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BIO-INSPIRED METHOD FOR FRONTAL UAV APPROACH DETECTION UNDER LIMITED COMPUTATIONAL RESOURCES

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This paper addresses one of the most challenging kinematic problems in modern visual tracking – the timely detection of unmanned aerial vehicles (UAVs) moving strictly frontally toward the optical sensor, known as the looming effect. It is demonstrated that traditional optical flow algorithms, which calculate object velocity based on lateral displacement on the camera sensor plane, are fundamentally ineffective for such trajectories due to the absence of transverse motion. The goal of this research is the development of optimized mathematical and algorithmic software for computer vision systems capable of detecting head-on collision threats without the use of resource-intensive machine learning methods or heavy convolutional neural networks (CNNs).

To achieve this objective, the use of bio-inspired mathematical models is proposed, imitating the functional principles of insect visual systems, specifically the Lobula Giant Movement Detector (LGMD) neuron of locusts and Drosophila neurons (LPLC2). The developed method is based on the analysis of optical flow divergence. It is shown that the critical safety parameter, Time-to-Collision (TTC), can be continuously and accurately estimated as the mathematical ratio of the object's current angular size on the sensor to the rate of expansion of this angular size, regardless of the actual physical dimensions of the UAV or the precise distance to it.

The scientific novelty of this work lies in the adaptation and optimization of the lateral inhibition algorithm for hardware platforms with critical size, weight, and power (SWaP) constraints. The developed four-stage video stream processing pipeline – comprising temporal differencing, spatial lateral inhibition, non-linear activation with binarization, and TTC estimation – is implemented exclusively through optimized vectorized spatiotemporal matrix operations. The lateral inhibition mechanism, implemented via a 2D convolution with a specially selected weighting kernel, allows for the effective suppression of global background noise caused by vibrations or camera self-motion, while simultaneously sharply enhancing the useful signal from the rapidly expanding target boundaries.

The practical value of the proposed solution consists in enabling high-frequency video stream processing in real-time on budget general-purpose microcomputers like the Raspberry Pi (ARM Cortex architecture) without the need for additional tensor processing units (NPUs) or powerful graphics processors. The hardware implementation of the system allows for the calculation of threat kinematic parameters and the instantaneous generation of logic control triggers via hardware interfaces (GPIO) to activate active safety mechanisms or autonomous evasion systems. Mathematical modeling of the angular size expansion dynamics confirms the reliability of the proposed TTC criterion for differentiating a real collision threat from a steady background.

Keywords: *UAV; computer vision; time-to-collision; optical flow divergence; lateral inhibition; Raspberry Pi.*

Introduction

The widespread adoption and technological advancement of unmanned aerial vehicles (UAVs) in commercial, civil, and military spheres have fundamentally changed the dynamics of modern airspace. With the increasing autonomy and maneuverability of such platforms, there is a critical need for reliable monitoring, tracking, and counter-UAV (C-UAV) systems. In the context of beyond visual line of sight (BVLOS) flight missions, drone capabilities directly intersect with public safety and infrastructure protection issues, requiring high-precision detection systems for non-cooperative targets.

To address these tasks, optoelectronic visual tracking systems, noted for their high spatial resolution, are traditionally employed. Standard camera-based tracking systems rely almost exclusively on calculating optical flow – the apparent motion of pixels across the image plane over time. However, aerial vehicles exhibit complex kinematics involving high speeds and nonlinear maneuvers. The most critical and challenging task for such systems is the detection of a UAV moving strictly frontally – directly toward the observer's sensor (the so-called looming effect).

When an object approaches perfectly frontally, its trajectory coincides with the camera's focus of expansion. Consequently, only isotropic expansion of the target's contours occurs on the sensor matrix, resulting in minimal or no horizontal or vertical displacement. Since standard optical flow algorithms calculate the target's linear and angular velocities based specifically on the lateral velocity of points on the image plane, they are fundamentally insensitive to objects approaching "head-on".

