system, where non compensated image motion leads to the image degradation [8], [9]. The image motion field is non-uniform across the field of view, but depends linearly on the camera motion velocities [10]. The general methodology for image motion field calculation was developed long ago [9], [11]. It gives opportunity to create the navigation sensors. In this work the general procedure for OF calculation as a function of the camera (aircraft) motion velocities had been developed. With the algorithms of the OF calculation on the basis of real video sequence this procedure can serve as the additional navigation sensor for UAV velocities. We intend to use the real measured OF to determine linear and angular velocities which then will

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be incorporated with inertial-navigation system for autonomous UAV control.

2. Optical flow

In this work we use surface-UAV-image model (see Fig. 1) and pinhole camera model (see Fig. 2) described in [12].

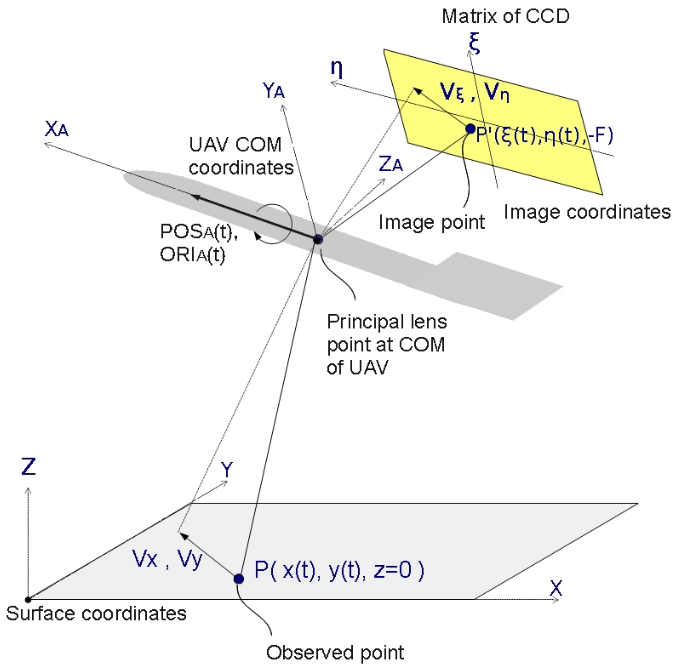

Figure 1. Surface-UAV-image model

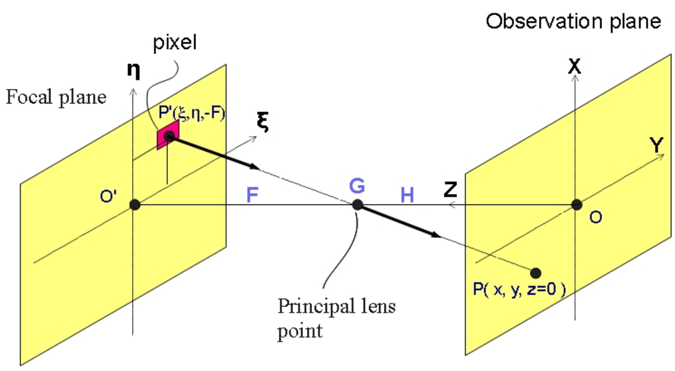

Figure 2. Pinhole camera model

Assume the image point coordinates are $(\xi,\eta,-F)$. From the pinhole camera model one can derive in analytical form the point P coordinates on the observed surface visible to the image point P' as the intersection point of the optical ray passing through principle lens point G and image point P' in conjugate focal plane with surface plane $z=0$ (see Fig. 2). And for the image motion velocities at given image point (ξ,η) we get the following relations [11, 14]

$$\begin{pmatrix} V_\xi \\ V_\eta \end{pmatrix} = -\begin{pmatrix} \frac{\partial x}{\partial \xi} & \frac{\partial x}{\partial \eta} \\ \frac{\partial y}{\partial \xi} & \frac{\partial y}{\partial \eta} \end{pmatrix}^{-1} \begin{pmatrix} \frac{dx}{dt} \\ \frac{dy}{dt} \end{pmatrix} \Bigg|_{\substack{x=x(\xi,\eta,t); \\ y=y(\xi,\eta,t).}} \tag{1}$$

