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Fast Visual Orientation of UAV Relative to the Moving Landing Site Using Neural Networks

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Abstract

Precise and fast computer vision based 3D reconstruction of the 6DOF-position relative to the moving site is an important problem for reliable automatic UAV landing on ships and other dynamic structures. At the final stage of landing fast relative position and orientation feedback is needed for UAV control system to facilitate the smooth touchdown. INS of the UAV alone is not capable of estimating relative position because of the unknown platform motion component. Computational resource required for the solve PNP algorithm to reconstruct UAV 6DOF-position using given 2D landmarks of the known landing site may be prohibitive in terms of the required feedback speed for UAV control at the final landing phases of the flight. Non-iterative direct method for determination of UAV position and orientation relative to the known landing site is proposed. This method is based on the use of neural network approach to solving inverse problems. Training and testing of the developed method was performed using computer simulation modeling. Our study showed that the developed algorithm is robust, fast and simple and easy to implement in hardware. Since the developed method has low computational costs, it can be implemented on almost any on-board computing platform, including FPGA.

Keywords: UAV landing, solve PNP, Neural Network, pose estimation, final landing phase

INTRODUCTION

Automatic landing of the UAV on a ship is a complex scientific and technical problem. The estimation of the position and orientation of the UAV based on the detected landmarks is one of the key algorithms to ensure the automatic landing on the ship.

The UAV landing process can be divided into 3 stages: 1) a large distance to the target and small angular size of the target. Inertial navigation system (INS) can be applied to estimate the positions and orientations of UAV at this stage; 2) the medium distance to the target and the possibility of observing the oriented projection of the ship as a linear object. INS can also be applied at this stage; 3) the final stage of the UAV landing using visual landmarks of the ship capture device. At this stage, the relative orientation of the UAV and the landing site must be calculated in real time with low latency (<0.01 sec).

The problem of estimating position and orientation for the final landing phase represents the greatest complexity and scientific interest, since the use of standard photogrammetric approaches to solving this problem is possible, but not optimal in the case of limited computational resource of the onboard computer, because it requires solving a system of nonlinear equations by iterative methods "on the fly".

LITERATURE REVIEW

The estimation of the position and orientation of the UAV to the final stage of landing is a Perspective-n-Point problem. The aim of the Perspective-n-Point problem (PnP) is to estimate the position and orientation of a camera given a set of *n* correspondences between 3D points and their 2D projections [1].

Many works focused on solving the PnP problem for a limited number n=3,4,5 [2, 3, 4, 5, 6, 7, 8]. Often the RANSAC [9] algorithm is used to remove outliers when solving the P3P problem, which leads to an increase in the computational time of solving the PnP problem. New weighted RANSAC method was developed for image based 6-DOF pose estimation [10]. Method w-RANSAC 3D leads to more robust pose estimation while needing significantly less iterations.

Many non-iterative O(n) methods for solving the PnP problem have been developed in the last decade: EPNP [1], DLS [11], RPNP [12]. EPNP is the first non-iterative method with complexity O(n). The disadvantage of this method is that it does not guarantee global optimality. A common feature of modern non-iterative methods for solving the PnP problem is to use the solutions of polynomial equations. The DLS method finds all the stationary points that satisfy the Karush-Kuhn-Tucker (KKT) condition solving the system of nonlinear polynomial equations. DLS method employs a singularity-affected rotation matrix parametrization. The DLS method was improved by Nakano [13] to achieve the best stability and efficiency. ASPnP [14] and OPnP [15] algorithms replace the Cayley parametrization by the singularity-free non-unit quaternion parametrization, thus leading to improved accuracy.

In CEPPnP [16], EPPnP was reformulated in order to integrate feature uncertainties and estimate the camera pose based on an approximated Maximum Likelihood procedure. In contrast to the CEPPnP, where the Maximum Likelihood estimator is used to obtain an estimation of the control point subspace, MLPNP [17] optimize directly over the unknown quantities, i.e. rotation and translation and thus, directly obtain pose uncertainties.

