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UNMANNED AERIAL VEHICLES TRAJECTORY ANALYSIS CONSIDERING MISSING DATA

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Abstract. Researches very often deal with the problem of missing data. This issue is caused by impossibility of data obtaining, its distortion or concealment. The goal of present paper is to recover missing data and to analyse Unmanned Aerial Vehicles (UAV) trajectory based on the degree of deviation from pre-planned trajectory. The range probability approach is used to assess flight situation. The results of trajectory analysis for real position data of UAV are demonstrated.

Keywords: unmanned aerial vehicle, trajectory, data processing, data recovery, flight situation, spline interpolation.

Introduction

Usage of Unmanned Aerial Vehicle (UAV) has been increasing rapidly not only as an effective way of transport but as a mean of search, rescue, monitoring, collaborative indoor and outdoor surveillance and protection. Moreover, UAV applications include fire-fighting, some level of policing, and support in case of natural disasters, remote sensing, scientific research, and geographical surveying (Harchenko, Prusov 2012). It is commonly acknowledged that development of UAV gives the possibility to perform missions that are too dull, dirty or dangerous for humans (Kharchenko, Prusov 2012). The absence of a pilot on board of UAV introduces additional features related to flight safety involving detection and avoiding of dangerous situations, management and control, communication with air traffic controller and prevention of accidental or unlawful interference (Kharchenko, Kuzmenko 2013).

An aircraft operating without a pilot on board creates a wide range of hazards to civil aviation system. These sources of danger must be identified and threats to safety should be reduced (ICAO 2011).

According to ERSG (2013) and EC (2012) one of the basic principles underlying the integration of UAV, aligned with the principles of ICAO, is that UAV should be considered the same as aircraft with a pilot on board while taking into account UAV specifics. Roadmap offers integration through a phased approach up to 2028 year ensuring appropriate level of safety for all the users of non-segregated airspace.

Errors of UAV measuring equipment (various flight information sensors) can lead to necessity of parameters recovery (Chowdhary, Jategaonkar 2010; George *et al.* 2013; Kharchenko *et al.* 2016). In addition, the frequency of measurements related to flight safety imposes strong requirements for computation time. From another point of view, the approach of UAV data recovery must comply with flight safety requirements and provide the necessary reliability for flight data recovery (Kharchenko *et al.* 2014).

It is known that secure system should allow the presence of risk factors for safety that arise as a consequence of hazards during the operation (Hayhurst *et al.* 2007). As long as risk factors for safety and operational errors are controlled within reasonable limits, this dynamic system is safe. In other words, risk factors for safety and operational errors, which are controlled within reasonable limits are acceptable in inherently safe system. An assessment of UAV risk factors determines the conditions of flight, which in turn requires estimation of flight situation that can be used for UAV trajectory analysis (Hardier, Bucharles 2010; Sujit *et al.* 2013).

Therefore, the goal of the present paper is analysis of UAV trajectory based on the degree of deviation from pre-planned trajectory caused by measurement errors considering flight data recovery.

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1. UAV trajectory analysis

UAV trajectory analysis will consist of the several stages. Initially, flight data processing, missing data detection and its recovery take place. Further, complete UAV parameters are compared with pre-planned set to determine deviation and detect normal or specific UAV flight situation. Existing flight situation plays a key role for predictive control and trajectory analysis.

The principle of UAV trajectory analysis is represented in Figure 1.

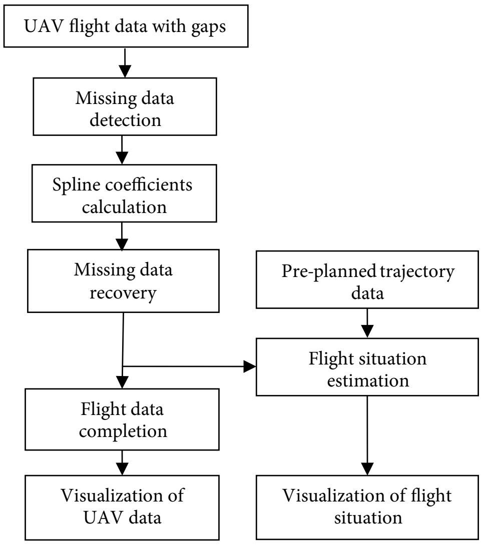

Figure 1. Scheme of UAV flight trajectory analysis

Missing data is detected using health status information of flight parameters. Health status information contains binary data indicating operability of sensors. Detected fault or missing data of some parameter can be recovered using spline interpolation. Spline coefficients calculation for each parameter is applied for the whole set of correlated parameters. Interpolated data compliments the initial data with gaps and composes complete flight data. The set of complete data is compared with pre-planned data with subsequent UAV flight situation estimation. On the final step both complete flight data and UAV flight situation are visualized for operator to be able to make appropriate decision.