According to the optical flow definition it appears as an image translation, which determines the signal evolution. By observing the sequence of images caused by the camera motion one can get the equation to OF determination. As the result we have got the linear form for $V_x, V_y, V_z, \omega_p, \omega_r, \omega_y$, which can be written as the following matrix equation:

$$\begin{aligned} \begin{pmatrix} V_\xi \\ V_\eta \end{pmatrix} &= D_1(\xi,\eta,t) \begin{pmatrix} V_x \\ V_y \end{pmatrix} + \\ D_2(\xi,\eta,t) &\begin{pmatrix} \omega_p \\ \omega_r \\ \omega_y \end{pmatrix} + D_3(\xi,\eta,t)V_z, \end{aligned} \tag{2}$$

where $(V_x,V_y)^T$ are the linear velocities of the UAV in horizontal directions, $(\omega_p,\omega_r,\omega_y)^T$ are the angular velocities relative to UAV's center of masses (COM), and V_z is the vertical linear velocity of the UAV. So the equations (2) with estimations of the lhs via Lucas-Kanade algorithm [13] give the system of equations for the velocity navigation parameters determination. The resulting system of equations has the sufficient dimension to determine the velocity navigation parameters with high accuracy by least squares algorithm. Thereby, the explicit model of the OF (1), which is joint with the direct estimation of the OF gives the means for the UAV velocities estimation.

The exact matrices D_1, D_2, D_3 depend on the current attitude of the UAV, including position and the angular orientation, which must be estimated either on the basis of the OF or the INS measurements, or both. Here we use the angles estimation obtained from the OF. The great majority of existing works use the set of formulae for zero orientation angles with camera directed in nadir (see, for example, [14, 15]).

3. UAV motion parameters estimation using OF and Kalman filtering

The model of UAV motion is described below, it includes the UAV dynamic model and generic measurements model based on OF estimation of the UAV attitude velocities.

3.1. The UAV linear velocity estimation

The UAV velocity vector $\mathbf{V} = col(V_x, V_y, V_z)$ by coordinates x, y, z:

$$\mathbf{V}(t_{k+1}) = \mathbf{V}(t_k) + \mathbf{a}(t_k)\Delta t + \mathbf{W}(t_k), \tag{3}$$

where t_k is current time, $t_k = t_0 + k\Delta t$, $\mathbf{a}(t_k) = col(a_x, a_y, a_z)$ — the vector of accelerations, $\mathbf{W}(t_k)$ — is vector of the current perturbations in UAV motion. It consists of white noises with variances $(\sigma_x^2, \sigma_y^2, \sigma_z^2)$.

Velocity measurements using OF have the following general form:

$$\mathbf{m}_V(t_k) = \mathbf{V}(t_k) + \mathbf{W}_V(t_k), \tag{4}$$

where $\mathbf{W}_V(t_k)$ — are uncorrelated white noises with variances $(\sigma_{V_x}^2, \sigma_{V_y}^2, \sigma_{V_z}^2)$.

Consider relations (3) and (4) for the velocity along x axis:

$$V_x(t_{k+1}) = V_x(t_k) + a_x(t_k)\Delta t + W_x(t_k),$$

$$m_{V_x}(t_k) = V_x(t_k) + W_{V_x}(t_k).$$

Velocity along x axis estimation on the $k+1$ step:

$$\hat{V}_x(t_{k+1}) = K_x(t_{k+1}) m_{V_x}(t_{k+1}) + (1 - K_x(t_{k+1}))\tilde{V}_x(t_{k+1}),$$

$$\tilde{V}_x(t_{k+1}) = \hat{V}_x(t_k) + a_x(t_k)\Delta t.$$

We should minimize the mean squared of the following:

$$\begin{aligned} &V_x(t_{k+1}) - \hat{V}_x(t_{k+1}) = \\ &\quad (1 - K_x(t_{k+1}))(V_x(t_k) - \hat{V}_x(t_k) + W_x(t_k)) - \\ &\quad K_x(t_{k+1}) W_{V_x}(t_{k+1}). \end{aligned}$$