All non-iterative methods described earlier assume that there are no outliers. The RANSAC algorithm does not allow for fully effective use of non-iterative methods. The method of REPPnP [18] integrates the outlier rejection within the pose estimation. This method enables to achieve significant acceleration (>100x) compared with the RANSAC approach.

The researchers used both the solution for n = 3 (P3P), and the solution for n> 3(PnP) to estimate the position and orientation of the UAV. A numerical algorithm was developed in [19] for the solution of P3P problem which was applied for navigation of the UAV relative to the ship using three infrared points. The authors [20] proposed a method which combines PnP and a novel pattern evaluation scheme to achieve more robust measurement for above-the-deck hover. The method [21] uses a framework based on a Kalman filter (KF) [22] and an efficient perspective-n-point (EPnP) [1] approach to estimate the position, attitude and velocity of the target (landing system). The authors of the article [23] propose a method which first introduces pose estimation based on the solutions of PnP problem, and then uses the EKF to improve the accuracy and stability.

Most of the methods of automatic landing are using visual reference points. In case of poor visibility a small number of landmarks may be available. To solve this problem, the authors [24] developed computationally an effective and robust algorithm for external orientation based on positions of 2 known reference points and a gravity vector.

For the practical solution it is possible to use PNP algorithms that are implemented in the OpenGV library [25].

In this work the authors have developed a neural network method to solve the problem of estimating position and orientation of the UAV relative to the ship landing site with a minimum of computational cost and acceptable precision and resistance to noise. This method is based on the use of neural network approach to solving inverse problems that have a range of benefits: no need for iterative search, simple implementation, allowing for efficient implementation on the microprocessor of an onboard computer or even using FPGA.

MATERIALS AND METHODS

In this work computer simulation was used to imitate the observed coordinates of the landing site landmarks that could have been captured by the on-board computer vision system on the UAV approach including noise in pixel coordinates. The known random ground-truth positions and orientation of the UAV were generated as well as the corresponding landmark pixel coordinates with additive noise. The UAV observing system is described in Section 1 below and the overall inverse problem definition is given in Section 2. The approach to solving the inverse problem with neural networks is described in Section 3. Visual examples of the computer simulated positions of the landing site landmarks are given in Section 4.

1) A mathematical model of the observing system

Vector diagram of the observing system is shown in Figure 1.

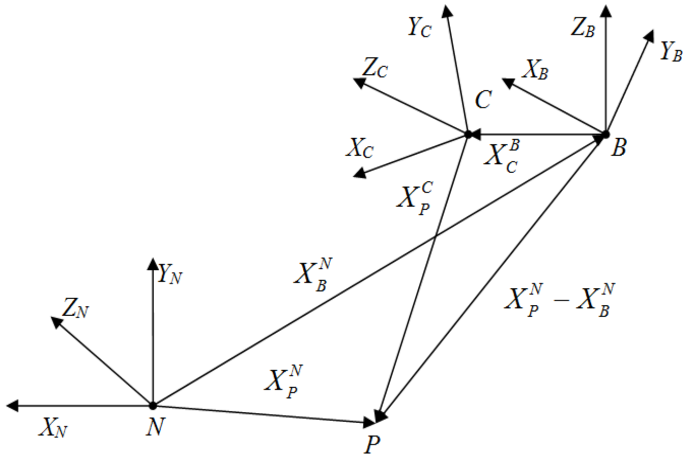

Figure 1: Vector diagram of the observing system

In this observing system a fixed coordinate system $NX_NY_NZ_N$ is considered, whose origin is at point N. The other basic system is the so-called linked coordinate system $BX_BY_BZ_B$, whose origin is at the center of mass of the UAV (B).

Axis BX_B is directed along the longitudinal axis of the UAV straight forward, the axis BY_B lies in the plane of symmetry of the UAV and is oriented upward. The cross axis BZ_B is directed to the right, and the vector $\mathbf{x}_B^N = [x \quad y \quad z]^T$ shows the location of the UAV in the fixed coordinate system. Origin of the coordinate system of the onboard equipment is located in the center of the onboard surveillance equipment (C), and the vector $\mathbf{x}_C^B$ gives the relative coordinates of the on-board surveillance equipment in relation to the linked coordinate system.