2. Flight data processing and recovery

During the flight, a variety of events may affect the operation of UAV. They include faults, or malfunctions, and failures, or complete breakdowns, in flight-critical components, platform damage, faults and failures in information flow, anomalous behaviour or extreme weather.

During the flight, UAV on-board systems exchange the necessary information via the communication network. Let us consider the situation when one of the actuators of a UAV develops a fault. If the control system of the faulty UAV is not equipped with some form of robustness to fault, or if the control system is not capable of providing sufficient recovery to the fault, the vehicle may lose stability and exhibit an unpredictable behaviour.

Faulty aerial vehicles fail to fulfil mission objectives and represent a danger to humans.

Thus, continuous UAV data flow monitoring and its recovery have an extreme importance and is a key challenge for predictive control.

In case of detected missing data of certain parameters, it is proposed to use spline interpolation for data recovery.

There are different approaches for data recovery in case of information faults. Existing methods of data recovery allow choosing the most appropriate one with regard to input data, technical possibilities and aims of research (Allison 2003; Royston 2004; Twisk, De Vente 2002).

In most cases civil UAV are equipped with autopilot system using simple approaches of data recovery such as mean imputation, latest or constant value imputation. Regression approach and other more sophisticated methods are used in advanced UAV.

Usage of spline functions allows to represent discrete values in continuous form and smoothing measurement errors.

Spline approach has several advantages related to its good approximation and algorithmic properties. Based on splines, experimental information that has discrete nature (e.g., the values of a process at different time moments) can be converted to continuous form recorded as a function that approximately reflects a real process.

Using discrete data as an input for various calculations can lead to significant distortion of the result. Spline smoothing in many cases allows transforming initial information to a form suitable for further use.

In comparison with other approaches, spline interpolation has advantage of high processing speed of computations, because spline is a piecewise polynomial function, and at the same time data is processed by a small number of measurement points.

Estimation of control coefficients of spline functions is possible for all correlated parameters. Respectively, all parameters are grouped by certain characteristics and treated separately.

According to the obtained control coefficients of spline functions, missing data can be estimated by interpolation procedure. The estimated results complement the original data and create a complete data of the system.

In general, the matrix of measurements y can be represented as a spline function with certain error:

$$\vec{y}_i = \vec{S}_0(t_i) + \vec{\xi}_i,\ i = 1, 2, \ldots, n, \tag{1}$$

where: $\vec{S}_0(t) = \left[S_0^{(1)}(t),\ \ldots,\ S_0^{(k)}(t)\right]^T$.

The components $S_0^{(j)}(t)$ are cubic C^2-smooth splines with known nodes:

$$\tau_0 = 0 < \tau_1 < \ldots < \tau_N = T.$$

The moments of observations are ordered:

$$t_1 < t_2 < \ldots < t_n < T,\ t_n > \tau_{N-1}.$$

Random errors $\vec{\xi}_i$ are centered:

$$\mathbf{E}\vec{\xi}_i = \vec{0},\ i \geq 1,$$

where: **E** stands for expectation of a random vector; variance-covariance matrix of $\vec{\xi}_i$ is known up to a constant:

$$\mathbf{D}\vec{\xi}_i = \sigma_0^2 \cdot S_i,$$

where S_i is given positive definite matrix and positive factor σ_0^2 is unknown; **D** denotes covariance matrix of a random vector.

We use *B*-splines as algebraic basis in the space of all C^2-smooth splines with fixed nodes. Cubic splines possess good interpolation and approximation properties for UAV data processing and recovery.

Spline expression can be represented as:

$$\vec{S}(t_i) = X^T \cdot \vec{a}_i,\ i = 1, 2, \ldots, n, \tag{2}$$

where: $\vec{S}(t_i)$ is interpolational spline evaluated at moment t_i;

$$\vec{a}_i = \begin{bmatrix} B_1(t_i) \\ B_2(t_i) \\ \vdots \\ B_{N+3}(t_i) \end{bmatrix},\ X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,k} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ x_{(N+3),1} & x_{(N+3),2} & \cdots & x_{(N+3),k} \end{bmatrix};$$

X is $(N+3) \times k$ matrix of control coefficients of the parameters; $\vec{a}_i$ is vector of *B*-splines values calculated by standard Cox–De Boor relation for moment t_i (Ambrosius 2005):

$$B_{j,m}(t) = \frac{t - \tau_j}{\tau_{j+m-1} - \tau_j} \cdot B_{j,m-1}(t) + \frac{\tau_{j+m} - t}{\tau_{j+m} - \tau_{j+1}} \cdot B_{j+1,m-1}(t),$$

where: j is a basic function number, m is a spline function degree.

