Lecture Notes in Networks and Systems 667

Serhiy Shkarlet · Anatoliy Morozov · Alexander Palagin · Dmitri Vinnikov · Nikolai Stoianov · Mark Zhelezniak · Volodymyr Kazymyr *Editors*

Mathematical Modeling and Simulation of Systems

Selected Papers of 17th International Conference, MODS, November 14–16, 2022, Chernihiv, Ukraine

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Preface

The International Conference "Mathematical Modeling and Simulation of Systems" (MODS) was formed to bring together outstanding researchers and practitioners in the field of mathematical modeling and simulation from all over the world to share their experience and expertise.

The conference MODS was established by the Institute of Mathematical Machines and Systems Problems of the National Academy of Sciences of Ukraine (NASU) in 2006. MODS is now an annual international conference held by Chernihiv Polytechnic National University with the assistance of the Ministry of Education and Science of Ukraine, the NASU, and the State Research Institute for Testing and Certification of Arms and Military Equipment, universities and research organizations from UK, Japan, Sweden, Bulgaria, Poland, Estonia, and Ukraine participating as co-organizers of the conference.

The XVIIth International Conference MODS'2022 was held in Chernihiv, Ukraine, during November 14–16, 2022. MODS'2022 received 48 paper submissions from different countries. All papers went through a rigorous peer-review procedure including pre-review and formal review. Based on the review reports, the Program Committee finally selected 24 high-quality papers for presentation on MODS'2022, which are included in "Lecture Notes in Networks and Systems" series.

This book contains papers devoted to relevant topics including tools and methods of mathematical modeling and simulation in ecology and environment, manufacturing and energetics, information technology, modeling, analysis and tools of safety in distributed information systems, mathematical modeling and simulation of special-purpose equipment samples, and cyber-physical systems. All of these offer us plenty of valuable information and would be of great benefit to the experience exchange among scientists in modeling and simulation.

The organizers of MODS'2022 made great efforts to ensure the success of this conference despite the active military operations on the territory of Ukraine. We hereby would like to thank all the members of MODS'2022 Advisory Committee for their guidance and advice, the members of Program Committee and Organizing Committee, the referees for their effort in reviewing and soliciting the papers, and all authors for their contribution to the formation of a common intellectual environment for solving relevant scientific problems.

Also, we are grateful to Springer-Verlag and Janusz Kacprzyk as the editor responsible for the series "Lecture Notes in Networks and Systems" for their great support in publishing these selected papers.

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A Conceptual Model for Increasing the Speed of Decision-Making Based on Images Obtained from UAVs

Volodymyr Voytenko, Yuriy Denisov, Roman Yershov, and Maksym Solodchuk

Abstract To reduce the load on the operator of an unmanned aerial vehicle (UAV) during long search and rescue, and monitoring missions, the concept of an automatic system is proposed, which directly on board performs a preliminary analysis of images received from a high-resolution navigation video camera, determines areas of interest, and sets the position of an additional camera with a reduced viewing angle to scale the image of the selected area. This allows the operator to speed up the final decision and reduces the response time to the detection, identification of an object, as well as to the preparation of a mission report. To develop a technical system that will be able to solve the tasks, a complex hierarchical model is considered, consisting of three components: a software system for image pre-processing and analysis, an electromechanical camera positioning system, and a higher-level human–machine complex. It is determined that the model of the first component should be based on the use of a deep learning artificial neural network using inference trees. The Simulink model of the positioning system contains a controller that improves the dynamics of two interconnected electric drives by using three control loops in each of them. The features of information perception by the operator of the UAV control complex are analysed and the need to consider the effect of global precedence is noted. The results of the simulation of the electromechanical link are presented and the complexes of further research are outlined.

Keywords Unmanned Aerial Vehicle (UAV) · Image processing · Pattern recognition · Electric drive · Automatic control · Human-machine interaction

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1 Introduction

To carry out search and rescue, surveillance, intelligence, and reconnaissance missions, unmanned aerial vehicles (UAVs) are widely used with sensor units installed on board, and which operate in various ranges of electromagnetic (EM) waves: from infrared to ultraviolet [1]. For navigational and other purposes, the visible EM-range is essential, allowing the UAV operator to rely on a familiar view of the terrain and objects located on it. In this case, images are created by one or more high-resolution video cameras [2], which can be placed on gyro-stabilized platforms [1], and this ensures, in particular, high image quality.

