Support subspace method and conforming estimation in autonomous navigation tasks

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Abstract. The article discusses the technology of autonomous navigation by optical observations. A scheme based on the recognition of three-dimensional landmarks is considered. To improve the accuracy and reliability of recognition, a survey model is constructed for each landmark. When calculating the parameters of this model, the most conformed data is selected. The problem of recognition is solved using the method of support subspaces. Support subspaces are formed from a set of vectors of each reference landmark. An important advantage of the technology is the ability to refine the landmark models based on the results of current observations during operation.

1. Introduction
The task of autonomous navigation is to determine the parameters of the movement of the center of mass of the aircraft by natural or specially created landmarks. It is conducted with measuring the spatial characteristics of landmarks and parameters of the aircraft movement on-board sensors [1]. Consequently, the main task of on-board navigation aids is to recognize and determine the spatial position of landmarks, which is a typical pattern recognition task.

Nowadays the autonomous navigation based on optical observations is increasingly being used in the space industry. This is evidenced by the publications of recent years. The work [2] shows that in modern technological capabilities it is possible to effectively use the lunar center and lunar landmarks for optical autonomous navigation in a vicinity of the Moon and Earth. Article [3] proposes an integrated navigation scheme, which uses both optical observations and one-way Doppler measurements. It has been shown that integrated navigation errors are reduced when the optical observation target is Mars. The work [4] demonstrates that the spacecraft can move autonomously in far space using only optical navigation measurements. In particular, it is shown the problem can be solved on the assumption that at least two asteroids are observed simultaneously. All-weather aircraft navigation based on optical observations has been used for decades in take-off and landing procedures [5], [6]. However, the autonomous aircraft navigation using optical observations of the underlying surface of the Earth has not yet found wide application. This is due to objective difficulties.

The images of objects are changing significantly depending on the direction of the light source and the viewing angle, the parameters of the recording devices, etc. In particular, depending on the viewing angle, can be obtained significantly different images of the three-dimensional object used as a reference. The creation and storage of reference images for all possible motion parameters and observation conditions (angles, lighting, scale, etc.) is practically impossible even with a relatively small number of landmarks. In addition, navigation based on optical observations is impossible in the cause of heavy clouds, fog and smoke.
Therefore, in recent years, the main efforts of researchers have been aimed at the new methods, algorithms and technologies creation about navigation along with three-dimensional landmarks, which are formed by both optical and other means of observation. It is evident that in this way there is possible to increase the reliability of detection and identification of landmarks with a significant reduction in the number of reference landmarks copies been stored. However, other difficulties appear in this approach. In this case, the main problem is the formation of three-dimensional models of current landmarks, intended for comparison with reference ones. These three-dimensional models should be formed from different views 2D images obtained in the vicinity of the expected landmark.

A large number of methods and algorithms for image recognition are known. Usually, researchers consider the following main groups of methods: methods based on the analysis of contours and descriptions; neural network methods and methods based on comparison with the reference image. Within the framework of the first two directions, impressive results of recognition accuracy have been obtained, but these methods require a lot of effort and time consumption at the training stage. At the same time, navigation systems usually characterized by high requirements for speed and reliability of decision making. In addition, it is important to be able to quickly turn on previously prepared landmarks, as well as quickly form new landmarks on the routes.

This article deals with methods and algorithms within the framework of the paradigm based on comparison with the reference image. In this main direction, the authors have formulated and over the past few years have studied the effectiveness of the methods of support subspaces [7] and conforming estimation [8] at a number of image processing and analysis problems. This article presents the results related to the application of these methods and algorithms in autonomous navigation systems. The main attention is paid to the problems of recognition and formation of three-dimensional landmarks models by current images of different views.

2. Problem formulation
We are considering the navigation task using three-dimensional landmarks. Three-dimensional landmark models are presented as height values that characterize the shape of technogenic objects and/or relief of natural landmarks at the specified points of underlying surface. We will refer to these landmark models as height maps. Thus, in a three-dimensional case, the vector components which are formed from two-dimensional image of a landmark, unfolded in rows or columns, correspond to the relief heights or man-made objects used as landmarks. The three-dimensional landmarks navigation technology on can be represented in the form shown in Figure 1.