For example, in Figure 2 spline functions are represented for value $m = 3$ and for period of 200 s.

The expression for control coefficients of spline functions is as follows:

$$vec(X) = \frac{\sum_{i=1}^{n} vec\left(\vec{a}_i \cdot \vec{y}_i^T \cdot S_i^{-1}\right)}{\sum_{i=1}^{n}\left(\left(S_i^{-1}\right)^T \otimes \left(\vec{a}_i \cdot \vec{a}_i^T\right)\right)}, \tag{3}$$

where: *vec* denotes the vectorization operator, which transforms a matrix into a column vector that reads the entries column-wise; $\otimes$ is Kronecker product.

Estimated control coefficients matrix $\hat{X}$ can be obtained by the Weighted Least Squares (WLS) method used in linear regression (Seber, Lee 2003). Based on $\hat{X}$ it is possible to compute the parameter value at any moment t_i by Equation (2).

One of the most important problems in spline interpolation is selection of nodes. Typically, interpolation intervals are equal and the problem is to estimate the optimal mesh width. However, for more precise fitting it is suitable to use non-uniform partitions. In that case, the most appropriate methods of interval calculation are chord length and centripetal methods.

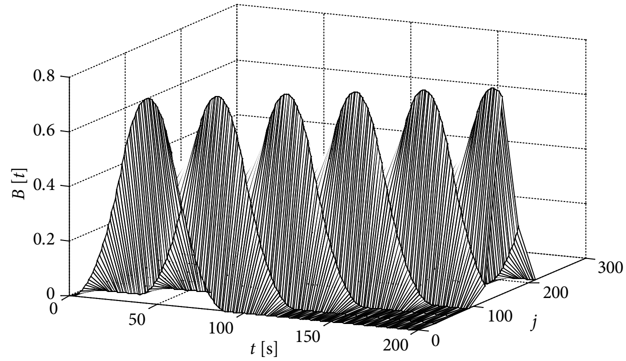

Figure 2. Basic functions of the 3rd degree spline

During the flight, UAV transmits a set of flight data. Usually, it includes all sensors data. One of the most valuable information is UAV position information in specific coordinate system. A UAV position information fault is one of the major hazards during the flight.

In trajectory analysis, the real UAV flight data of *Cessna 350 Corvalis* type was used. The UAV has the following specifications: wingspan – 1450 mm; wing area – 23.3 dm^2; wing loading – 43 g/dm^2, weight – 1020 g; length – 965 mm; electrical engine.

UAV avionics contained flight computer, Global Positioning System (GPS) module, current sensor, airspeed sensor and radio modem with 433 MHz frequency and 10 km range. Positioning accuracy by GPS in horizontal plane was equal to 2.5 m. Baud rate was equal to 19200 b/sec.

The UAV operated with on-board *Panda II* hardware. Flight data were transmitted via radio channel to the Ground Control Station (GCS). GCS consisted of laptop with installed *GCS for Panda II* software and data radio modem equipment. The data were processed in real-time mode by mentioned above software (Figure 3). Its main features include: electronic mapping, telemetry data monitoring, recording and playback of telemetry data, route editing, map loading.

Experimental flight data is a basis for accuracy estimation of trajectory and its analysis. The goal of an experiment was to perform several UAV flights with its flight parameters registration for further data analysis, missing data recovery and trajectory visualization with flight situation estimation. The trajectory of flight plan was considered within line of sight without flight under mountains, settlements or artificial constraints.

The flight contained the following stages:
– take off in manual mode;
– climb in stabilization mode;
– automatic flight in navigation mode;
– stabilization mode before landing;
– landing on the surface.

