Improving the efficiency of visual navigation of an unmanned aerial vehicle by choosing the most informative route

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ABSTRACT:
The problem of estimating the coordinates of unmanned aerial vehicles (UAVs) using visual navigation in the absence of satellite navigation signals is considered. The UAV has a camera pointing towards the underlying surface to adjust its position using correlation algorithms. It is assumed that the UAV can choose one of several alternative route options as part of the implementation of the target task. The aim of the study is to increase the effectiveness of visual navigation by choosing a route with maximum information content. When assessing the information content, it is proposed to take into account the size and shape of the correction areas that can be observed during flight along the appropriate routes, based on the predicted density of the distribution of errors in measuring the coordinates of the UAV. During the flight, this estimate can be updated at any time when new information is received. An adaptation of the algorithm for calculating information content for the task under consideration is proposed. As an example, the flight of a UAV with a known model accumulation of an error in determining its coordinates, loaded with a table of landmarks and a correction system is considered. Model calculations show that the proposed approach can significantly increase the probability of correctly estimating the coordinates of the UAV compared to a random choice of route. It should be noted that the estimated informative value of the routes is the average predicted value. Specific implementations can produce results that differ significantly from the calculated averages, however, the proposed algorithm allows to adapt the assessment of informativeness using new information.

1. Introduction

Currently, navigation (UAVs) is carried out mainly on the basis of global navigation satellite systems (GNSS). However, this approach leads to a known dependence of the UAV on the presence of a satellite constellation, which is a serious limitation for operation in certain areas of the earth, premises or conditions of active jamming of the satellite signal. Visual navigation methods are used to correct the operation of the inertial navigation system (INS) (Semenova, 2018), which is the core of the UAV navigation system, in the absence of satellite signals (Geng and Chulin, 2017).

The complexity of the implementation of visual navigation is associated with the uneven information content of the navigation fields used, observation conditions that can reduce the observability of navigation landmarks, etc. In some cases, the use of visual navigation may be ineffective due to the lack of landmarks by which the coordinates of the UAV can be unambiguously estimated or insufficient observability of landmarks that do not allow them to be detected or identified (recognized).

We will assume that the most important required attributes of visual landmarks, which can be assessed by their informativeness, include:
- observability is a property that provides the ability to detect and identify a landmark;
- uniqueness is a property that ensures the elimination of ambiguity in estimating the coordinates of the UAV when tied to a found landmark.

The purpose of this work is to increase the probability of making a correct reference to the terrain in conditions of limited visibility of the underlying surface by choosing a route over sections containing the most informative landmarks.

2. The methodology of route selection based on the assessment of useful information

Let's assume that the UAV can choose one of *N* routes on which it is possible to implement visual navigation and adjust the estimate of its own coordinates. The current uncertainty of the position of the UAV in horizontal coordinates *X0Y* is determined by the known (in particular, according to the passport data of the INS) error distribution density $p(x, y, t)$, where t is the flight time without correction of the INS.

It is required to determine the route (out of *N* possible ones), the flight along which will ensure the maximum probability of estimating the coordinates of the UAV using visual navigation with the required accuracy Δx, Δy.

Let's denote, *S* is the surface area in *X0Y*, on which the probability of the presence of a UAV is close enough to one, $\Delta s = \Delta x \Delta y$ is the area of the surface area that determines the required accuracy of estimating the coordinates of the UAV. Since the uncertainty zone of the UAV position is limited by the area *S*, and the required accuracy , the number of possible sites (positions of the UAV in *S*), in which it is required to determine the coordinates of the UAV, it is equal to:

$$M = \frac{S}{\Delta s}. \tag{1}$$

Suppose there are *K* different types of landmarks on the routes. The total amount of useful information during flight along the n - th route (informative route) about the desired coordinates of the UAV can be calculated based on entropy (Shannon and Weaver, 1949). Entropy has previously been used for route planning in work (Kim et al., 2019).