We can assume that the vector $\mathbf{x}_C^B = [L \quad 0 \quad 0]^T$ is constant, because the on-board surveillance equipment is rigidly joined to the UAV. If the coordinates of point P represent the coordinates of the observed element of surface, then the coordinates of the point are defined by the vector $\mathbf{x}_P^N = [x_P \quad y_P \quad z_P]^T$ in the fixed coordinate system.

The coordinates of the observed surface element in the coordinate system of the onboard equipment (vector $\mathbf{x}_P^C = [x_{CP} \quad y_{CP} \quad z_{CP}]^T$) can be written on the basis of these coordinate systems according to equation:

$$\boldsymbol{x}_P^C = \boldsymbol{C}_B^C \boldsymbol{C}_N^B (\boldsymbol{x}_P^N - \boldsymbol{x}_B^N) - \boldsymbol{C}_B^C \boldsymbol{x}_C^B, \qquad (1)$$

where $\mathbf{C}_B^C$ is the constant transition matrix of the linked coordinate system in the coordinate system of the onboard equipment;

$\mathbf{C}_N^B$ is a transition matrix from the coordinate system of the onboard equipment in the fixed coordinate system;

$$\mathbf{C}_B^C = \begin{bmatrix} \cos\delta & -\sin\delta & 0 \\ \sin\delta & \cos\delta & 0 \\ 0 & 0 & 1 \end{bmatrix},$$

$$\mathbf{C}_N^B = \begin{bmatrix} \cos\psi\cos\vartheta & \sin\vartheta & -\sin\psi\cos\vartheta \\ \sin\psi\sin\gamma - \cos\psi\sin\vartheta\cos\gamma & \cos\vartheta\cos\gamma & \cos\psi\sin\gamma + \sin\psi\sin\vartheta\cos\gamma \\ \sin\psi\cos\gamma + \cos\psi\sin\vartheta\sin\gamma & -\cos\vartheta\sin\gamma & \cos\psi\cos\gamma - \sin\psi\sin\vartheta\sin\gamma \end{bmatrix}, \qquad (2)$$

where δ is an angle of vision of the on-board observation equipment;

γ, ϑ, ψ are angles of roll, pitch, and yaw, respectively.

Equation (1) shows the relationship between the coordinates of the UAV and its orientation and coordinates of the observed surface element in the coordinate system of the onboard equipment.

Vector equation (1) in scalar form is the scalar equations:

$$\begin{aligned} x_{CP} &= (\cos\delta\cos\varphi\cos\theta - \sin\delta\sin\varphi\sin\gamma + \sin\delta\cos\varphi\sin\theta\cos\gamma)\cdot(x_P - x) \\ &+ (\cos\delta\sin\theta - \sin\delta\cos\theta\cos\gamma)\cdot(y_P - y) \\ &+ (-\cos\delta\sin\varphi\cos\theta - \sin\delta\cos\varphi\sin\gamma - \sin\delta\sin\varphi\sin\theta\cos\gamma)\cdot(z_P - z) - \cos\delta\cdot L \\ y_{CP} &= (\sin\delta\cos\varphi\cos\theta + \cos\delta\sin\varphi\sin\gamma - \cos\delta\cos\varphi\sin\theta\cos\gamma)\cdot(x_P - x) \\ &+ (\sin\delta\sin\theta + \cos\delta\cos\theta\cos\gamma)\cdot(y_P - y) \\ &+ (-\sin\delta\sin\varphi\cos\theta + \cos\delta\cos\varphi\sin\gamma + \cos\delta\sin\varphi\sin\theta\cos\gamma)\cdot(z_P - z) - \sin\delta\cdot L \\ z_{CP} &= (\sin\varphi\cos\gamma + \cos\varphi\sin\theta\sin\gamma)\cdot(x_P - x) \\ &+ (-\cos\theta\sin\gamma)\cdot(y_P - y) \\ &+ (\cos\varphi\cos\gamma - \sin\varphi\sin\theta\sin\gamma)\cdot(z_P - z) \end{aligned} \qquad (3)$$

The components of the vector of coordinates $\mathbf{x}_P^C$ are related with the pixel coordinates on the image plane (u_P, v_P) by the following relationship:

$$u_P = -f\cdot\frac{y_{CP}}{x_{CP}} + u_C, \qquad (4)$$

$$v_P = -f\cdot\frac{z_{CP}}{x_{CP}} + v_C, \qquad (5)$$

where u_C, v_C are the coordinates (in pixels) of the center of the onboard surveillance equipment relative to the origin of the onboard equipment; f is the focal length of the onboard equipment.