For processing large areas of the earth's surface, aircraft-type devices are more appropriate, since, unlike various rotor structures, they have a significantly higher speed and flight range [3]. The high flight speed of the UAV during the mission leads to an increase in the information flow from the screen of the display device, causing operator fatigue and even the emergence and development of occupational diseases. Reduced attention, in turn, increases the likelihood of mistakes and missed targets. Therefore, the task of building a technical system that automatically performs preliminary processing of video information and helps to reduce the load on the human operator is relevant.

These video sensor units are often equipped with two high-resolution video cameras: the main (navigation) camera with a sufficiently wide viewing angle for reliable orientation of the UAV crew in space, and an additional (spot) camera with a small viewing angle and an enlarged image that this camera can form [1]. Provided that the angle of view of the main video camera remains unchanged, an increase in the UAV flight height allows expanding the area of the terrain displayed on the monitor screen by reducing the detail, however, using the spot camera, an additional enlarged image appears, which makes it easier for the operator to identify the target, reducing the time for making a decision on further actions.

It is essential for modern conditions to implement as many functions as possible, performed directly on board the UAV [4], so that the operator has almost the last step: considering the hint generated by the technical system, complete the image analysis, and perform the prescribed mechanical action. Work on board allows, in particular, to perform (or continue to perform) a task autonomously when it is carried out in search mode along a given route, which increases stealth and stability when exposed to various external factors.

Saving even one second or a certain fraction of it on this path is a task that requires efforts on several levels.

2 The Structure of the System with Advanced Capabilities for Analyzing Images Obtained from UAVs

Figure 1 shows a UAV flying at a height H with a speed v. The gyro-stabilized platform P, on which the camera unit is installed, is directed forward at an angle α relative to the normal to the ground surface, which allows the operator to better navigate the route. The main (navigation) video camera has a fairly wide angle of view β, which determines the size of the terrain area (b is the width, h is the "height", i.e., the size along the direction of the UAV movement), which is converted into an image of the format $K_f = b{:}h$, defined by the video standard.

In the context of solving the task of accelerating the decision-making process, the UAV operator scales the image of a fragment in which an object of interest may be located. This is usually done through the operator's own actions, which, using the appropriate controls, directs the gyro-stabilized platform with the sensor unit installed on it. The next action of the operator should be exactly the increase (zooming) of the image, remotely implemented using the appropriate electric drive, which increases the focal length of the lens, while simultaneously reducing the viewing angle of the camera. In this case, as a rule, an autofocusing procedure is additionally carried out, for which a separate electric drive with its own electromechanical system and a dedicated control algorithm is used. Thus, the operator, having previously assessed the image, must perform several successive control actions, accompanied by the reaction of electromechanical devices. All this increases the time for obtaining a scalable image, which in this case gets to the operator in a single video stream. And this, in turn, reduces the amount of information about the flight, which makes it difficult to document after the mission is completed.

To overcome these shortcomings in practice, an additional video camera (spot camera) with a small viewing angle, which is located on the same platform as the main (navigation) one, next to other necessary sensors, can be used to zoom in on the image. Switching the image on the video monitor can again be performed by the operator as a result of additional actions. However, since the main and spot cameras are located on the same platform, the operator can observe only that fragment of the surface, the direction of which coincides with the center of the original image (or another predetermined point that was set before the start of the mission). But

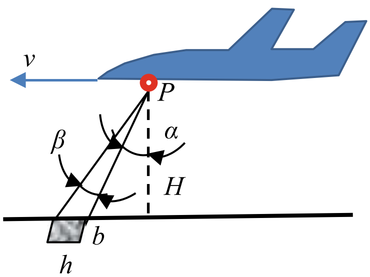


Fig. 1 Definition of symbols

since the area of interest can be located in another part of the input image, additional positioning of the gyro-stabilized platform will be required, followed by a return to the original position to continue navigation. This, again, wastes valuable time and additional workload and fatigue for the operator.

A solution is proposed (Fig. 2), which provides for the placement of a narrow-angle spot camera (SC) on its own platform (1), which can move relative to the base gyro-stabilized (2) along two coordinates. In this case, two video channels actually work in parallel and independently of each other, which, even if it is impossible to transmit the entire video stream, for example, due to interference, limited bandwidth of the video channel, or other reasons, allows you to accumulate an array of information from both cameras. This, in particular (but not only), reduces the need for repeat missions along the same route, which is the most stressful for the operator.