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Then the expression of informativeness when observing all possible landmarks is equal to:

$$I_n = H(m) - H(m|U_n) = -\sum_{m=1}^{M} P(m) log_2 P(m) + \sum_{l=1}^{M} P(l) \sum_{m=1}^{M} \sum_{k=1}^{K} P(U_{nk}|l) P(m|U_{nk}) \, log_2 P(m|U_{nk}), \quad (2)$$

where I_n - informative value of the route n;
m, l - sections of the M-possible area S;
$H(m)$ - a priori entropy of the UAV position;
$H(m|U_n)$ - a posteriori entropy of the presence of an object on the area m;
U_{nk} – information about the landmark k obtained on the n-th route;
$P(m), P(l)$ - the probability of the presence of UAVs in the areas m, l, respectively;
$P(U_{nk}|l)$ - conditional probability of receiving information U_{nk} about the k-th landmark of K in the presence of the l-th object;
$P(m|U_{nk})$ - the a posteriori probability of the presence of an object on the area m, provided that U_{nk}.

A priori probabilities $P(m)$ can be determined from a known density $p(x, y, t)$, when fixed t.

Probabilities $P(m|U_{nk})$ determines the uniqueness of the k-th landmark on the nth route, because when $P(m|U_{nk}) = 1$ specific outcome or position of the UAV is uniquely determined with the required accuracy. $P(m|U_{nk})$ is determined by the Bayes formula. To calculate the descriptions of landmarks in the form of a conditional probability $P(U_{nk}|m)$ It is proposed to use an algorithm based on a normalized correlation coefficient.

Conditional probability $P(U_{nk}|l)$ determines the observability of the k-th landmark on the l-th section of the n-th route.

The informative nature of the route I_n shows how much the initial uncertainty (entropy) of the UAV position decreases $H(m)$ when the UAV passes along route n and receives the corresponding image of the underlying surface (a posteriori entropy $H(m|U_n)$). The proposed approach allows to choose a route that provides the maximum amount of useful information in terms of estimating the coordinates of the UAV.

It should be noted that the estimated informative value of the routes is the average predicted value. Specific implementations when receiving current images may produce results that differ significantly from the calculated averages. Also note that formula (2) is valid only for one route point and to analyze the entire route, it must be recalculated iteratively for each point.

Figure 1 shows a fragment of the flowchart of the general UAV control algorithm associated with choosing the most informative route.