So we are solving

$$\hat{P}^{V_xV_x}(t_{k+1}) = E[(V_x(t_{k+1}) - \hat{V}_x(t_{k+1}))^2] =$$

$$= (1 - K_x(t_{k+1}))^2 (\hat{P}^{V_xV_x}(t_k) + \sigma_x^2) + (K_x(t_{k+1}))^2 \sigma_{V_x}^2 \to \min_{K_x(t_{k+1})}$$

Here we get the estimation $\hat{V}_x$:

$$\begin{aligned} &\hat{V}_x(t_{k+1}) = K_x(t_{k+1}) m_{V_x}(t_{k+1}) + \\ &\quad (1 - K_x(t_{k+1}))(\hat{V}_x(t_k) + a_x(t_k)\Delta t), \\ &K_x(t_{k+1}) = \frac{\hat{P}^{V_xV_x}(t_k) + \sigma_x^2}{\hat{P}^{V_xV_x}(t_k) + \sigma_x^2 + \sigma_{V_x}^2}, \\ &\hat{P}^{V_xV_x}(t_{k+1}) = \frac{\sigma_{V_x}^2 (\hat{P}^{V_xV_x}(t_k) + \sigma_x^2)}{\hat{P}^{V_xV_x}(t_k) + \sigma_x^2 + \sigma_{V_x}^2}. \end{aligned} \tag{5}$$

The formulae for $\hat{V}_y$ and $\hat{V}_z$ are analogous.

3.2. The UAV angles and angular velocities estimation

UAV angular position estimation is given by three angles $\theta(t_k), \varphi(t_k), \gamma(t_k)$ (pitch, roll and yaw, respectively), angular velocities $\omega_p(t_k), \omega_r(t_k), \omega_y(t_k)$ and angular accelerations $a_p(t_k), a_r(t_k), a_y(t_k)$.

Pitch angle and pitch angular velocity dynamics described by the following relations:

$$\theta(t_{k+1}) = \theta(t_k) + \omega_p(t_k)\Delta t + a_p(t_k)\frac{\Delta t^2}{2},$$

$$\omega_p(t_{k+1}) = \omega_p(t_k) + a_p(t_k)\Delta t + W_p(t_k).$$

where $W_p(t_k)$ — is the white noise with variance σ_p^2.

The pitch angular velocity measurement using the OF has the following form:

$$m_p(t_k) = \omega_p(t_k) + W_{\omega_p}(t_k),$$

where $W_{\omega_p}(t_k)$ — is the noise in the angular velocity measurements using OF, which is the white noise with variance $\sigma_{\omega_p}^2$.

Similarly to the linear velocity estimation we get the pitch angle $\theta(t_k)$ and pitch angular velocity $\omega_p(t_k)$ estimations:

$$\begin{aligned} &\hat{\theta}(t_{k+1}) = \hat{\theta}(t_k) + \hat{\omega}_p(t_k)\Delta t + a_p(t_k)\frac{\Delta t^2}{2} \\ &\hat{\omega}_p(t_{k+1}) = K_p(t_{k+1}) m_p(t_{k+1}) + \\ &\quad (1 - K_p(t_{k+1}))(\hat{\omega}_p(t_k) + a_p(t_k)\Delta t), \\ &K_p(t_{k+1}) = \frac{\hat{P}^{\omega_p\omega_p}(t_k) + \sigma_p^2}{\hat{P}^{\omega_p\omega_p}(t_k) + \sigma_p^2 + \sigma_{\omega_p}^2}, \\ &\hat{P}^{\omega_p\omega_p}(t_{k+1}) = \frac{\sigma_{\omega_p}^2 (\hat{P}^{\omega_p\omega_p}(t_k) + \sigma_p^2)}{\hat{P}^{\omega_p\omega_p}(t_k) + \sigma_p^2 + \sigma_{\omega_p}^2}. \end{aligned} \tag{6}$$

The formulae for $\hat{\varphi}, \hat{\gamma}$ and $\hat{\omega}_r, \hat{\omega}_y$ are analogous.