To implement the idea, you need to add one more remote-controlled electric drive (SCED) of the spot camera (SC) to the existing remote-controlled electric drive (MCED) of the main camera (MC). Now the main camera has a fixed angle of view β_1, and the spot camera has a fixed angle of view β_2, and the zoom factor (magnification) of the image is

$$M = \beta_1/\beta_2.$$

The angle β_2 can be fixed, or it can change with a discrete step, which will further simplify the interaction of two systems in automatic mode. To facilitate the use of digital software and hardware, it is advisable to discretize the input image by dividing its entire plane into zones – rectangular sections that have the same format as the

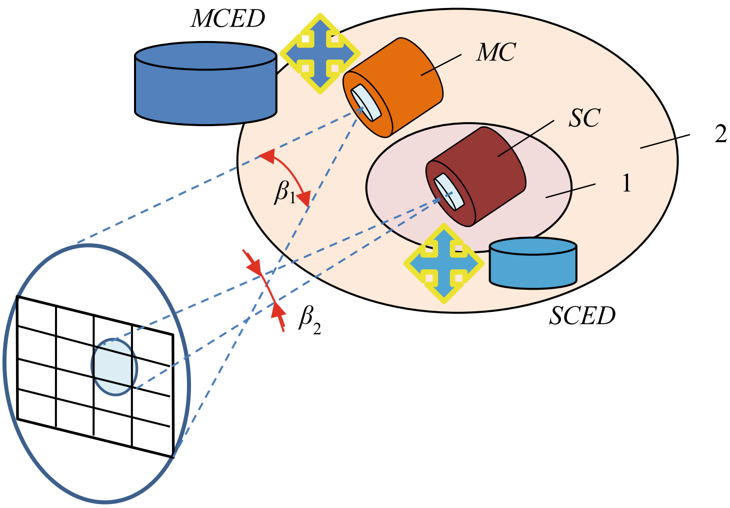


Fig. 2 Constructive model of interaction between two cameras

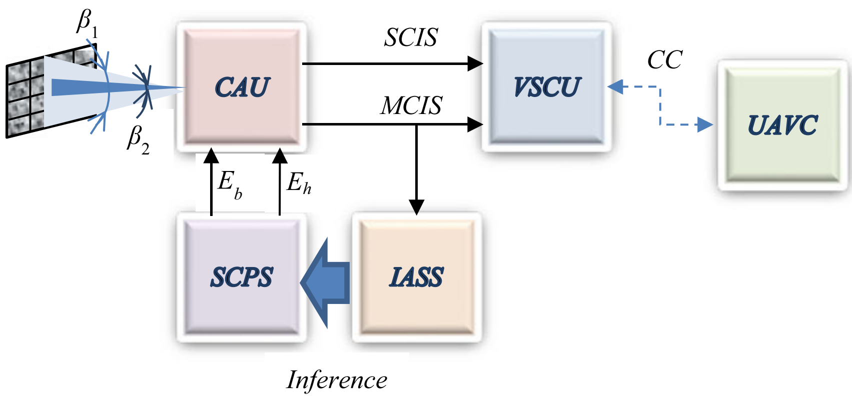


Fig. 3 Advanced system structure

input image. Figure 2 shows the division into $N_z = 16$ zones, providing for the use of a spot camera with a viewing angle $\beta_2 = \beta_1/16$.

The proposed solution has such disadvantages as increased weight, dimensions, and complexity of the entire complex of sensors, since in addition to additional mechanical elements, there is also a two-position electric drive of the spot camera. However, the use of the varifocal lens of the main camera in the basic version also requires two drives (for changing the focal length and for focusing). In addition, such a lens itself is more complex, more expensive, less stable, and reliable compared to a device with fixed parameters. The additional spot camera platform is simpler than the main one (it has fewer degrees of freedom), it is designed for a smaller load, and is therefore less inertial.

Therefore, the proposed structure (Fig. 3) contains:

CAU – Camera Apparatus Unit;

VSCU – Video Signal Conversion Unit;

IASS – Image Pre-processing and Analyzing Software System;

SCPS – Spot-Camera Positioning System;

UAVC – UAVs Control Complex.