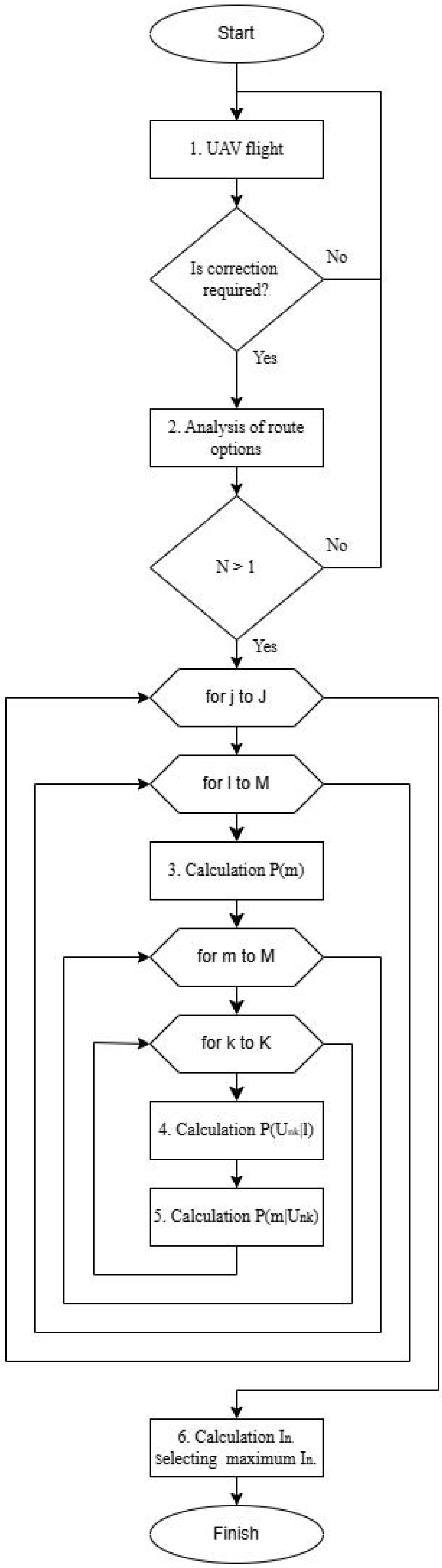


Figure.1. Route selection algorithm

During the flight (Fig. 1, block 1), the condition "Is correction required?" is checked. If the coordinate estimation errors exceed the permissible ones and there is no correction from GNSS, then a transition to visual navigation mode is necessary.

The analysis of possible route options for the most known position is carried out based on the downloaded library of landmarks (Fig. 1, block 2). If there are no alternative route options (N = 1), then there is only one possible route option. In the case when (N > 1), it is necessary to implement the procedure for choosing the most informative route.

A priori probabilities of the actual realization of the location of the UAV on the area m (Fig. 1, Block 3) are determined from a known density $p(x, y, t)$, when fixed t, by integrating the function within each of the M sections.

To calculate the conditional probability (Fig. 1, block 4), it is necessary to obtain information about the k-th landmark. The information can be interpreted as some description of the k-th landmark, in particular, its visual feature or a set of features. Descriptions of landmarks can be implemented in various ways. In particular, in raster, vector, and semantic. One of the most common options for descriptions is a description in the form of raster images of individual terrain areas or landmarks. For identification, the stored reference images are compared with the received current images using correlation algorithms, for example, a normalized correlation coefficient. The values of the extremes of the correlation function show the degree of similarity of the current and reference images. In practice, there are often many local extremes, among which there is both the desired landmark and a landmark with a sufficient degree of similarity. This fact creates the need for a correct interpretation of the results of correlation algorithms in such a way that allows we to obtain either a single extreme or a probabilistic assessment of the correspondence of each extreme to the true reference point.

To calculate the a posteriori probability (Fig. 1, Block 5), a similar calculation of conditional probability is used, followed by the application of the Bayes formula.

In the presented article, it is proposed to use this algorithm to assess the informativeness of the compared UAV routes. At the final stage of calculations (block 6), the information content I_n of each route is calculated. The best route is selected according to the maximum value of information content.

3. Experiments and Results

As an example, an autonomous UAV flight option (without using GNSS) with a video camera installed on board and a visual navigation system based on the calculation of a normalized correlation coefficient (Forssyth and Ponce, 2003) is considered to compare the reference and current images of the underlying surface. There is a preloaded table of landmarks (reference images) on board.

In the article (Pazychev and Sadekov, 2020), the authors explore the possibility of modeling the coordinate and velocity errors of the IMU 500, IMU 501 sensors. The authors calculated the standard deviation (STD) of the coordinate error, which corresponds to 15811 and 2012 meters for each sensor, respectively, during a flight of 11000 seconds. According to the work (Instrument Laboratory Team, 2021), the coordinate error is a quadratic dependence on time. Then the function of the dependence of the coordinate in meters on the elapsed time is equal to:

$$\begin{gathered} \mathrm{STD}_{IMU_{500}}(t) = \frac{15811 * t^2}{11000^2} = 0.00013 * t^2, \\ \mathrm{STD}_{IMU_{501}}(t) = \frac{2012 * t^2}{11000^2} = 0.00000166281 * t^2. \end{gathered} \tag{3}$$