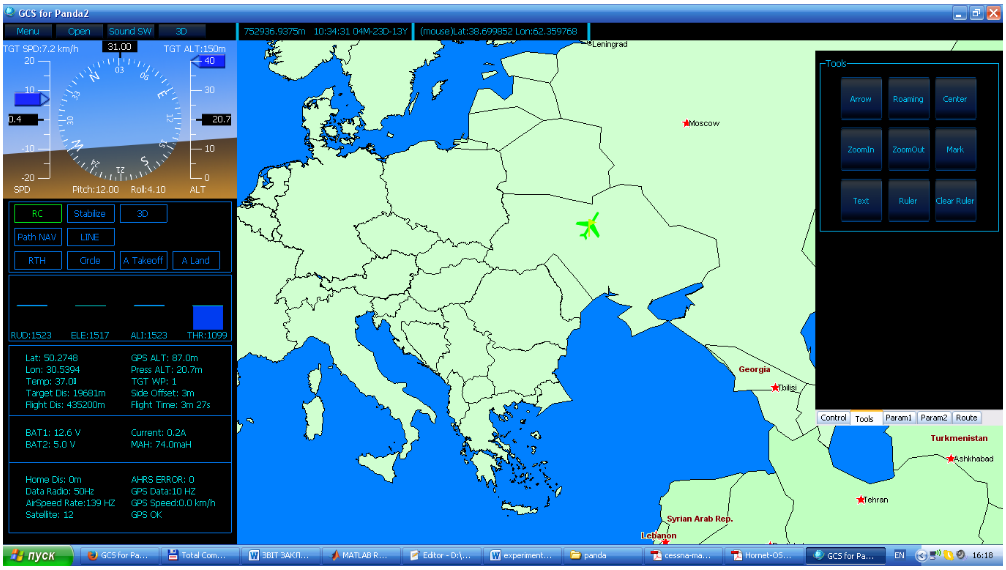

Figure 3. Representation of *GCS for Panda II* interface

An automatic mode of the flight was performed with negligible wind component by pre-planned trajectory shaped as "eight" (Figure 4).

Real UAV trajectory data are represented in local North-East-Down (NED) coordinate system. Coordinates are represented as a distance from the starting point in meters in Figure 5 indicated by stars. *Z*-axe has downside direction.

During the fault simulation, data of some short time interval were missing. The fault period was randomly chosen to be the interval from 128 to 148 s of flight time. Data of the fault period was recovered using interpolational spline (Equation (2)). The results of recovery are represented in Figures 6–8 by stars.