2) The problem of estimating position and orientation as a problem of multivariate vector function approximation

As is known from photogrammetry, the solution of the 3D reconstruction problem exists and is unique only in the presence of a sufficient number of projection points of an object with the known geometry in the field of view;

therefore, it is possible to define a single-valued continuous vector-function of the form:

$$y = \begin{pmatrix} \omega_x \\ \omega_y \\ \omega_z \\ x \\ y \\ z \end{pmatrix} = F(p_1..p_n) \quad (6)$$

where $\omega_x, \omega_y, \omega_z$ are three values that define the orientation (in this algorithm the Rodriguez representation was chosen for its continuity, three-dimensionality and the absence of the problem of the singularity of the Euler angles), *x*, *y*, and *z* are the values that determine the position of the UAV surveillance camera (if the vision angles are known, then the UAV orientation search is trivial, so we will further consider these values as the UAV position), $p_1..p_n$ are 2D coordinates of key points of visual landmarks of the ship capture system of the UAV.

Neural network approximator function is constructed in the proposed algorithm.

3) Neural network solution of the inverse problem

Function (6) has no analytical expression. However, it is obvious that the function of the inverse to F (projective transformation of the 3D coordinates of the key points of visual reference points into the observation chamber with the known external and internal parameters) has an analytical form. In the developed method, the neural network solves the inverse problem by the scheme, which is presented in Figure 2.

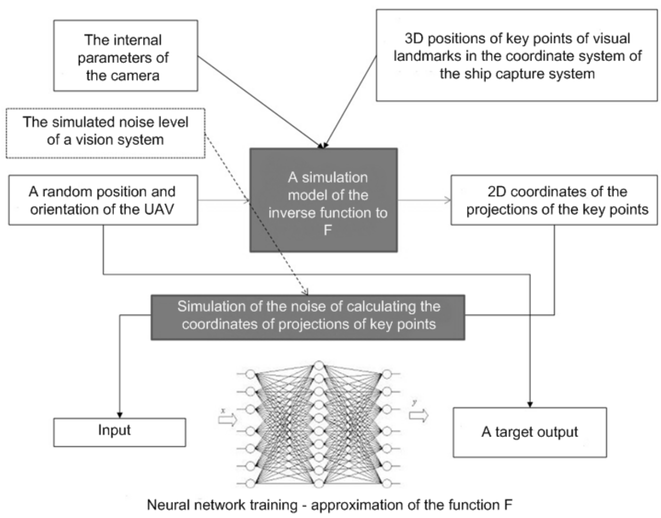

Figure 2: Neural network approach to solving inverse problems – approximation of the function F (which does not have an analytical representation) by using the analytical model of the inverse function

Training samples for training the weighting coefficients of the neural network are created using a simulation model of the projective transformation (the function inverse to F).

For the approbation of the developed solution we have performed computer simulation of the developed algorithm. The key components of a computer model include:

- simulation model;

- model for training the neural network.

4) Simulation model

The developed simulation model allows generating the coordinates of the sets of projected key points of visual reference for the set of random positions and orientations of the camera of the UAV with the specified internal camera parameters (focal length, etc.) and with the specified noise level of the coordinate projections. Figure 3 shows examples of sets of projections generated by the simulation model for the conditional visual reference of 5 key points.