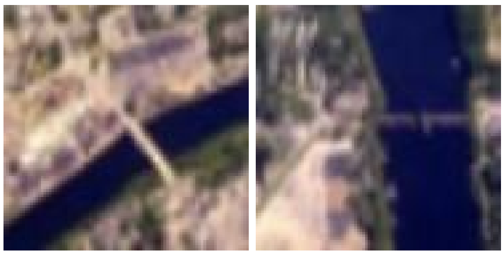
In this paper, the flight of an airplane-type UAV is considered. Let's assume that the UAV is moving uniformly at a constant speed of 10 meters per second. The flight altitude for the simulation is chosen such that 1 pixel of the coordinate grid represents a distance of 20 meters. Then the speed of the UAV is 0.5 pixels per second. Let's rewrite the equation in pixels and through the distance traveled $length$ in pixels:

$$\begin{gathered} length = 0.5 * t, \\ \mathrm{STD}_{IMU_{500}}(length) = 0.00052 * length^2, \\ \mathrm{STD}_{IMU_{501}}(length) = 0.00000665124 * length^2. \end{gathered} \tag{4}$$

Let's assume that the density $p(x, y, t)$ cit corresponds to the normal distribution law with zero mathematical expectation and a known standard deviation (for example, take $\mathrm{STD}_{IMU_{500}}$).

$$p(x, y, t) \sim N(0, \mathrm{STD}_{IMU_{500}}(t)) . \tag{5}$$

Consider a moment in time $t = 0$, when UAV first lost the GNSS signal. At this point in time, it is necessary to analyze possible routes. Based on the table of landmarks, the current position of the UAV and the coordinates of the end point of the route, we will build a graph of possible routes. In this work, bridges over the river are used as landmarks. The corresponding images of the landmarks are shown in Fig. 2, (a) and Fig. 2, (b).



(a) (b)
Figure. 2. Images of landmarks.

Since two landmarks are used, we will consider three route options in total: flying towards each of the landmarks or flying to the end point without attempting correction. In accordance with the sequence shown in Fig. 1, we will calculate the probabilities for each of the 3 routes. We will make a model calculation for each point of the route $\mathrm{STD}_{IMU_{500}}$. For the subsequent algorithm, we will consider a scattering ellipse with boundary values $\pm \mathrm{STD}_{IMU_{500}}$. Routes with scattering ellipses and overlaying on the terrain map are shown in Fig. 3.

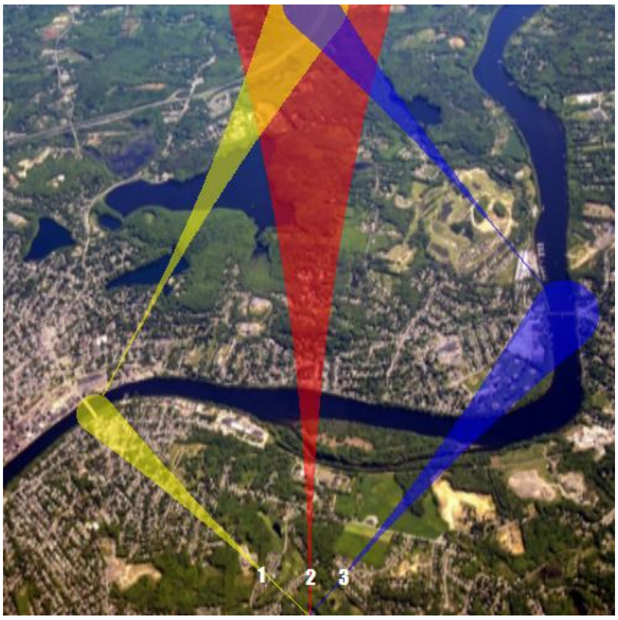


Figure.3. Route options with scattering ellipses

It is worth noting that in case of reaching the landmarks, the UAV corrects its position. As a result, at the end point, the route will have the greatest possible error in determining the coordinates of the UAV without visiting the correction areas.

In the future, at each point of the route, the resulting scattering ellipse will be divided into m sections based on (in this article Δs = 500 meters, that is, 25 pixels). For each m-th section, we obtain an a priori probability $P(m)$ integrating the probability density. An example of the output probability density is shown in Figure 4.