3.3. Joint estimation of the UAV attitude

So (5) and (6) give the estimation $\hat{\mathbf{V}}$ of the attitude parameters vector, namely:

$$\mathbf{V} = col(V_x, V_y, V_z, \omega_p, \omega_r, \omega_y)$$

This vector measured via OF for each pixel in each frame, which gives according to (2) the overdetermined system of linear equation for $\mathbf{V}$ entries.

Since all noises are uncorrelated the covariance matrix P for $\mathbf{V}$ is diagonal with entries (5),(6).

4. Computation procedure

Here the general computational algorithm for the UAV attitude velocities (linear and angular) has been provided. It is described in natural language in the form of definitions and function-style calls without using notation of a specific programming language. The algorithm consists of the following steps:

1. Initialization step
   - Set UAV current state vector at the moment t_0
     $$\hat{\mathbf{S}}(t_0) : \left(\hat{V}_x, \hat{V}_y, \hat{V}_z, \hat{\omega}_p, \hat{\omega}_y, \hat{\omega}_r, \hat{\theta}, \hat{\varphi}, \hat{\gamma}, \hat{X}, \hat{Y}, \hat{Z}\right)$$
   - Set camera matrix M (see below at Section 5)
   - Set start time t_0 and finish time T
   - Set time step $\Delta t = \dfrac{1}{FPS}$, where FPS is the number of frames per second for the video sample
   - Set Kalman Filter's (see Section 3) values for the first iteration
   - Assign RMS values of measurement error
   - Set constant image dimensions $\overline{\xi}, \overline{\eta}$ of the whole video sequence
   - Define acceleration function $\mathbf{a}(t) = (a_x(t), a_y(t), a_z(t), a_p(t), a_r(t), a_y(t))$
2. Run function that calculates Optical flow field $\overrightarrow{E}^{[\overline{\xi},\overline{\eta}]}(t_{k+1})$ with the aid of Lucas-Kanade algorithm
   $$\overrightarrow{E}^{[\overline{\xi},\overline{\eta}]}(t_{k+1}) = LK(I^{[\overline{\xi},\overline{\eta}]}(t_{k+1}), I^{[\overline{\xi},\overline{\eta}]}(t_k)),$$
   where $I^{[\overline{\xi},\overline{\eta}]}(t_{k+1})$ and $I^{[\overline{\xi},\overline{\eta}]}(t_k)$ are the successive images of the video sequence and the vector field $\overrightarrow{E}^{[\overline{\xi},\overline{\eta}]}(t_{k+1})$ consists of elements described by (1)
3. Run function that solves linear system, described in subsection 3.3, with least squares method using $\hat{\mathbf{S}}(t_k)$ for the current angular attitude and height, and M provides nominators for image coordinates units to metric units transformation
   $$\mathbf{m}(t_{k+1}) = (m_{V_x}, m_{V_y}, m_{V_z}, m_p, m_r, m_y) = LS(\overrightarrow{E}^{[\overline{\xi},\overline{\eta}]}(t_{k+1}), \hat{\mathbf{S}}(t_k), M)$$
4. Run function for calculation of the recurrent Kalman Filter formulae along with covariance matrix P
   $$\hat{\mathbf{S}}^1(t_{k+1}) = (\hat{V}_x, \hat{V}_y, \hat{V}_z, \hat{\omega}_p, \hat{\omega}_r, \hat{\omega}_y) = KF(\mathbf{m}(t_{k+1}), P)$$
5. Run function which integrates estimated velocities with time step Δt
   $$\hat{\mathbf{S}}^2(t_{k+1}) = (\hat{\theta}, \hat{\varphi}, \hat{\gamma}, \hat{X}, \hat{Y}, \hat{Z}) = Euler(\hat{\mathbf{S}}^1(t_{k+1}), \hat{\mathbf{S}}^2(t_k), \mathbf{a}(t_k), \Delta t)$$
6. Renew the estimated state vector
   $$\hat{\mathbf{S}}(t_{k+1}) = \{\hat{\mathbf{S}}^1(t_{k+1}), \hat{\mathbf{S}}^2(t_{k+1})\}$$
7. Make a time step $t_{k+1} = t_k + \Delta t$ and continue from Step 2 until the finish time T reached.