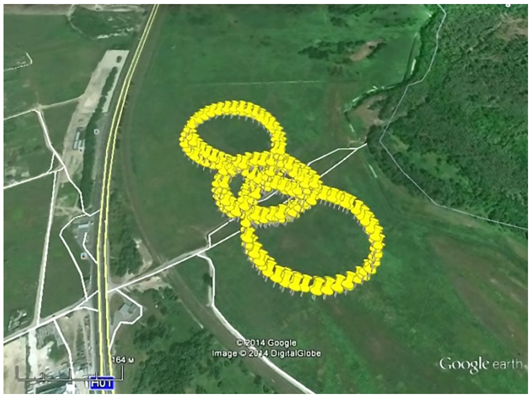

Figure 4. UAV flight trajectory

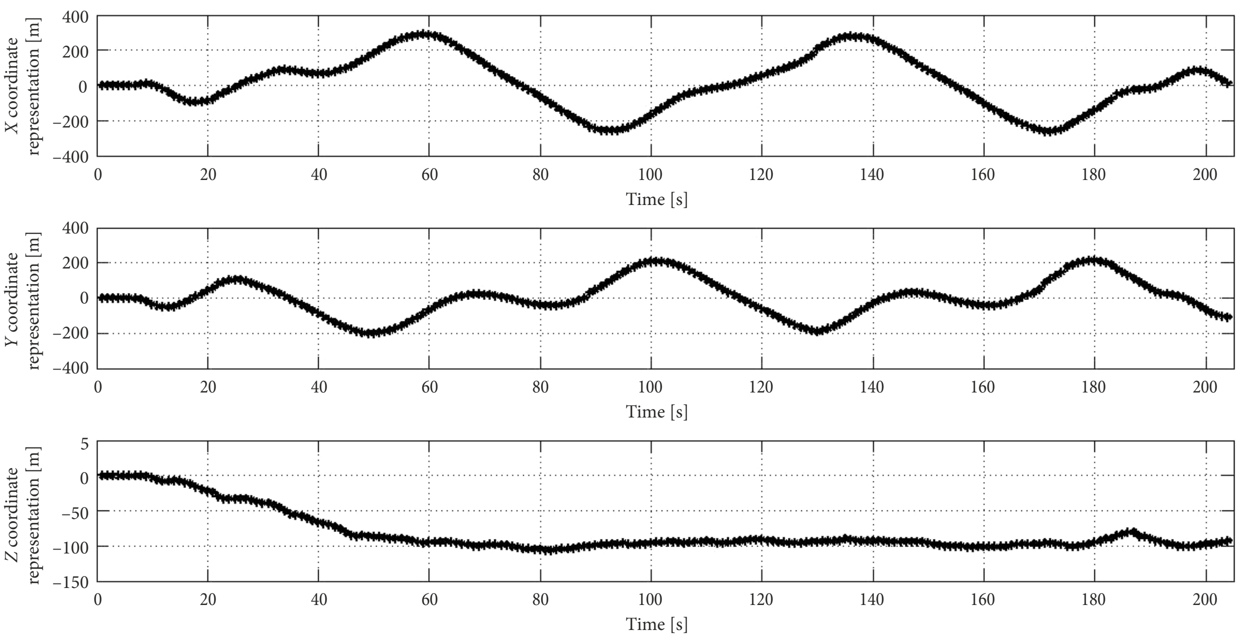

Figure 5. UAV position coordinate representation

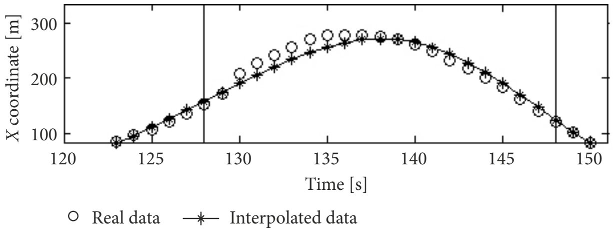

Figure 6. *X*-coordinate spline interpolation

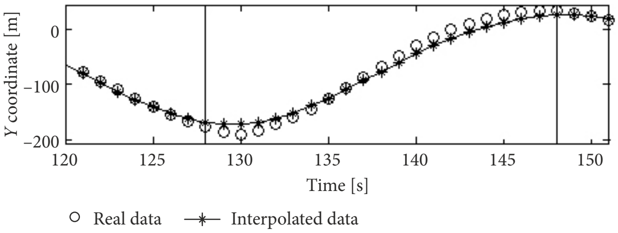

Figure 7. *Y*-coordinate spline interpolation

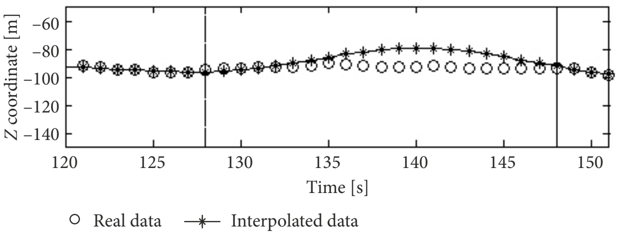

Figure 8. *Z*-coordinate spline interpolation

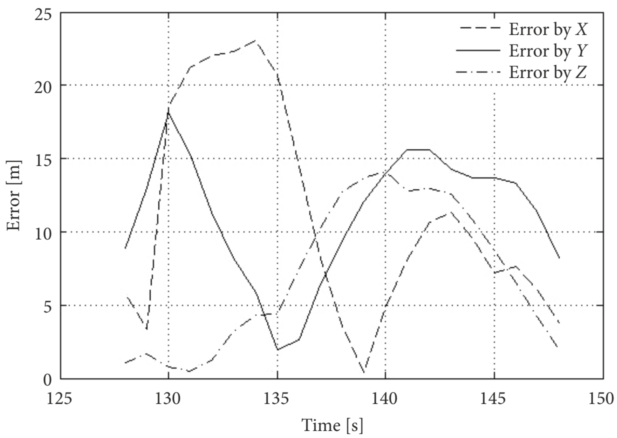

Figure 9. Spline interpolation errors of position data

Spline interpolation errors of position data are shown in Figure 9. Maximal error value is less than 23 m. In comparison with other previously mentioned statistical approaches, spline approach provides better data accuracy and fitting (Kanchana, Thanamani 2014).

Adverse weather conditions, worsening of positioning accuracy, system faults and ground systems failures can lead to various intervals of UAV data loss. These factors determine the stochastic nature of lost data recovery. Flight interval of missing data is a typical example of random factors that affect the flight. The prolonged absence of data and mutual loss of several parameters can cripple the safety of flight.

3. UAV flight situation estimation

Safe UAV flight largely depends on the presence, duration and number of risk factors. If the effect of risk factors is missing or the result of their action does not affect the safety of flight and makes no threat to people, then it is possible to assume that such requirements correspond to normal flight conditions. The latter conditions are the key to successful implementation of UAV flight.