This structure uses both the main camera and an additional spot camera with fixed focal lengths and focusing, but with different viewing angles β_1 and β_2.

CAU forms two separate digital streams – Spot-Camera Image Signal (*SCIS*) and Main Camera Image Signal (*MCIS*), which arrive at the *VSCU*, and then through the Communication Channel (*CC*) enter the *UAVC*. During the mission, *CC* is a radio link with the UAV. When setting up the device on the ground and reading information from on-board drives, both wired and wireless technologies can be used. In some cases, there may be no CC (execution of an autonomous flight with subsequent access of the operator to the information stored on the built-in drive during the mission).

IASS, based on the images received from the main camera, forms one of the possible conclusions about the number of the zone to which the spot camera should be positioned. Logical information from this block (*Inference*) enters the *SCPS*, where electrical signals for positioning the spot camera along the yaw angle E_b and pitch angle E_h are generated.

UAVC is the cutting edge of the human-machine system. Here, telemetry and video information are received, visualized, converted, and the response initiated by the operator is carried out by performing predetermined actions: the use of controls for transmitting commands in the opposite direction (to the UAV), as well as further processing of information, documenting the mission, transferring it to other authorities, etc.

3 Image Pre-processing and Analyzing Software System

Image pre-processing may be required to correct visibility conditions, angle, eliminate interference, noise, etc. [5]. In remote sensing applications, where the geometric parameters of the sensor's field of view are known (which is a common situation), knowing the height of the sensor above the observed surface can be sufficient to normalize the image size if the shooting angle is constant. Similarly, rotation normalization requires knowing the angle by which the image (or sample) should be rotated, which again requires spatial hint. In this remote sensing problem, information about the direction of flight may be sufficient to rotate the resulting images to a standard orientation. If additional spatial information is not available, normalizing the size and rotation can be a very difficult task. To solve it, it is necessary, using known methods, to automatically find features in the image that could be a spatial hint.

So, general approaches to solving all the necessary problems listed above are known and will not be the subject of discussion in this article. The final purpose of the analysis within our system is to determine the region of interest and generate commands for positioning the spot camera. Initially, we see the primary task of pattern detection and classification.

The question of choosing and using certain methods of image processing requires a separate study. However, we can say that today this area is dominated by algorithms based on the use of artificial intelligence methods, which are based on machine learning of artificial neural networks. The theoretical foundations of machine learning have been laid down for a long time, and their classification and application features for solving pattern recognition problems are described, in particular, in [6].

If the data is not big data (which could have been solved by simple technology and tools), then the machine-learning techniques like the supervised learning and the dimensionality reduction techniques are useful [7].

A real breakthrough in the field of pattern recognition and computer vision was the development of a convolutional neural network AlexNet [8, 9]. AlexNet implementation is easier after the releasing of so many deep learning libraries like PyTorch, TensorFlow, Keras [10].

When designing our system, one of the main requirements formulated earlier should be kept in mind: most functions must be performed directly on board the UAV. After all, this not only improves the dynamic performance of the man-machine system, but also allows you to perform parts of the mission offline, accumulating information directly on the UAV, which is very important in some cases. However, it should be noted that most embedded systems are based on the use of microcontrollers that are not very high performance. In some cases, this is due not so much to economic considerations as to purely constructive and energy constraints. To an even greater extent, this applies to UAVs, where the requirements for weight and size indicators of any onboard equipment are much more stringent than for ground vehicles.

The issues of solving the problem of applying algorithms based on the use of artificial neural networks of deep learning in the conditions of constructive limitations by means of embedded systems have recently received more and more attention [11, 12].

An accent on hardware electronics, processor architecture, and connections to memory is done in [12]. This shows us that the results are obtained with greater reliability due to the achievements of modern electronic technologies, the structure of the ANN and in combination with more advanced software methods.

In [13], we can see an attempt to use the concept of CNN-based inference for IoT edge clusters. As you know, IoT is a device with a hard resource limit, and often it is stronger than that of UAVs. Here authors offer DeepThings, a special framework for the adaptive-distributed launch of CNN. To minimize the required memory, DeepThings uses a special scalable partitioning of convolutional layers while maintaining parallelism. Perhaps this approach will be useful when organizing a "multi-drone" mission in the future, but not in our case.