![Figure 1. Navigation technology by 3D-landmarks.](image-url)
The initial data for building a three-dimensional model are 2D images of the Earth's surface, obtained from various angles. The technology for constructing a three-dimensional terrain model contains several stages: image rectification; determination of the corresponding points in two or more images of the same terrain and determination of three-dimensional coordinates. For the coordinate referencing of objects on the ground, an imaging model (shooting model) is required. This model should be built for terrain areas in the vicinity of each landmark. In essence, this is the training stage is of the technology which form a three-dimensional terrain model in the landmark vicinity.

A three-dimensional terrain model can be constructed using images with different views. These images possible cover a significant area in the vicinity of the proposed landmark. Therefore, the resulting heightmap can have dimensions that significantly exceed the projection dimensions of the landmark on the local horizon plane. To reduce the search time and improve the reliability of a landmark recognition on a heightmap, it is necessary to localize the landmark area on the current image.

Localization of the landmark image fragments is an important problem, the solution of which has a large (sometimes decisive) impact on the recognition accuracy. We use the approach suggested by the authors in [7]. In this method, the "centers of gravity" of the brightest areas of the images are combined. These bright areas correspond to the highest altitudes of the landmarks. Due to the limited scope of this article, we will not discuss this issue in detail and send the reader to the paper [7] mentioned above.

The final stage of the technology is the recognition of the landmark been localized on the heightmap. Since the heightmap is represented as the normalized brightness samples, this task can be reduced to the known task of the image recognition.

Among the described technology there are two main stages: image rectification and search for the corresponding points in the images for which we use standard procedures [9]-[11]. This article proposes methods and algorithms for implementing the following steps: construction of the image registration model, 3D terrain model construction, landmark localization and landmark recognition. The arguments for the detailed development of methods and algorithms for the implementation of the above stages were as follows. We want to increase the speed and reliability of the landmark recognition. In addition, we aim to provide the ability to quickly generate reference images of landmarks during a navigation system process.

3. Construction of the image registration model

The sensor model is necessary at the stage of the coordinate georeferencing of objects on the ground. The most popular is the polynomial model of the aircraft camera, which establishes a relation between the geodetic coordinates of an object and its coordinates on the image using the rational polynomial coefficients (RPCs). To build this model, it is necessary to specify a small number of so-called ground control points in the observation area with known geodetic coordinates and object-space coordinates.

The sets of the required RPC coefficients are the parameters of the satellite camera image formation model [12]:

\[ Y = a^T u / b^T u \quad (1) \]
\[ X = c^T u / d^T u . \quad (2) \]

Here \( Y, X \) are the normalized coordinates of an image point:
\[ Y = (y - Y_o) / Y_s , \quad X = (x - X_o) / X_s , \quad (3) \]

where \( y, x \) are the pixel coordinates of the row and column, respectively, \( Y_o, X_o \) are the normalized offset parameters, and \( Y_s, X_s \) are the normalized scaling parameters.

The vector \( u \) is composed of various degrees (usually, up to the third degree inclusive) of the three-dimensional point coordinates \( (P, L, H) \) obtained by normalizing the corresponding geodetic point \( (\phi, \lambda, h) \):
\[ P = (\varphi - \varphi_0) / \varphi_3, \quad L = (\lambda - \lambda_0) / \lambda_3, \quad H = (h - h_0) / h_3. \]

where \( \varphi, \lambda, h \) are the latitude, longitude and altitude, respectively, \( \varphi_0, \lambda_0, h_0 \) are normalized offset parameters and \( \varphi_3, \lambda_3, h_3 \) are the normalized scaling parameters.