However, during the flight UAV operates in real airspace interacting with technical systems, and depends on the human factor. All these issues create conditions for the appearance of a range of risk factors that adversely affect the safety of air traffic and may cause a specific situation of flight (Harchenko *et al.* 2007; Ostroumov *et al.* 2007). The latter situation is a result of hazards affect and makes a significant impact on safety of flight.

A specific situation is characterized with a deviation of UAV parameters from the planned values. However, since the UAV parameters are measurements from various flight information sensors, an indispensable component in assessing the current flight situation is consideration of measurement errors. Typically measurement errors are distributed normally. Thus, to identify a specific situation of flight it makes sense to use $2 \cdot \sigma$ rule that meets the requirements of safe flight execution objectives by Performance Based Navigation, approved by the ICAO and are necessary for the implementation for all airspace users (ICAO 2008).

According to the $2 \cdot \sigma$ rule, the measurement error in 95.4% of cases is realized in the range $\pm 2 \cdot \sigma$ from the true value of the measured parameter, where σ is a standard deviation of measurement error.

An important step in estimation of parameters missing values is to construct confidence intervals that allow assessing the UAV flight situation with underlying confidence probability.

The main criterion for flight situations construction takes into account the deviation from the requirements of UAV flight. Thus, the flight task should include a set of planned values of the parameters, that are fixed before the flight regarding all its complexities and peculiarities.

In order to construct confidence intervals it is proposed to use some of coordinates k_1, rather than all of them. For this purpose a $k_1 \times k$ matrix P is used, that cuts the required values from the prediction results:

$$P = \begin{bmatrix} 1 & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \cdots & 1 & 0 & \cdots & 0 \end{bmatrix}.$$

The restricted prediction results are:

$$P \cdot \hat{\vec{S}}(t) = P \cdot \hat{X}^T \cdot \vec{a}(t). \quad (4)$$

The covariance matrix of the estimated values for the cut parameters (Equation (4)) can be represented in vectorised form:

$$\mathbf{D}\left(P\cdot\hat{\vec{S}}(t)\right)=\mathbf{D}\left(\vec{a}(t)^T\otimes P\right)\cdot\left(vec\left(\hat{X}^T\right)\right), \quad (5)$$

where:

$$vec\left(\hat{X}^T\right)=\frac{\sum_{i=1}^{n}\left(\left(\vec{a}_i\otimes S_i^{-1}\right)\cdot vec\left(\vec{y}_i\right)\right)}{\sum_{i=1}^{n}\left(\left(\left(\vec{a}_i\cdot\vec{a}_i^T\right)\otimes S_i^{-1}\right)\right)}.$$

Covariance matrix of $vec\left(\hat{X}^T\right)$ is:

$$\mathbf{D}vec\left(\hat{X}^T\right)=\sigma_0^2\cdot\frac{\sum_{i=1}^{n}\left(\vec{a}_i\otimes S_i^{-1}\right)\cdot S_i\cdot\left(\vec{a}_i\otimes S_i^{-1}\right)^T}{\left(\sum_{i=1}^{n}\left(\left(\left(\vec{a}_i\cdot\vec{a}_i^T\right)\otimes S_i^{-1}\right)\right)\right)\cdot\left(\sum_{i=1}^{n}\left(\left(\left(\vec{a}_i\cdot\vec{a}_i^T\right)\otimes S_i^{-1}\right)\right)\right)^T},$$

it can be denoted that:

$$H=\frac{\sum_{i=1}^{n}\left(\vec{a}_i\otimes S_i^{-1}\right)\cdot S_i\cdot\left(\vec{a}_i\otimes S_i^{-1}\right)^T}{\left(\sum_{i=1}^{n}\left(\left(\left(\vec{a}_i\cdot\vec{a}_i^T\right)\otimes S_i^{-1}\right)\right)\right)\cdot\left(\sum_{i=1}^{n}\left(\left(\left(\vec{a}_i\cdot\vec{a}_i^T\right)\otimes S_i^{-1}\right)\right)\right)^T}.$$

Then:

$$\mathbf{D}vec\left(\hat{X}^T\right)=\sigma_0^2\cdot H. \quad (6)$$

The Equation (5) is transformed taking into account Equation (6):

$$\mathbf{D}\left(P\cdot\hat{\vec{S}}(t)\right)=\sigma_0^2\cdot\left(\vec{a}(t)^T\otimes P\right)\cdot H\cdot\left(\vec{a}(t)^T\otimes P\right).$$