Deep Neural Networks (DNNs) are now a mainstream machine learning technology. However, running DNNs on resource-constrained devices is not trivial, as it requires high performance and energy costs. Deploying a DNN to run in the cloud or splitting a DNN with adaptive distribution of computing between the device and the edge to use hybrid computing resources nearby to determine the DNN in real time [14] during the performing of the above missions is impossible even in terms of the limitations of the UAV radio link itself. So, we need to find a more standalone embedded solution.

Advancements in compression of neural networks and neural network architectures, coupled with an optimized instruction set architecture, could make microcontroller-grade processors suitable for specific low-intensity deep learning applications [15]. There, a simple extension of the instruction set was proposed with two main components – hardware loops and dot product instructions.

The influence of the depth of a convolutional network on its accuracy in the large-scale image recognition setting was studied in [16]. Careful evaluation of increasing depth networks using an architecture with very small (3×3) convolution filters has shown that a significant improvement over previous configurations can be achieved by increasing the depth to 16–19 weight layers. These conclusions formed the basis of successes in the localization and classification tracks. It is also shown that the authors' representations generalize well to other datasets, where they achieve state-of-the-art results. The two most powerful ConvNet models are now publicly available to facilitate further research into the use of deep visual representations in computer vision.

Two efficient approximations to standard convolutional neural networks were proposed in [17]. In one case, the filters are approximated by binary values, which reduces the required memory by a factor of 32. In another case, the input to the convolutional layers is also binary. The use of mainly binary operations allows not only saving memory, but also significantly speeding up convolutions. The proposed method in real time allows you to run convolutional networks on processors (not only on graphics). As a result, such networks can solve complex visual problems with simple and energy-efficient devices placed on UAVs. This approach was evaluated in the ImageNet classification problem, where it showed almost the same accuracy as a comparable version of the AlexNet network. The authors claim that comparing the proposed Binary-Weight-Networks and XNOR-Networks with other binarized networks such as BinaryConnect and BinaryNets also shows better accuracy results.

Before we move on to practical machine learning, we need to touch on one aspect regarding the data set we need in "aerial vision" as a new frontier of computer vision [18]. It is noted that the existing UAV data sets are mainly focused on object detection, and not on recognition. These datasets can be used in our case because we assume that more reliable recognition can currently be performed by a human.

DeepCluster [19] may turn out to be a very promising solution in the context of the formulated tasks. This clustering method iteratively groups features using a standard clustering algorithm (K-means method) and uses subsequent assignments as a supervision to update neural network weights. What can be extremely important is the potential effectiveness of this model for learning deep representations in specific domains when no labeled dataset is available. In this case, a detailed description of the input data and domain-specific knowledge is not required.

Considering the very good results of object detection in images obtained by DNN AlexNet [8], we will choose it as the basis for building our future classifier. The results obtained can be further used as a benchmark for comparison with other developed network architectures. The essential differences of our case from traditional problems are that the number of classes can be much less than in the standard problem of pattern recognition. The concept of a class itself has a different meaning than usual: it is just a number – the number of a rectangular area of the image where the probability of the presence of an object of interest exceeds a certain specified value. This opens up the possibility of detecting an object of interest directly on board the UAV with relatively low-performance microcontrollers.

Suppose the main camera's view angle is $\beta = 23°$. Moreover, if the UAV is at a height of $H = 100$ m, the height of the image on the surface is $h = 20$ m (Fig. 1). At a speed $v = 72$ km/h, the UAV travels a distance $s = 20$ m, i.e., the image frame is updated by 100% at $T_r = 1$ s.

Today, the most popular image format formed by video cameras installed on UAVs is HD n_xx $n_y = 1920 \times 1080$ ($K_f = 16{:}9$). This implies the size of one pixel for $H = 100$ m, $\beta = 23°$:

$$\Delta = h/n_y = 2000/1080 \approx 1,85cm.$$

Table 1 The number and format of split zones of the input image

N_1	1	2	3	4	5	6	8	10	12	15
N_z	1	4	9	16	25	36	64	100	144	225
N_h	1920	960	640	480	384	320	240	192	160	128
N_v	1080	540	360	270	216	180	135	108	90	72
h, m	35,5	17,8	11,8	8,9	7,1	5,9	4,4	3,6	3	2,4
b, m	20	10	6,7	5	4	3,3	2,5	2	1,7	1,3

Here n_x, n_y are the number of pixels along the horizontal and vertical lines, respectively.