Without loss of generality, consider the simplest case of a first-order model. In this case, the vector \( \mathbf{u} \) has the form

\[
\mathbf{u} = [1, L, P, H]^T. \tag{5}
\]

The task is to determine the parameter estimates \( a^*_1, b^*_1, c^*_1, d^*_1, a^*_b, b^*_b, c^*_b, d^*_b \) from the known three-dimensional coordinates of the ground control points \( (P, L, H) \) and the corresponding observed normalized coordinates \( Y, X, Y, X \) on the images of a different view.

Since relations (1), (2) differ only in the indices of the parameters, only equation (1) is considered below. For one \( i-\text{th} \) reference point (according to the normalization conditions, the coefficient \( b_0 = 1 \)), equation (1) can be represented as

\[
Y' + Y' \begin{bmatrix} \mathbf{b}^T \mathbf{u}' \end{bmatrix} = \mathbf{a}^T \mathbf{u}, \tag{6}
\]

where \( \mathbf{b}^T = [b_1, b_2, b_3], \mathbf{u}' = [L, P, H]^T, \mathbf{a}^T = [a_0, a_1, a_2, a_3] \).

Let us transfer the term \( Y' \begin{bmatrix} \mathbf{b}^T \mathbf{u}' \end{bmatrix} \) from the left side of equation (6) to the right side. Further, taking into account the designations of the vector components \( \mathbf{b}', \mathbf{u}', \mathbf{a}, \mathbf{u} \), we rewrite equation (6) in the form

\[
Y' = a_0 + a_1L + a_2P + a_3H - b_1LY' - b_2PY' - b_3Y'H, \tag{7}
\]

For the \( N \) control points, in accordance with equation (7), the matrix equation can be written

\[
\mathbf{Y} = \mathbf{MJ} + \xi, \tag{8}
\]

where

\[
\mathbf{M} = \begin{bmatrix}
1 & L_1 & P_1 & H_1 & -Y_1L_1 & -Y_1P_1 & -Y_1H_1 \\
1 & L_2 & P_2 & H_2 & -Y_2L_2 & -Y_2P_2 & -Y_2H_2 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
1 & L_N & P_N & H_N & -Y_NL_N & -Y_NP_N & -Y_NH_N
\end{bmatrix},
\]

\[
\mathbf{J} = \begin{bmatrix}
a_0, a_1, a_2, a_3, b_1, b_2, b_3
\end{bmatrix}^T, \quad \mathbf{Y} = \begin{bmatrix}
Y_1, Y_2, \ldots, Y_N
\end{bmatrix}^T,
\]

and \( \xi = [\xi_1, \xi_2, \ldots, \xi_N]^T \) is the vector of errors reduced to the output of the model, associated with errors in the order of the model, inaccurate assignment of three-dimensional geodetic coordinates and errors in measuring the coordinates of control points on a real two-dimensional image.

In accordance with equation (8), the least squares estimate of the parameters of the rational functional model, composed of the sought RPC coefficients, has the form:

\[
\hat{\mathbf{J}} = (\mathbf{M}^T\mathbf{M})^{-1}\mathbf{M}^T\mathbf{Y}. \tag{9}
\]

Note that the number of observations used to find estimate (9) is usually small, moreover, in some observation cases, the matrix \( \mathbf{M}^T\mathbf{M} \) may be ill-conditioned. Therefore, large errors in the RPC-coefficient estimates are possible, even with small errors in the initial data. To improve the accuracy, we propose an iterative consistent estimation algorithm that eliminates gross errors.