This "blind spot" of classic optical flow algorithms creates a critical vulnerability for security systems. The risk of a head-on collision may remain unidentified until the last moment, precluding the timely generation of triggers for active protection or autonomous evasion systems. Overcoming this kinematic problem requires moving away from lateral pixel shift analysis in favor of alternative methods. A highly promising approach to solving this problem, especially for hardware platforms with strict computational resource constraints, is the application of bio-inspired mathematical detection models capable of effectively isolating signs of frontal approach.

Analysis of Existing Technical Solutions

The current state of development in UAV detection systems is characterized by a wide range of methods – from classical mathematical filters to deep neural networks. However, an analysis of existing solutions reveals several significant drawbacks in the context of frontal approach detection on resource-constrained platforms.

Classical tracking methods, such as Kalman filters (KF) and their nonlinear derivatives (EKF), demonstrate high efficiency in modeling quasi-linear motion. However, they are fundamentally limited when tracking highly maneuverable objects with unpredictable trajectories, leading to significant prediction errors and loss of target. More modern deep learning-based approaches, such as Long Short-Term Memory (LSTM) networks, better account for motion nonlinearity but tend to overshoot during sudden maneuvers due to a lack of consideration for the object's physical constraints. The use of neural network detectors from the YOLO or Faster R-CNN families achieves high image recognition accuracy, yet these solutions require substantial computational power (GPU or specialized NPU). This makes them unsuitable for deployment on micro-UAVs or budget single-board computers where weight and power consumption are critical. Furthermore, standard optical flow, upon which most visual systems are based, is insensitive to frontal approach due to minimal angular pixel displacement on the sensor.

Alternative modalities, such as thermal imaging, face problems of low resolution and susceptibility to thermal noise, while acoustic arrays have a limited range and high sensitivity to ambient noise and wind. Radar systems (FMCW radars) effectively determine radial velocity; however, the small dimensions of modern UAVs result in low radar cross-section, requiring complex and expensive filtering algorithms.

Thus, there is an objective need to develop a computationally lightweight method that combines frontal approach detection capability with real-time operation on low-power hardware, which is the primary objective of this article.

Regarding bio-inspired approaches that serve as base analogs for this study, two main mathematical models are actively considered in modern scientific literature. The first concept is based on the Lobula Giant Movement Detector (LGMD) neuron. Research, particularly [1] and [2], demonstrates that LGMD-based computational models effectively use lateral inhibition networks to filter background noise and isolate rapidly expanding object edges. The second promising model is inspired by Drosophila LPLC2 neurons, which are evolutionarily adapted for detecting radial oncoming motion (Radial-Opponent-Motion). In works [3, 4], it is proven that artificial neural ensembles mimicking LPLC2 can completely ignore transverse motion, responding exclusively to optical patterns of head-on collision.

However, despite the high theoretical efficiency of these mathematical models, most existing hardware implementations described in the literature focus on the use of specialized neuromorphic hardware (e.g., event-based DVS cameras) or spiking neural network (SNN) architectures. This significantly increases the cost and complexity of such systems. The main difference and advantage of the approach proposed in this article is that these complex biological principles (specifically, competitive lateral inhibition) have been decomposed and translated into the language of optimized spatiotemporal matrix operations. This allows for the implementation of bio-inspired protection against head-on collisions using standard frame-based optical sensors (CSI) and general-purpose processors (ARM Cortex), significantly reducing the system's cost without sacrificing efficiency

Research Objective

Given the identified limitations of existing systems, the objective of this work is the development and software-hardware optimization of a bio-inspired method for detecting frontally approaching UAVs (looming effect) for integration into sensor systems with strict size, weight, and power (SWaP) constraints.