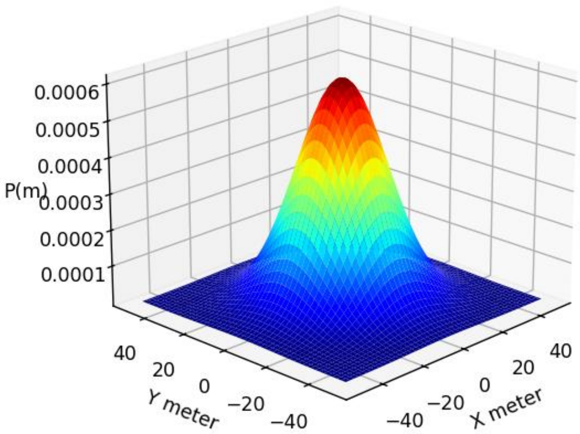


Figure. 4. Probability density of the second route at the end of the trajectory.

As mentioned earlier, the estimates $P(U_{nk}|l)$ they are formed using a correlation algorithm. At the same time, the conditional probability $P(U_{nk}|l)$ determines the uniqueness of the objects that allow we to uniquely link the UAV to the terrain. Let's define the conditional probability as follows (6).

$$P(U_{nk}|l) = \frac{1}{K_n}, \tag{6}$$

where K_n is the number of peak values of the correlation function.

The number of peaks is determined using the threshold value of the correlation function, equal to 0.9. For simplicity, we divide the original image with a size of 500 by 500 pixels into identical areas Δs and make sure that the selected landmarks are unique. Examples of the obtained correlation functions with a threshold for areas with landmarks are shown in Fig. 5 and Fig. 6.

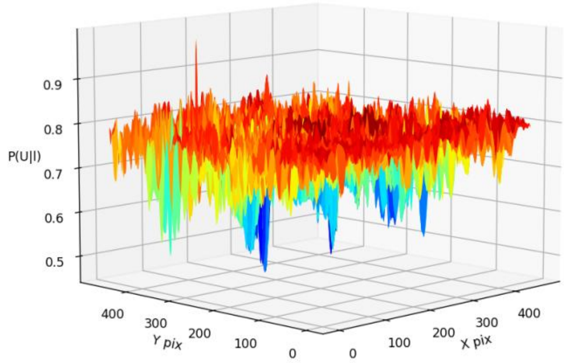


Figure. 5. Correlation function with threshold cutoff for the first reference point

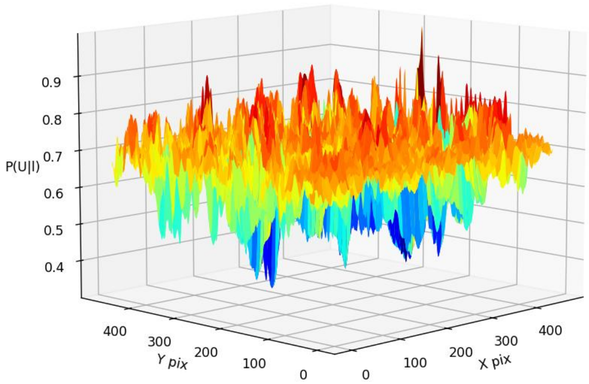


Figure. 6. Correlation function with threshold cutoff for the second reference point

As we can see on the graphs of correlation functions, when applying the threshold value, the absolute majority of false positives are filtered, which indicates the uniqueness of the selected landmarks. At the same time, if the landmark is located beyond the boundary of all the currently analyzed areas l the probability takes the form (7)

$$P(U_{nk}|l) = 0. \tag{7}$$

After analyzing equation (2), we note that in the case when the conditional probability takes a zero value, the final entropy, due to its nature, also takes the value zero. As a result, the information content in this area will be maximum, which, however, does not give an understanding of the location of the UAV, but gives an understanding of where the UAV is not located. Also, as noted earlier, formula (2) is valid for one route point, but by itself it does not analyze the entire route. To eliminate the disadvantages described above, we modify equation (2) into equation (8).