The idea of the method consists in the iterative elimination of “bad” observations from the initial system so that at each iteration the dimension of the system decreases by one [13]. As applied to system
(1), (2), this means that at each iteration one row is excluded from the original system. The problem is
to find the "worst" string in the absence of a priori information about errors.
At each step, one, and moreover, non-repeating row is excluded from the original system. As a result,
from the original system (1), (2) we obtain a set of \(N\) subsystems with \((N-1) \times M\) dimension each.
On each \((i-th)\) subsystem, subsystems of the dimension \(M \times M\) are formed by cyclic shift along the
lines and the estimate \(\hat{c}_{i,j}, i=1,N-1\) is calculated. Further, for each subsystem with the \((N-1) \times M\)
dimension, the conformity function is calculated:

\[
W(l) = \frac{2}{N(N-1)} \sum_{j \neq i}^{N} \| \hat{c}_{i,j} - \hat{c}_{i,j} \|, \tag{10}
\]

where \(\| \hat{c}_{i,j} - \hat{c}_{i,j} \|\) is the Euclidean distance of one pair of estimates from all possible pairwise
combinations of \((N-1)\) estimates, which can be obtained in a \(k\) lower-layer subsystem. The most
conformed subsystem \(\hat{l}\) on a high level can be defined as:

\[
W(\hat{l}) : W(\hat{l}) = \min_{l \in L} W(l), \tag{11}
\]

The hypothesis is that the \(\hat{l}\) subsystem satisfying criterion (11) is the most error-free. Therefore, we
will consider the best solution obtained on this subsystem:

\[
\hat{c}_{l} = \left[ X_{l}^{T} X_{l} \right]^{-1} X_{l}^{T} Y_{l}, \tag{12}
\]

If the number of outstanding errors in the original system is large, the process of selecting the most
conformity \((N-2) \times M\)-subsystem can be continued by excluding one row from the
\((N-1) \times M\)-subsystem according to the described scheme.

4. Generation of the heightmap
The initial data for determining the three-dimensional coordinates are images of the underlying Earth's
surface obtained from different viewing angles and the sensor model described above. After matching
images for each pair of corresponding points using a set of RPC-coefficients, a point in three-
dimensional object space can be calculated. For this, using the above data, equation systems for the left
and right images are compiled:

The algorithm for solving the system of equations (1) and (2), as a result of which the three-
dimensional coordinates of a point in the global coordinate system are determined, consists of two stages
[14].

Stage 1. Calculation of the initial values of geodetic coordinates:

\[
Y^{i} = \frac{a_{0} + a_{1} L^{0} + a_{2} P^{0} + a_{3} H^{0}}{b_{0} + b_{1} L^{0} + b_{2} P^{0} + b_{3} H^{0}}, \tag{13}
\]

\[
X^{i} = \frac{c_{0} + c_{1} L^{0} + c_{2} P^{0} + c_{3} H^{0}}{d_{0} + d_{1} L^{0} + d_{2} P^{0} + d_{3} H^{0}},
\]

where \(i\) is the image index \((i \geq 2)\), and \((a_{k}, b_{k}, c_{k}, d_{k}), k = 0,3\) denote the RPC-coefficients. After
transformations, equations (13) can be rewritten as:

\[
((a_{0} - b_{0} X) + (a_{1} - b_{1} X)L^{0} + (a_{2} - b_{2} X)P^{0} + (a_{3} - b_{3} X)H^{0})' = 0, \tag{14a}
\]

\[
((c_{0} - d_{0} Y) + (c_{1} - d_{1} Y)L^{0} + (c_{2} - d_{2} Y)P^{0} + (c_{3} - d_{3} Y)H^{0})' = 0.
\]
Let us write equations (18) in matrix form for two images

$$\mathbf{y} = \mathbf{A}\mathbf{\xi} + \mathbf{e},$$

where

$$\mathbf{A} = \begin{bmatrix} a_{0,L} - b_{0,L}X_{L} \\ c_{0,L} - d_{0,L}Y_{L} \\ a_{0,R} - b_{0,R}X_{R} \\ c_{0,R} - d_{0,R}Y_{R} \end{bmatrix}, \quad \mathbf{\xi} = \begin{bmatrix} \mathbf{L}^0 \\ \mathbf{P}^0 \\ \mathbf{H}^0 \end{bmatrix}.$$

An estimate of the initial approximation vector \( \mathbf{\hat{\xi}} \) can be found using Least-Squares Method (LSM).