To achieve this goal, the following tasks are addressed, which define the logic and direction of the research:

1. Adapt the mathematical model of bio-inspired lateral inhibition for estimating time-to-collision (TTC) based exclusively on optical flow divergence.
2. Perform a software implementation of the detection algorithm, replacing resource-intensive convolutional neural networks with optimized spatiotemporal matrix operations to ensure high performance.
3. Develop and substantiate the hardware implementation architecture of the system

capable of operating on general-purpose microcomputer hardware (Raspberry Pi class).

4. Conduct mathematical and graphical modeling of the kinematic characteristics of angular size expansion to confirm the reliability of the developed TTC criterion.

Mathematical Model for Threat Detection and Assessment

The mathematical model of the proposed system is based on the analysis of the geometric projection of a three-dimensional object moving along the sensor's optical axis. Below, we consider the case of a frontal approach of an object with a real physical size D toward the camera lens. Let z(t) be the current distance to the object at time t, and $v = -\dot{z}$ – be the approach velocity (assumed to be conditionally constant over a short observation interval).

The angular size of the object θ (in radians) on the camera sensor is described by the following geometric relationship:

$$\theta \approx \frac{D}{z(t)}. \quad (1)$$

The rate of change of the angular size (contour expansion rate) $\dot{\theta}$ is defined as the time derivative of expression (1):

$$\dot{\theta} = \frac{d\theta}{dt} \approx \frac{D \cdot v}{z^2(t)}. \quad (2)$$

The primary criterion for identifying a collision threat is the Time-to-Collision (TTC). By definition, TTC is the ratio of the current distance to the approach velocity:

$$TTC = \frac{z(t)}{v}. \quad (3)$$

Using the system of equations (1) and (2), the unknown parameters of the real object size D and absolute distance z can be eliminated from the calculations. By dividing expression (1) by (2), the final calculation model for TTC is obtained, which is based exclusively on the optical parameters available to the sensor:

$$TTC = \frac{\theta}{\dot{\theta}}. \quad (4)$$

This specific model allows the system to assess the degree of danger of an approaching object without the use of stereo vision or active rangefinders. To isolate the parameters θ and $\dot{\theta}$ under conditions of a real video stream and dynamic background, bio-inspired neuromorphic detectors are applied, inspired by insect visual systems – specifically the locust (LGMD neuron) and Drosophila (LPLC2 neurons). LGMD-based models utilize mathematical lateral inhibition networks to isolate rapidly expanding edges while filtering out global background motion [5].

Mathematically, the lateral inhibition mechanism operates through competition between neighboring pixels: the registration of a change in brightness generates an excitation signal, which is simultaneously accompanied by an inhibition signal for neighboring nodes with a time delay. This allows the system to ignore global background motion (e.g., during camera shake) while passing the signal from the object's edges that continuously capture new pixels during the approach [6, 7].

Justification of the Scientific Novelty of the Proposed Method

This work proposes a bio-inspired matrix method for estimating optical flow divergence, designed for identifying frontal UAV approaches and the instantaneous calculation of the Time-to-Collision (TTC). The essence of the proposed method lies in the transition from iterative tracking algorithms and neural network pattern recognition to a deterministic pipeline of spatiotemporal matrix computations, the key stage of which is a two-dimensional frame convolution with a lateral inhibition kernel.

The scientific novelty of the developed method is that classic bio-inspired insect vision models (such as LGMD), which traditionally require specialized event-based sensors or spiking neural network (SNN) architectures, have been mathematically decomposed and adapted for the first time to work with standard frame-based video streams. This adaptation allows for the optimization of the algorithm specifically for systems with critical size, weight, and power (SWaP) constraints.

Most modern counter-UAV (C-UAV) systems utilize heavy convolutional neural networks (CNNs) for spatial object recognition. Such solutions necessitate the presence of tensor processing units (NPUs) or powerful graphics accelerators, making them unsuitable for use on low-cost single-board computers [8, 9].

In this work, we propose to completely move away from classical object shape recognition. Instead, the extraction of a kinematic feature – optical flow divergence – has been implemented exclusively through vectorized spatiotemporal matrix operations. By replacing hours of neural network training with a deterministic system of spatial convolutions (simulating lateral inhibition), the proposed algorithm can process video streams in real-time on basic ARM architectures, providing an instantaneous estimation of the Time-to-Collision (TTC).