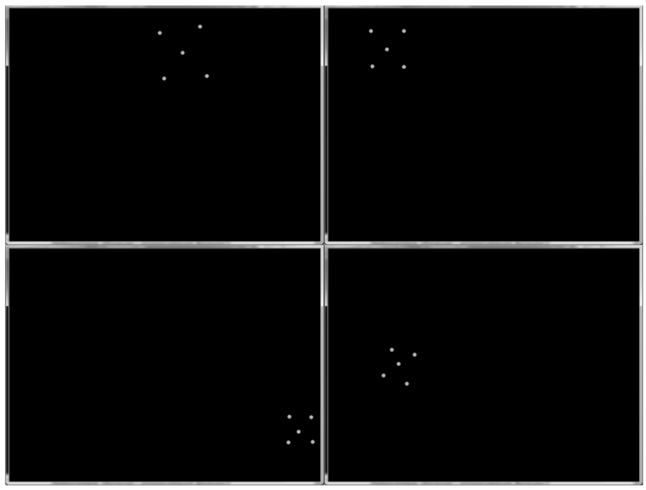

Figure 3: An example of artificial "visual images" of projections of key points of landmarks of the ship capture system, which were synthesized by the simulation model (projection noise level = + \ - 5 pixels)

RESULTS

In the experiments, a neural network of the MLP [26] type was used. To achieve higher accuracy, separate training of neural networks is necessary. One neural network is used to calculate the position, and the other is used to calculate the orientation. To achieve a good generalizing ability, the regularization technique “Weight decay” [27] was applied. To prevent overfitting, the “Early stopping” [26] method was used. The neural network was trained using the RPROP method [28]. These experiments showed that the required size of the training sample for a successful solution of the inverse problem ranges from 10.000 to 100.000 examples.

As a result of numerous experiments, the optimal parameters of the neural network training model were found (Table 1).

Table 1: Optimal parameters of the neural network training model

Parameter	Values
Type of neural network	MLP
Activation function	Symmetric sigmoidal activation function for the hidden layers, linear activation function for the output layer
Number of layers	2
Number of neurons in the hidden layer	256
Number of inputs	2*n, where *n* is the number of the observed projections (in ordered sequence)
Number of outputs	3 (Two separate networks are used – one for calculating the orientation, the second for calculating the position)
Regularization	“Weight decay”
Method of learning	“RPROP”
Overfitting control	“Early stopping” criterion on the validation set (20% of the training set)

Real algorithms of vision systems give errors in the determination of the coordinates of key points of visual landmarks; therefore, the developed algorithm should be resilient to the presence of white noise in the coordinates of the projections, which are an input to the neural network. The results of studying the noise impact on the accuracy of reconstructing the position and orientation are given in Table 2.

Table 2: Effect of noise in the projections of reference points on the algorithm of neural network reconstruction of the UAV position and orientation

The noise level (in pixels)	The average relative reconstruction error of the UAV position (Cartesian coordinates)	The average relative reconstruction error of the UAV orientation (angular coordinates)
0.0	2.6%	3.4%
0.1	2.61%	4.2%
1.0	2.8%	20.0%
3.0	3.2%	51.0%

DISCUSSION

On the basis of experimental results it can be concluded that the vision system must be able to determine the position of the 2D projections of the key points of visual reference points with sub-pixel accuracy that is achievable by modern methods of computer vision.

The computational complexity of the developed neural network algorithm for estimating position and orientation of the UAV is O(n), where *n* is the number of visual landmarks. This is comparable to modern non-iterative methods for solving the PnP problem.

For on-board computer with performance of 200 MFlops (ARM Cortex A7) calculation of the 3D position and orientation of the UAV takes ~0.1 ms, while the application of the classical iterative algorithm SolvePnP requires 2 orders of magnitude more time.

The developed algorithm is very simple in software implementation and can work with real fixed-point numbers, while SolvePnP implementation of the classical photogrammetric approach requires a floating point (usually double precision).

CONCLUSION

In this article, a new method has been developed for fast estimation of the UAV position and orientation relative to the landing site of the ship at the final stage of landing. The developed method uses a neural network approach with computational complexity O(n) that corresponds to the global trend in the development of methods for solving the PnP problem. Since the developed method has low computational costs, it can be implemented on almost any on-board computing platform, including FPGA. In the future, we plan to perform practical implementation of the developed method using the UAV and to conduct field tests.

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