It is also denoted that:

$$\Phi=\left(\vec{a}(t)^T\otimes P\right)\cdot H\cdot\left(\vec{a}(t)^T\otimes P\right)^T,$$

then:

$$\mathbf{D}\left(P\cdot\hat{\vec{S}}(t)\right)=\sigma_0^2\cdot\Phi. \quad (7)$$

From Equation (7) we get:

$$\sigma_0^2=\Phi^{-1}\cdot\mathbf{D}\left(P\cdot\hat{\vec{S}}(t)\right). \quad (8)$$

A random variable is introduced:

$$\hat{Z}=\left(P\cdot\hat{\vec{S}}(t)-P\cdot\vec{S}_0(t)\right)^T\cdot\Phi^{-1}\cdot\left(P\cdot\hat{\vec{S}}(t)-P\cdot\vec{S}_0(t)\right). \quad (9)$$

Let us suppose that measurement errors in $P\cdot\hat{\vec{S}}(t)$ have normal distribution. Then Equation (9) is proportional to chi-square distributed random variable:

$$\hat{Z}\sim\sigma_0^2\cdot\chi_{k_1}^2. \quad (10)$$

A standard WLS estimator of σ_0^2 is distributed as:

$$\hat{\sigma}^2\sim\frac{\sigma_0^2\cdot\chi_m^2}{m},\ m=N-k\cdot(n+3)>0. \quad (11)$$

Taking into account stochastic independence of $\hat{Z}$ and $\hat{\sigma}^2$ (Seber, Lee 2003), we have from Equations (10) and (11) that:

$$\frac{\hat{Z}/k_1}{\hat{\sigma}^2}\sim\frac{\chi_{k_1}^2/k_1}{\chi_m^2/m}=F_{k_1,m}. \quad (12)$$

where: $F_{k_1,m}$ denotes a random variable that has Fisher's distribution with k_1 and m degrees of freedom.

Based on Equation (12) the confidence region for the true values $P\cdot\vec{S}_0(t)$ is as follows:

$$E=\left\{P\cdot\vec{S}_0(t)\cdot R^{k_1}:\frac{\hat{Z}}{k_1\cdot\hat{\sigma}^2}\le F_{k_1,m}^{\alpha}\right\}. \quad (13)$$

where: α is the confidence probability; $F_{k_1,m}^{\alpha}$ the quantile of Fisher's distribution, with:

$$\mathbf{P}\left\{F_{k_1,m}>F_{k_1,m}^{\alpha}\right\}=\alpha.$$

In order to assess the flight situation we use the deviation of UAV parameters from the planned values. Let a vector of planned parameter values at the control moment t be:

$$z(t)=\begin{bmatrix} z_1(t) \\ z_2(t) \\ \vdots \\ z_{k_1}(t) \end{bmatrix},\ t\in[0,T]. \quad (14)$$

Denoting:

$$I=\left(P\cdot\hat{\vec{S}}(t)-z(t)\right)^T\cdot\Phi^{-1}\cdot\left(P\cdot\hat{\vec{S}}(t)-z(t)\right).$$

According to Equations (13) and (9) the confidence region can be constructed as:

$$E=\left\{z(t)\in R^{k_1}:\frac{I}{k_1\cdot\hat{\sigma}^2}\le F_{k_1,m}^{\alpha}\right\}. \quad (15)$$

The condition for the normal flight situation is:

$$z(t)\in E.$$

To establish different ranges of flight situations it is possible to introduce scaling factor $\eta\ge1$, which enlarges the confidence region (Equation (15)):

$$E_\eta=\left\{z(t)\in R^{k_1}:\frac{I}{k_1\cdot\hat{\sigma}^2}\le\eta^2\cdot F_{k_1,m}^{\alpha}\right\}. \quad (16)$$

A statistic is introduced in the following manner:

$$\Lambda=\frac{\left(P\cdot\hat{\vec{S}}(t)-z(t)\right)^T\cdot\Phi^{-1}\cdot\left(P\cdot\hat{\vec{S}}(t)-z(t)\right)}{k_1\cdot\hat{\sigma}^2\cdot F_{k_1,m}^{\alpha}}. \quad (17)$$

The computed value (Equation (17)) displays the information of existing flight situation range.

Relation $\Lambda\le1$ corresponds to normal flight situation. In case of dual flight situations (i.e., normal and specific situations), for the selection of threshold $\eta_1=1$, the probabilistic approach was used. The confidence probability $\alpha_1=0.95$ was chosen.