5. Modeling results

This approach was presented in [14], where we demonstrated the possibility to determine the linear and angular velocities for UAV "flying" over the artificial landscape. Here we provide a series of other experimental results based on real video sequence. We run the computation procedure described in Section 4 on the video sequence containing a movie captured by on-board camera from UAV flying at almost constant altitude with almost constant linear velocity as it looks like from the first glance. The data was taken from openly available resource. However the Lucas-Kanade method operates with the pairs of sequential intensity-only frames. Thereby the additional pre-processing step is necessary to convert components of RGB color space values to intensity. In order to work with the video sequence taken by the real camera one needs to evaluate camera matrix M (see, for example [16],[17]). We were able to restore the camera parameters and the initial UAV's height and thereby to measure the OF which gives the information about the real velocities.

5.1. Numerical parameters

To start the computational procedure the following initial conditions were used:

- UAV vector initialization at the moment t_0
  $$\hat{\mathbf{S}}(t_0) : \big(\hat{V}_x = 0m/s, \hat{V}_y = 0m/s, \hat{V}_z = 0m/s, \\ \hat{\omega}_p = 0rad/s, \hat{\omega}_y = 0rad/s, \hat{\omega}_r = 0rad/s, \\ \hat{\theta} = 0, \hat{\varphi} = 0, \hat{\gamma} = 0, \hat{X} = 0m, \hat{Y} = 0m, \hat{Z} = 400m\big)$$
- Initialize the camera matrix M. These values were calculated for the video sample.
  $$M = \begin{pmatrix} 1152,77 & 0,0 & 969,2111 \\ 0,0 & 1150,483 & 535,3755 \\ 0,0 & 0,0 & 1,0 \end{pmatrix}$$
- Set time $t_0 = 10s$, finish time $\bar{t} = 160s, FPS = 25$ frames per second, time step $\Delta t = 0,04s$
- Set $K(t_0)$ corresponding to $\hat{\mathbf{S}}(t_0)$
- Assume these RMS values of measurement error:
  $$\sigma_{V_x} = \sigma_{V_y} = \sigma_{V_z} = 0,3 \quad m,$$
  $$\sigma_{\omega_p} = \sigma_{\omega_r} = \sigma_{\omega_y} = 0,00015 \quad rad,$$
  $$\sigma_x = \sigma_y = \sigma_z = 0,1 \quad m,$$
  $$\sigma_p = \sigma_y = \sigma_r = 0,017 \quad rad$$
- Set image dimensions for full-HD video data $\overline{\xi} = 1920, \overline{\eta} = 1080$

- Acceleration function $\mathbf{a}(t) = \overrightarrow{0}$. We forced to make this assumption due to the lack of the flight telemetry data which could provide the acceleration value series.