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$$\begin{cases} I_n = \sum_{j=1}^{J} (H(m) - H(m|U_n)), \\ P_{check} = \sum_{m=l}^{M} \sum_{k=1}^{K} P(U_{nk}|l), \\ P_{apos}(l,m,k) = P(U_{nk}|l)P(m|U_{nk}) * log_2 P(m|U_{nk}), \\ H(m|U_n) = \begin{cases} H(m) & if\ P_{max} > 0, \\ \sum_{l=1}^{M} P(l) \sum_{m=1}^{M} \sum_{k=1}^{K} P_{apos}(l,m,k) & otherwise \end{cases} \end{cases} \quad (8)$$

where $j = 1 \dots J$ - the points that make up the route *n*;
P_{check} = checking for the presence of at least one landmark within the analyzed areas;
$P_{apos}(l,m,k)$ - auxiliary parameter for more compact recording;

In the future, an assessment is carried out for each route I_n according to formula (8). Note that this estimate can be carried out at any time *t*. Thus, when new information is received (for example, fog detection during the route), this estimate can be clarified. Simulation results at the moment $t = 0$ are shown in Table 1.

n	1	2	3
H(m)	553.24	613.355	541.449
$H(m\|U_n)$	545.749	613.355	521.74
I_n	7.49084	0	19.7094
$D_n[m]$	12403.1	10020	13082.1
$\mathrm{STD}_{finish}[m]$	1221.12	2610.41	829.325

Table 1. Simulation results.

where $D_n[m]$ - the distance of the route in meters;
$\mathrm{STD}_{finish}[m]$ - error at the end of the trajectory in meters.

After analyzing Table 1, we note that route number 2 is a route without correction and it has the largest final trajectory error. However, at the same time it is the shortest, which can be critical in certain tasks. Route number 3 has the least error at the end of the trajectory. It is also the most informative and longest of the routes.

Since it is assumed that the choice of a route without the presented algorithm occurs randomly, we calculate the average error at the end of the trajectory in meters (9)

$$\mathrm{STD}_{rand} = \frac{1221{,}12 + 2610{,}41 + 829{,}325}{3} = 1553{,}619. \quad (9)$$

Compare the result (9) with the most informative route we obtain a measure of the effectiveness of the proposed method for the example under consideration (10)

$$\text{Effectiveness} = \frac{1553{,}619 - 829.325}{1553{,}619} * 100\% = 46{,}61. \quad (10)$$

Effectiveness (10) shows that choosing a trajectory using an algorithm, compared with randomly choosing a trajectory, reduces the error by an average of 46,61%.

Thus, model calculations show that the proposed approach can significantly increase the probability of correctly estimating the coordinates of the UAV compared to a random choice of route. The assessment of the informative value of the route allows us to take into account the most important attributes of landmarks and choose the route where it is possible to obtain the greatest amount of useful information. It should be noted that this formula gives predictive averages. Specific implementations can give both better and worse results compared to the calculated ones. Also, this formula does not take into account such important parameters as the duration (distance) of the route and can be used as an additional criterion for choosing an effective route.

4. CONCLUSIONS

1. In this paper, a methodology for choosing a route based on an assessment of useful information was proposed.
2. 2. As an example, a variant of a UAV flight with a video camera loaded with a table of landmarks and a video navigation system based on the use of a normalized correlation function is considered.
3. A modification of the formula for calculating information content for the task under consideration, taking into account its specifics, has been made.
4. The simulation results showed a decrease in error by an average of 46.6% at the time of reaching the end point of the route on average.
5. The proposed algorithm is adaptable depending on changes in the density of the probability distribution of errors in measuring the coordinates of the UAV.
6. As part of improving the effectiveness of the proposed approach, it is proposed to consider alternative methods of visual navigation. And also consider options for taking into account critical route parameters, such as distance.

5. ACKNOWLEDGEMENTS

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