Table 1 shows the quantitative parameters of image zoning of the main UAV video camera operating in HD format.

The following designations are used in the table:

N_1 – number of image zones along one of the axes;

N_z – total number of image zones;

N_h – the number of pixels in one zone of the image horizontally;

N_v – the number of pixels in one zone of the image vertically;

h, b – the size of the zone on the ground at a flight altitude $H = 100$ m, the angle of view of the main camera $\beta = 23°$.

Compared to the standard parameters of the AlexNet network [8], where the input image format is 224 × 224, and the number of outputs is 1000, the resource requirements in our network are less, which increases the possibility of its successful deployment on board the UAV using the appropriate element base.

In the case of the parallel mode of detection of the zone of interest, each zone can be processed independently from one another, and the result will be formed at the same time. However, taking into account the time interval for updating the image frame of the main camera, it is also possible to perform zoning in sequential mode. In both modes, of course, we are talking about the work of pre-trained neural networks, but not about their training, the execution time of which can be significantly longer than the longest mission.

4 Spot-Camera Positioning System

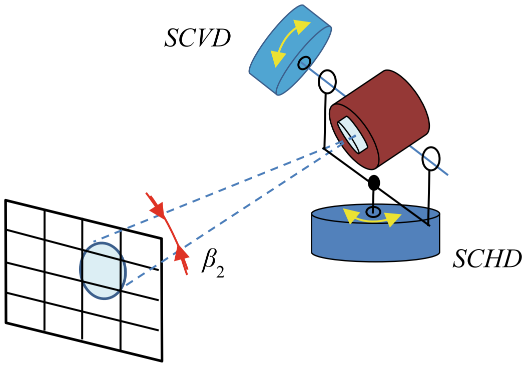
Figure 4 shows a structural model of the system designed to position the spot camera to the zone determined at the previous stage using the Image Pre-processing and Analyzing Software System.

The model contains two electric positioning drives:

SCVD – Spot-Camera Vertical Drive;

SCHD – Spot-Camera Horizontal Drive.

Fig. 4 Constructive model of the spot camera positioning system



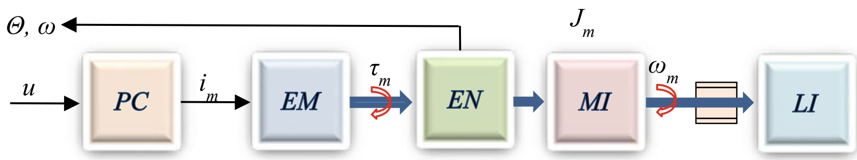


Fig. 5 Key components of one of the electric actuators for positioning a spot camera with mechanical links

To solve the tasks which are set, it is advisable to use rotating brushless electric motors as part of these electric drives. Figure 5 shows the key components of one of the spot camera positioning motors with mechanical links affecting the actuators.

The reference voltage u controls the motor current i_m, which is generated by the power converter *PC* and flows through the motor windings *EM*. The motor generates a torque that accelerates the rotational inertia *MI* and counteracts the friction. The encoder *EN* measures the speed and rotation angle. The inertia of load is modeled using the *LI* block.

The power converter in the first approximation provides current

$$i_m = K_{pc} u,$$

which is linearly related to the applied control voltage u. Here K_{pc} is the conductivity of the converter. The torque generated by the motor is proportional to the current

$$T_m = K_m i_m,$$

where K_m is the motor torque constant. The torque generated by the motor overcomes the rotational inertia of the motor J_m, and the rotating part is accelerated to the rotational speed ω. Friction effects are modeled by the coefficient B_m, and the friction moment itself is proportional to the rotation speed and is approximately $B_m\ \omega_m$.

The current is controlled by an electronic AC voltage source with feedback on the actual motor current. The AC voltage source is implemented using a pulse-width modulated (PWM) pulse converter. When designing the voltage control system on the windings, we will take into account the electrical dynamics of the motor, due to its resistance and inductance, as well as the back EMF.