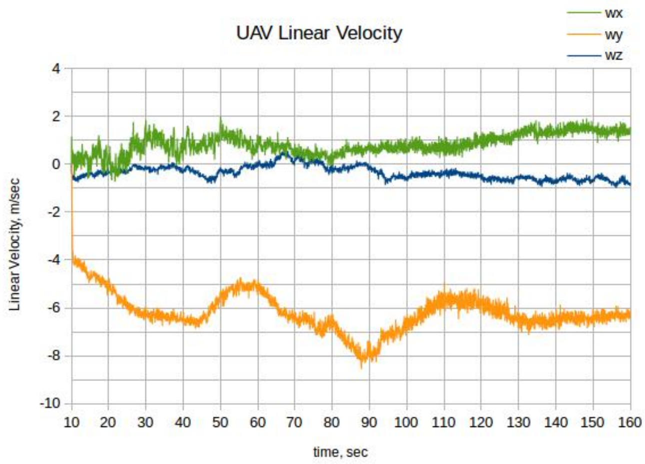

Figure 3. UAV linear velocity estimation by means of the OF sensor

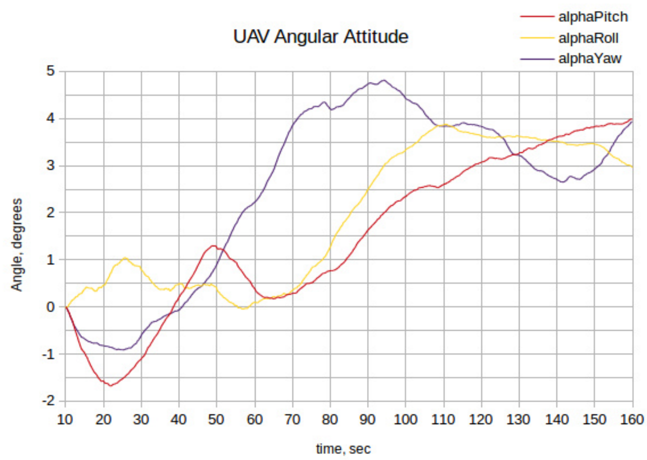

Figure 4. UAV angular attitude estimated using computation procedure

5.2. Discussion

We have compared qualitatively the visual observation of the video sequence with the estimated velocities and coordinates Fig. 3,4,5. It is interesting that OF methodology was able to capture the descent of the UAV (about 50 m), practically indistinguishable by direct visual observation (see Fig. 3) and the side shift (about 100 m) along the whole path (about 1 km). The

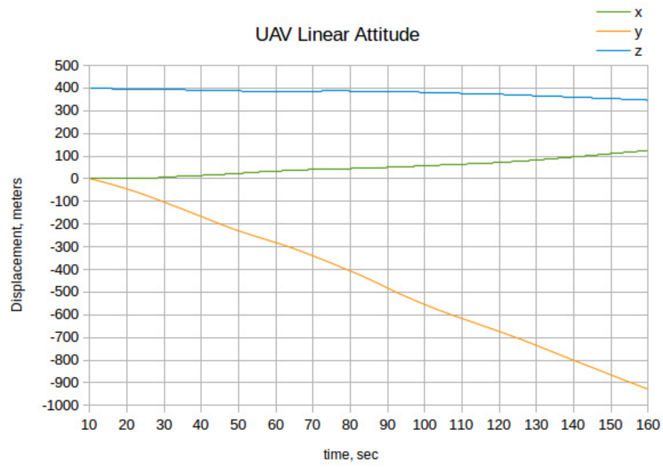

Figure 5. UAV linear attitude estimated using computation procedure

usage of current values of angles, which looks very irregular (see Fig. 4) meanwhile gives very reliable estimation of linear velocities. Therefore the integral displacement of the UAV looks quite linear (see Fig. 5).

6. Conclusion

Most of existing implementations of the OF for UAV navigation relates to indoor applications and intended mainly to avoid the collisions with obstacles. For this reason they need just qualitative behavior of the OF in approaching to walls and other obstacles. In this case they do not need the serious mathematical tools for evaluation of the UAV attitude, just simple formulas related to simple mutual locations. Otherwise, general situation needs more sophisticated algorithms which were provided earlier in [13] and tested here. Future work will be intended to the data fusion of the OF with other optical devices and INS.