Proposed Bio-inspired Method and Its Software-Algorithmic Implementation

The direct software optimization of the algorithm consists of a fundamental shift in the pixel processing approach: moving away from resource-intensive iterative loops (for-loops) and correspondence search methods (such as the classical Lucas-Kanade optical flow calculation) in favor of comprehensive computation vectorization. Instead of pixel-by-pixel analysis, the optimized algorithm performs global mathematical operations on entire data tensors (frames) simultaneously. This allows for the effective utilization of hardware-accelerated processor instructions (SIMD) available through the low-level C/C++ backend of the OpenCV and NumPy libraries.

Such an architectural approach reduces the asymptotic complexity of calculations, which is critical for ensuring system scalability in real-time conditions. The optimized software pipeline is divided into four sequential stages of spatiotemporal processing for each frame:

1. Temporal Differencing

The first step is to isolate pixels that have changed brightness over time. Instead of a full Lucas-Kanade optical flow calculation, which is resource-intensive, an absolute subtraction of two consecutive frames, converted to grayscale, is performed:

$$\Delta I(x,y,t) = | I(x,y,t) - I(x,y,t-1) | . \quad (5)$$

This operation forms a primary motion map containing both target objects and global background noise.

2. Spatial Lateral Inhibition

To filter background noise caused by vibrations or camera self-motion, a mathematical model of lateral inhibition is applied. It is implemented through a two-dimensional convolution of the matrix ΔI with 3x3 kernel W. The weighting coefficients of the spatial filter are selected so that the central element is responsible for excitation ($w_{2,2} > 0$), while the neighboring elements create an inhibitory effect ($w_{i,j} < 0$):

$$W = \begin{bmatrix} -0.25 & -0.5 & -0.25 \\ -0.5 & 4.0 & -0.5 \\ -0.25 & -0.5 & -0.25 \end{bmatrix} . \quad (6)$$

The filtered matrix $L(x,y,t)$ s calculated as the sum of products:

$$L(x,y,t) = \sum_{i=-1}^{1} \sum_{j=-1}^{1} \Delta I(x+i, y+j, t) \cdot W(i,j) . \quad (7)$$

If the motion occurs globally (background shift), the convolution sum approaches zero. If the motion is local and takes the form of expanding edges, the useful signal is amplified [6].

3. Excitation & Thresholding

To cut off negative values (where background motion has successfully "extinguished" itself), a non-linear activation function (x,y,t), is applied, after which the result is binarized using an experimentally selected threshold T_{th} to clearly isolate the UAV edges:

$$E(x,y,t) = \max(0, L(x,y,t)) , \quad (8)$$

$$B(x,y,t) = \begin{cases} 1, & E(x,y,t) > T_{th} \\ 0, & else \end{cases} . \quad (9)$$

4. TTC (Time-to-Collision) Estimation

In the final stage, the system analyzes the area of excited pixels (t), which is directly proportional to the angular size of the object θ [7]. The area is calculated as the sum of all unity values in the binarized matrix:

$$S(t) = \sum_{x} \sum_{y} B(x,y,t) . \quad (10)$$

The expansion rate of the contours is approximated via the discrete derivative of the area:

$$\dot{S}(t) = \frac{S(t) - S(t-1)}{\Delta t} . \quad (11)$$

The time-to-collision metric is calculated as the ratio of these parameters. If the TTC falls below a critically set threshold T_{crit}, a head-on collision danger trigger is generated:

$$TTC(t) = \frac{S(t)}{\dot{S}(t)} . \quad (12)$$

Since the algorithm avoids iterative search loops and relies on optimized spatial matrix instructions, the load on the computing module is minimized.