Spot camera positioning motors do not exist in separate but are connected to mechanical links. These links have two significant effects on the engine: they give additional inertia, and also create torque because of the imperfect balancing of the elements of the spot camera gimbal suspension. Both additional actions can vary depending on the rotation angles. In Fig. 5, the connected mechanical links are modeled using the *LI* block, however, at this stage, we will assume that the suspension of the spot camera is perfectly balanced, and the load inertia is a constant value.

We write the torque balance on the motor shaft as

$$K_m K_{pc} u - B\omega - \tau_c(\omega) = J\dot{\omega}, \tag{1}$$

where B, τ_c and J are the effective total viscous friction, Coulomb friction, and inertia due to the motor, bearings, and load:

$$B = B_m + B_l,\ \tau_c = \tau_{c,m} + \tau_{c,l}. \tag{2}$$

To analyze the dynamics (1), we neglect the nonlinearities

$$J\dot{\omega} + B\omega = K_m K_a u,$$

and then apply the Laplace transform:

$$sJ\Omega(s) + B\Omega(s) = K_m K_a U(s),$$

where $\Omega(s)$ and $U(s)$ are the Laplace transform of the signals in the time domain $\omega(t)$ and $u(t)$, respectively. The last expression can be turned into a linear transfer function

$$\frac{\Omega(s)}{U(s)} = \frac{K_m K_a}{Js + B}$$

of motor speed relative to the input control signal, having one (mechanical) pole.

Once we have the model in the form above, we can create a step response graph and use standard control system design tools.

To ensure good dynamic and static characteristics in both drives, we use three-loop automatic control systems, including [20]:

- internal current loop;
- speed loop;
- outer angle loop.

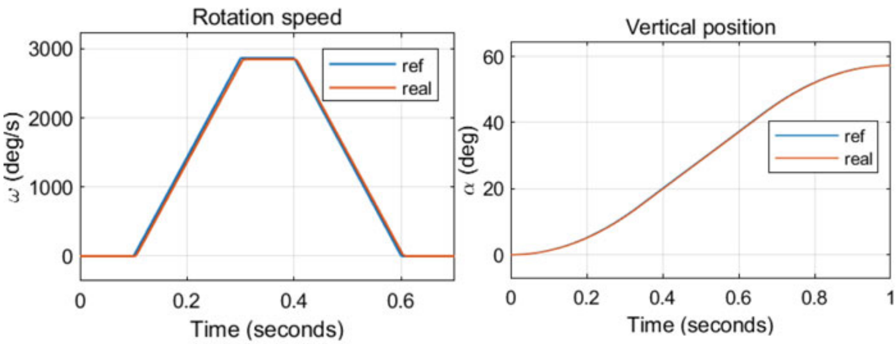


Fig. 6 The transient processes in the vertical angle positioning loop

Figure 6 shows the result of modeling of the speed loop and angle positioning of the spot camera along the direction of the UAV movement for various references.

It should be noted that the specifics of the UAV (limited energy resources and time) require the use of more advanced control algorithms than those used in this simplified model. These can be optimal (or quasi-optimal) controllers, in which it is possible to provide a transient process in a minimum time, without overshoot and with given energy costs [21]. An important issue is also taking into account the dynamics of the power converter.

The difference between the two electric drives (Fig. 4) is, first of all, that the positioning subsystem along the pitch angle is more powerful, since it contains, among other things, the positioning subsystem along the yaw axis together with the corresponding electric motor and power converter as a load. The less powerful yaw angle positioning subsystem is actually loaded only on the spot camera, which allows using lighter and more compact electromechanical components in it and obtaining better dynamic characteristics. At the final stage of system development, the parameters of the corresponding electric motors and power converters need to be clarified.

Additional analysis will require consideration of the features of two-coordinate positioning, considering the specifics of the gimbal on which the spot camera is located [3].

5 Human-Machine UAVs Control Complex

Within the framework of this part of the multidisciplinary study, we will limit ourselves to issues related to interaction with images from two cameras. From this point of view, the first question is to find out what exactly takes more time and strains the operator in the first place? What are the main features of a person's perception of information from a monitor screen that can affect the success and timeliness of a long-term mission with the participation of a UAV?