As one can see the OF itself gives the possibility to evaluate the linear and angular velocities of the UAV attitude parameters. It is not enough for navigation during the long term autonomous missions since the initial bias in the position and the attitude will grow up. So even if the OF gives rather high accuracy of velocity estimation the intermediate correction might be necessary. Of course the usual way of such correction is the use of GPS, but in the case of GPS denied environment the visual navigation on the basis of terrain landmarks could be possible [18], [19]. Application of landmarks methods needs two complementary approaches developed recently, namely: filtering on the basis of bearing-only observations [19], [20] and recurrent RANSAC for rejection of outliers [21]. The last one had been developed with aid of the pseudo-measurements Kalman filtering (PKF) [22], [23]. The analysis of joint OF and PKF navigation on the basis of the landmarks observation will be the matter of future research. Moreover, the usage of other OF estimations which are different from the Lucas-Kanade method might be more appropriate [24], [25], [26].

References

[1] J. K. Aggarwal and N. Nandakumar, *On the Computation of Motion from Sequences of Images-A Review*, in Proceedings of the IEEE, vol. 76, No. 8, 917–935 (1988).

[2] K. Sebesta and J. B. Baillieu *Animal-Inspired Agile Flight Using Optical Flow Sensing*, 2012 IEEE 51st IEEE Conference on Decision and Control (CDC), Maui, HI, (2012), pp. 3727-3734. doi:10.1109/CDC.2012.6426163

[3] H. Chao and Yu Gu and J. Gross and G. Guo and M. Fravolini and M. Napolitano, *A Comparative Study of Optical Flow and Traditional Sensors in UAV Navigation*, 2013 American Control Conference, Washington, DC, (2013), pp. 3858-3863. doi:10.1109/ACC.2013.6580428

[4] P. Serra and F. Le Bras and T. Hamel and C. Silvestre and R. Cunha: *Nonlinear IBVS Controller for the Flare Maneuver of Fixed-Wing Aircraft using Optical Flow*, 49th IEEE Conference on Decision and Control (CDC), Atlanta, GA, (2010), pp. 1656-1661. doi:10.1109/CDC.2010.5717829

[5] C. McCarthy and N. Barnes *A Unified Strategy for Landing and Docking Using Spherical Flow Divergence*, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 34, no. 5, pp. 1024-1031, May, (2012). doi:10.1109/TPAMI.2012.27

[6] P. Serra and R. Cunha and C. Silvestre and T. Hamel *Visual Servo Aircraft Control for Tracking Parallel Curves*, 2012 IEEE 51st IEEE Conference on Decision and Control (CDC), Maui, HI, (2012), pp. 1148-1153. doi:10.1109/CDC.2012.6426240

[7] Y. S. Liau, Q. Zhang, Y. Li and S. S. Ge, *Nonmetric navigation for mobile robot using optical flow*, 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems, Vilamoura, (2012), pp. 4953-4958. doi:10.1109/IROS.2012.6386221

[8] B. M. Miller and G. I. Fedchenko and M. N. Morskova, *Computation of the image motion shift at panoramic photography*, Izvestia vuzov. Geodesy and aerophotography, No. 4, 81–89 (1984).

[9] B. M. Miller and G. I. Fedchenko *Effect of the attitude errors on image motion shift at photography from moving aircraft*, Izvestia vuzov. Geodesy and aerophotography, No. 5, 75–80 (1984).

[10] B. Miller and E. Rubinovich, *Image Motion Compensation at Charge-coupled Device Photographing in Delay-Integration Mode*, Automation and Remote Control, vol. 68, No. 3, 564–571 (2007). doi:10.1134/S0005117907030162

[11] V. L. Kistlerov and P. I. Kitsul and B. M. Miller, *Computer-aided design of the optical devices control systems based on the language of algebraic computation FLAC*, Mathematics and Comp. Simulation, vol. 33, 303–307 (1991). doi:10.1016/0378-4754(91)90109-G

[12] A. Popov, A. Miller, B. Miller, K. Stepanyan, *Application of the Optical Flow as a Navigation Sensor for UAV*, Proceedings of the 39^{th} IITP RAS Interdisciplinary Conference & School September, 7-11, Olympic Village, Sochi, Russia, pp. 390–398 (2015). ISBN: 978-5-901158-28-9

[13] B. Lucas and T. Kanade, *An iterative image registration technique with an application to stereo vision*, IJCAI'81 Proceedings of 7^{th} International Joint Conference on Artificial Intelligence, Vancouver, Canada, vol. 2, 674–679 (1981).