$$\mathbf{\hat{\xi}} = \left( \mathbf{A}^T \mathbf{A} \right)^{-1} \mathbf{A}^T \mathbf{y},$$

Stage 2. Calculation of geodetic coordinates by linearizing the model (1), (2):

$$Y_{L} = g_{L}(P^0, L^0, H^0) + \frac{\partial g}{\partial P} \Delta P + \frac{\partial g}{\partial L} \Delta L + \frac{\partial g}{\partial H} \Delta H,$$

$$X_{L} = f_{L}(P^0, L^0, H^0) + \frac{\partial f}{\partial P} \Delta P + \frac{\partial f}{\partial L} \Delta L + \frac{\partial f}{\partial H} \Delta H.$$

Linearization is performed in the same way for the right image. The resulting system is solved in the same way as in the previous stage. The found estimate of the vector \( \left[ \Delta L \quad \Delta P \quad \Delta H \right]^T \) is summed up with the initial approximation \( \left[ L^0 \quad P^0 \quad H^0 \right]^T \).

As a result, we get the heightmap in the form of image brightness pixels at points of the terrain in the vicinity of the proposed landmark.

Figure 2 shows the terrain relief generated using the algorithms described.

![Figure 2. 3D terrain relief performed by 3D ground restitution.](image)

Figure 3 (a) shows the left satellite image of the stereo pair, and Figure 2 (b) shows the corresponding heightmap for the relief shown in Figure 3. A light square indicates the area most suitable for use as a landmark.
Figure 3. Left satellite image (a) and heightmap (b) obtained by 3D terrain relief.

5. Landmark recognition using the support subspace method

The task of identifying landmarks is solved using localized fragments of landmarks images on the heightmap. The two-dimensional map of the heights is presented in the form of a \( N \times 1 \)-vector, the components of which are the height values of the landmark:

\[
\mathbf{x}_j = \begin{bmatrix} x_1(j), x_2(j), \ldots, x_i(j), \ldots, x_N(j) \end{bmatrix}^T,
\]

where \( j \) is the index of the fragment (landmark), and \( x_i(j) \) is the value of the \( i \)-th sample of the brightness (relative altitude) on the fragment.

The task is to find and recognize a landmark when approaching a certain observation area. In other words it is necessary to find a fragment of the image for which there is a maximum match with the landmark reference by a given proximity criterion. As a measure of proximity, we use the so-called conjugation indicator. Next, we will consider this method.

From the \( M \) of vectors (18) obtained in different episodes of shooting one (for example \( k \)-th) landmark, we compose a \( NM \times N \)-matrix \( \mathbf{X}_k \). For \( K \) landmarks (classes), respectively, \( K \) matrices \( \mathbf{X}_k, \ k = 1, K \) will be obtained. The task is to decide whether the current vector \( \mathbf{x}_j \) belongs to a class.

The decisive function is constructed as follows. For each \( (k\)-th) class (landmark), a \( N \times N \)-matrix \( \mathbf{Q}_k \) is pre-formed according to the given reference (training) vectors:

\[
\mathbf{Q}_k = \mathbf{X}_k \left[ \mathbf{X}_k^T \mathbf{X}_k \right]^{-1} \mathbf{X}_k^T. \quad k = 1, K.
\]

For the current position of the landmark image, the vector \( \mathbf{x}_j \) is formed and the conjugation index of the vector and matrix \( \mathbf{Q}_k \), which correspond to the landmark in the given observation area is calculated:

\[
R_k(j) = \mathbf{x}_j^T \mathbf{Q}_k \mathbf{x}_j \left( \mathbf{x}_j^T \mathbf{x}_j \right)^{-1}.
\]

Landmark with index \( j^* \) is considered found on the heightmap in the case of

\[
R_k(j^*) = \max_{j} R_k(j).
\]