In [22], the idea is put forward, discussed, and tested that the global structuring of the visual scene precedes the analysis of local features. It has been experimentally established that global signals, which contradict local ones, inhibited reactions at the local level. It turned out that global differences were detected more often than local ones. It is proposed in [22] that perception proceeds from global analysis to more and more fine-grained analysis. The global precedence has several possible advantages such as utilization of low-resolution information, economy of processing resources, and disambiguation of indistinct details. Although evidence from the psychological literature (see references in [22]) supports the notion that global features are extracted earlier and/or better than local ones, in most previous research little attention has been given to the control over the complexity of global and local features.

So, we must have in mind that global processing is a necessary stage of perception. It turned out that global differences were detected more often than local ones. This may be interpreted as a support to the idea that global processing is done before more local analysis is completed.

By shifting this stage to a software system for analysing images from the main camera, we connect a person when he is aware of his abilities without fail to start with a global analysis, but for a scaled scene and more accurately identify an object of interest. Moreover, further reluctance of a person to study local elements promises additional bonuses in the context of the task of reducing reaction time and reducing operator fatigue.

The same “global precedence” effect was confirmed in [23] in contrast experiments with animals. Humans responded faster to global than to local targets, with human reaction time is independent of display size for both local and global processing. Finally, variations in stimulus density did not affect global search slopes in humans. Overall, results suggest that perceptual grouping of operations involved in the processing of hierarchical stimuli does not require human attention.

Human-machine interface (HMI) research related to the use of UAVs [24] highlights the extreme requirements in terms of operator workload. Real-time simulation of a system with a human in the control loop shows the directions for HMI cognitive optimization and equipping UAVs with appropriate levels of autonomy and intelligence.

So, when working on a system for determining the positioning zone of a spot camera, it is advisable to take into account a number of recommendations related to improving human performance and maintaining good awareness of the situation. This concerns the use of appropriate visual cues such as spatial arrangement, clustering, icon design, and category design to help the operator recognize information and events. Since our task so far is not to develop the HMI itself, but only to clarify the needs, capabilities and impact on the Image Pre-processing and Analyzing Software System, let us pay attention to the following.

UAV status not related to the current mission should be hidden unless requested by the operator or required for a critical decision.

The visual search models suggest that, in a fast parallel search, information about the location of a target’s visual template among distractions and identification of information are not available simultaneously. That is, the location of the target is recognized at earlier stages of visual processing than target identification [22].

The results of [25] showed that the search time does not increase with an increase in the number of distractors at both scales (local/global). However, target detection on a local scale required significantly more time than on a global scale. This latter finding agrees with the phenomenon of ‘global precedence’ [22].

Therefore, the global precedence (human) model can be used to refine the IASS (machine learning) decision making process.

It should also be noted that the specifics of the automotive industry focus mainly on how to create a secure interaction with technology that will help the driver complete the driving task, as well as give the driver more time to perform other tasks that are not related to driving [26]. However, this formulation of the problem and some other general approaches intensively developed for automobiles are fully consistent with the needs and can be useful for UAVs as well.

6 Conclusion

To reduce the load on the operator of an unmanned aerial vehicle (UAV) during long search and rescue and monitoring missions, the concept of an automatic system is proposed, which directly on board performs a preliminary analysis of images received from a high-resolution navigation video camera, determines areas of interest, and sets the positioning of an additional camera with a reduced viewing angle to scale the image of the selected area. This allows the operator to speed up the final decision and reduces the response time to the detection, identification of an object, as well as to the preparation of a mission report. To develop a technical system that will be able to solve the tasks, a complex hierarchical model is considered, consisting of three components: a software system for image pre-processing and analysis, an electromechanical camera positioning system, and a higher-level human-machine complex. It is determined that the model of the first component should be based on the use of a deep learning artificial neural network using inference trees, the number of inferences of which is equal to the number of zones into which the image of the main video camera is divided. The Simulink model of the positioning system contains a controller that improves the dynamics of two interconnected electric drives by using three control loops in each of them. The reference signal for the external loops is the rotation angles of the additional video camera in one of two directions, determined by the software pre-processing and image analysis system. Signals of the desired camera rotation speeds are formed at the outputs of the external loops. These signals are used to form a reference for the internal current loops of both motors’ windings, which provide the required torques of the rotors. The features of information perception by the operator of the UAV control complex were analysed and the main requirements for the construction of a human-machine interface were determined, considering the effect of global precedence. The results of the simulation of the electromechanical link were presented and the complexes of further research were outlined.

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