[14] A. Popov and B. Miller and A. Miller and K. Stepanyan, *Optical Flow as a Navigation Means for UAVs with Opto-electronic Cameras* Proceedings of 56th Israel Annual Conference on Aerospace Sciences, Tel-Aviv and Haifa, Israel, March 9-10, ThL2T5.2 (2016).

[15] Farid Kendoul, Isabelle Fantoni, Kenzo Nonami, *Optic flow-based vision system for autonomous 3D localization and control of small aerial vehicles*, Robotics and Autonomous Systems, Elsevier, (2009), 57 (6-7), pp.591-602. doi:10.1016/j.robot.2009.02.001

[16] Ma, Yi and Soatto, Stefano and Kosecka, Jana and Sastry, S. Shankar, *An Invitation to 3-D Vision: From Images to Geometric Models*, SpringerVerlag, 2003

[17] Forsyth, David A. and Ponce, Jean, *Computer Vision: A Modern Approach*, Prentice Hall Professional Technical Reference, 2002

[18] D. G. Lowe, *Object recognition from local scale-invariant features*, Proceedings of the International Conference on Computer Vision, vol. 2, Kerkyra, Greece, September 20–27, 1150–1157 (1999). doi:10.1109/ICCV.1999.790410

[19] K. S. Amelin and A. B. Miller, *An Algorithm for Refinement of the Position of a Light UAV on the Basis of Kalman Filtering of Bearing Measurements*, Journal of Communications Technology and Electronics, vol. 59, No. 6, 622–631 (2014). doi:10.1134/S1064226914060047

[20] A. B. Miller, *Development of the motion control on the basis of Kalman filtering of bearing-only measurements*, Automation and Remote Control, vol. 76, No. 6, 1018–1035 (2015). doi:10.1134/S0005117915060065

[21] I. Konovalenko and A. Miller and B. Miller and D. Nikolaev, *UAV navigation on the basis of the feature points detection on underlying surface*, Proceedings of 29-th European Conference on Modelling and Simulation, Albena (Varna), Bulgaria, May 26–29, 499–505 (2015). doi:10.7148/2015-0499

[22] S. Karpenko, I. Konovalenko, A. Miller, B. Miller and D. Nikolaev, *Stochastic control of UAV on the basis of robust filtering of 3D natural landmarks observations*, Proceedings of the 39^{th} IITP RAS Interdisciplinary Conference & School September, 7-11, Olympic Village, Sochi, Russia, pp. 442–455 (2015). ISBN: 978-5-901158-28-9

[23] S. Karpenko, I. Konovalenko, A. Miller, B. Miller and D. Nikolaev, *UAV Control on the Basis of 3D Landmarks Bearing-Only Observations*, Sensors, vol. 15, No. 12, 29802–29820 (2015). doi:10.3390/s151229768

[24] J. L. Barron, D. J. Fleet and S. S. Beauchemin, *Performance of Optical Flow Techniques*, International Journal of Computer Vision, vol. 12, No. 1, 43–77 (1994). doi:10.1007/BF01420984

[25] G. Farnebäck, *Fast and Accurate Motion Estimation using Orientation Tensors and Parametric Motion Models* Proceedings of 15th International Conference on Pattern Recognition, vol. 1, Barcelona, Spain, September 3–8, 135–139 (2000). doi:10.1109/ICPR.2000.905291

[26] G. Farnebäck, *Orientation estimation based on weighted projection onto quadratic polynomials* Proceedings of Conference on Vision, Modeling, and Visualization, 89–96 (2000).