Coordinates on the heightmap was fixed at found \( j^*\)-th position of landmark. Then the geodesic coordinates for these coordinates on the image are determined of the landmark on real terrain in accordance with the survey model described in Section 3. If several landmarks can fall into the observation area, the conjugation indexes (20) are calculated for all possible \( \mathbf{Q}_k \). In this case, the most similar \( k^*\)-th landmark is sought also and the decisive rule (21) takes the form
Thus, the training of the classifier is reduced to the formation of \( N \times M \)-matrices (spaces) of classes (landmarks) - \( X_k \), \( k = 1, K \) \( M < N \), from a certain set of vectors of each class. An important advantage of the method is the ability to build matrices \( X_k \) during the operation of the system. For example, if the first route pass has only one training sample \( x_k \) of the landmark image of each \( k \)-class, the proximity measure is calculated as

\[
 r_{k,m} (j) = \frac{\langle x'_j, x_k \rangle}{\|x'_j\|\|x_k\|}. \quad k = 1, K
\]

If the current landmark is successfully recognized, the corresponding vector is attached to the first. As a result, a \( N \times 2N \)-matrix \( X_k \) will be formed. Continuing in this way, during the operation of the system, multiple reference vectors of a given volume can be formed for all classes (landmarks). These learning sets form vector spaces. The following difficulties should be borne in mind when forming these spaces.

First, some class vectors may be "similar" to such an extent that the matrix may be poorly conditioned or even degenerate, leading to inability to calculate inverse matrix in (19). Secondly, some training sample vectors may differ significantly from other vectors of their class, which also leads to large recognition errors.

To overcome these difficulties, training images are pre-processed and the support subspaces \( [7] \) are formed. The formation of the support subspaces consists in the removal from matrix \( X_k \), \( k = 1, K \) of almost linearly dependent and standing out vectors.

It was found that the quality of recognition depends on the number of excluded vectors at the stage of preprocessing. An experiment was carried out to recognize the fractal images. The original images were subjected to additive random noise with different amplitudes. The results are shown in Figure 4. It can be seen from the figure that with an increase in the number of vectors in the reference subspace (up to 20-40), the recognition probability, as expected, increases. Further, the growth of the recognition probability stops and even decreases.

The table shows the results of comparing the recognition quality with the SVM method for two classes. The first column is a quality (in %) of the recognition SVM method; the second column - recognition by the conjugation index using 100 reference vectors; the third column - when some vectors are excluded (the number of remaining vectors in the support subspace is indicated in the last column of the table).

\[ \text{Figure 4. Dependencies of recognition accuracy on the number of vectors in the support subspace.} \]

The recognition probability increased by 1-3% despite a significant decrease in the number of vectors in the reference subspace (by 21-48%, depending on the degree of noise). The method of the support
subspace provides higher quality of the recognition for both undistorted and distorted images (1-3% higher) compared to SVM method.

Table 1. Recognition results.

| PSNR | $P_{\text{SVM}}$ | $P_0$ | $P_{\text{on}}$ | $n_{\text{on}}$ |
|------|----------------|-------|----------------|--------------|
| $\infty$ | 0.755 | 0.845 | 0.855 | 79 |
| 28 dB | 0.751 | 0.771 | 0.781 | 74 |
| 22 dB | 0.714 | 0.720 | 0.754 | 60 |
| 18 dB | 0.673 | 0.668 | 0.703 | 57 |
| 16 dB | 0.651 | 0.634 | 0.658 | 51 |

6. Conclusion
In the described technology for navigation on three-dimensional landmarks, we applied new algorithms for constructing a survey model and a new technology for identifying landmarks based on the method of support subspaces. The described methods and algorithms are quite universal. They, without any changes, allow solving the problems of the autonomous navigation using the optical and radar images. These methods and algorithms do not require significant effort and resources at the stage of the landmark models preparing. Moreover, these methods can be used to supplement a bank of training examples during the system operation. The considered method of building of a survey model based on algorithm of conforming estimation was implemented in conditions of complete absence of a priori information about measurement errors. This algorithm is robust in the class of estimation problems by a small number of observations.

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