In case of multiple situations, thresholds designation can be calculated as a ratio of two Fisher's distribution quantiles as follows:

$$\eta_i^2 = \frac{F_{k_1,m}^{\alpha_i}}{F_{k_1,m}^{\alpha_1}}. \quad (18)$$

The comparison of the statistic Λ with thresholds (18) determines the flight situation. α_i represents the confidence probability for *i*-th class of flight situation.

Results of coordinate deviation calculation from the pre-planned trajectory (Figure 10) represents sharp increase after 200 s. UAV flight situations (normal and specific) representation including coordinate deviation from the flight plan is shown in Figure 11. The situation is changed from normal to specific after 200 s that is explained by increase of coordinate deviation from the flight plan. Figure 11 illustrates normal situation up to 200 s and specific situation after 200 s as the statistics Λ exceeds 1.

Conclusions

Spline approach is a universal tool for processing and recovery of parameters with the help of computer-based techniques. UAV position data recovery with the help of spline approach is quite accurate (Figure 9).

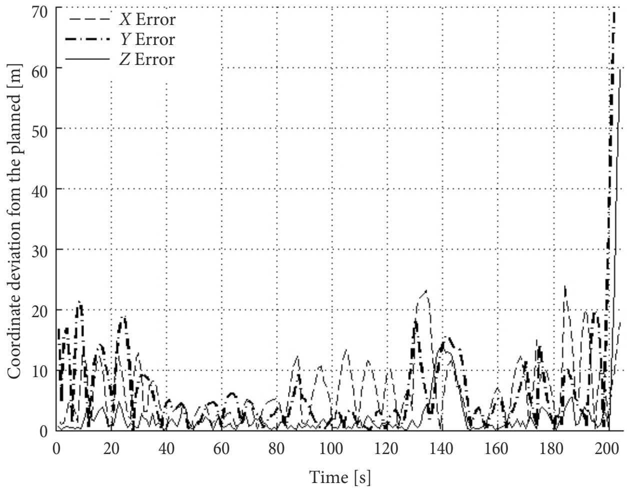

Figure 10. Results of coordinate deviation calculation

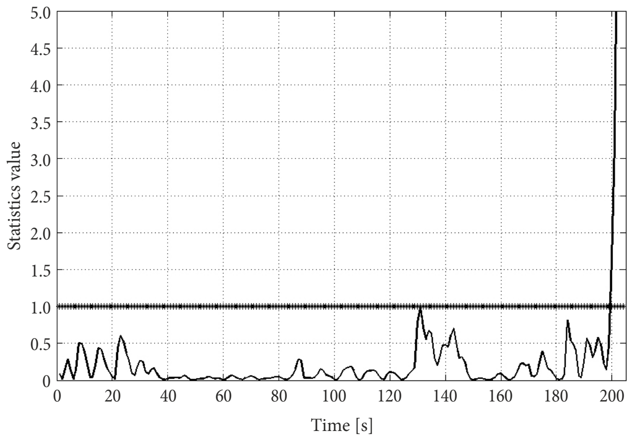

Figure 11. Flight situation representation

An assessment of UAV risk factors determines the conditions of flight, which in turn requires estimation of flight situation for trajectory analysis. The approach for estimation of normal and specific situations with different confidence probabilities was represented for real UAV flight data, based on the degree of deviation from the pre-planned trajectory caused by measurement errors and flight data recovery.

During experimental flight, the UAV had to fly by planned trajectory, which had been defined by a set of points in airspace. After take-off, the UAV was guided automatically by specific mode of on-board autopilot system. During automatic mode the UAV should have passed predefined trajectory. In 200 s the UAV guidance mode was changed to manual and the UAV was guided out from pre-planned trajectory. This deviation was made to check algorithm of flight situation estimation. Rapid increase of coordinates deviation from pre-planned trajectory (represented in Figure 10) was detected based on statistic (Equation (17)) and selected threshold value. Detection of flight situation (Figure 11) demonstrates the shift of flight situation from normal to specific one. In addition, detection of the UAV flight situation based on statistics regards errors of sensors and is more accurate than simple calculation of deviation from planned trajectory considering flight safety aspect.

Proposed approach for missing data recovery represents quite good results of recovery, and its errors have no significant impact on statistic Λ and on flight situation estimation correspondingly.

The represented approach for trajectory analysis can be used to increase situation awareness and to ensure predictive control of UAV.

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