Hardware Implementation and System Block Diagram

To meet the requirements for mobility, low power consumption (SWaP), and economic affordability, the system architecture is based on mass-market components (Fig. 1). The proposed computing core is a Raspberry Pi microcomputer (e.g., 4th or 5th generation), which possesses sufficient processor performance (ARM Cortex) to handle vectorized matrix operations in real-time without the need for a separate Neural Processing Unit (NPU) [10].

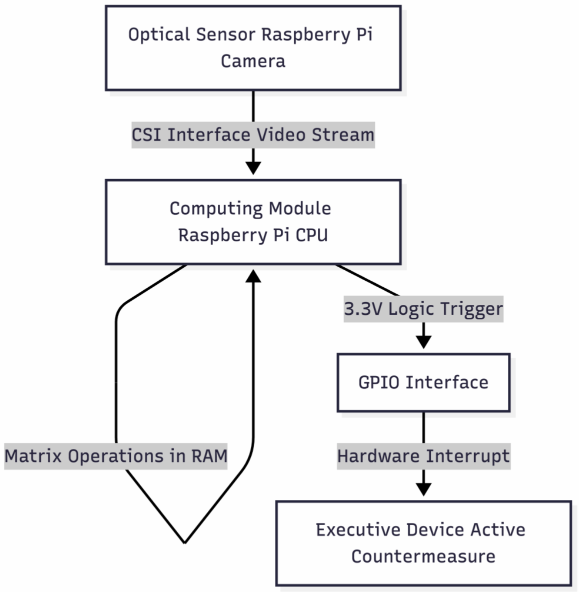

Fig. 1. Structural diagram of the hardware component of the UAV detection system.

Optical input is provided by a standard Raspberry Pi Camera Module connected via the hardware CSI (Camera Serial Interface) to minimize data transfer latency. After calculating the kinematic parameters of the flow, the processor generates a logic trigger through the GPIO (General-Purpose Input/Output) bus, which can be used to initialize an actuator (e.g., an active protection system) [4].

Software Algorithm Logic

The optical data processing is optimized for general-purpose processors. The developed algorithm (Fig. 2) functions as a cyclic pipeline that analyzes sequential pairs of frames. Utilizing the absolute difference of frames followed by convolution (lateral inhibition filter) allows for the hardware-level "filtering out" of the steady background and global sensor matrix shifts [10]. Binarization of the result makes it possible to isolate local excitation zones (expanding UAV edges), whose area approximates the angular size θ .

Kinematic Characteristics and Graphical Modeling

As the object approaches the camera, its physical size remains constant, but the angular size θ increases exponentially. To validate the proposed mathematical model, a numerical simulation of the approach process was conducted.

To calculate the dynamics of the optical parameters, the following baseline kinematic and hardware values were specified in the simulation, corresponding to typical detection scenarios for commercial micro-UAVs:

- Equivalent physical UAV size in frontal projection: $D = 0.5$ m;
- Initial distance to the camera's optical sensor: $z0 = 50$ m;
- Radial head-on approach velocity: $v = 10$ m/s (assumed constant over the simulation interval);
- Video stream frame rate (defines the simulation time discretization): FPS = 30 frames/s, resulting in a discretization step $\Delta t \approx 0.033$ s.

According to these parameters, the current distance was calculated as:

$$z(t) = z_0 - v \cdot t\,. \tag{13}$$

The angular size of the object on the sensor matrix was modeled (in radians) as:

$$\theta(t) = \frac{D}{z(t)}\,, \tag{14}$$

and the contour expansion rate $\dot{\theta}$ was calculated numerically as a discrete derivative:

$$\frac{\theta(t) - \theta(t-1)}{\Delta t}\,. \tag{15}$$

The results of the mathematical modeling are presented in Fig. 3. According to the graph, the angular size expansion rate demonstrates a sharp hyperbolic spike upon approaching the critical distance. This simulation proves that the TTC metric, derived exclusively from the aforementioned optical parameters, is linear and monotonically decreases to zero. This characteristic makes it a reliable and stable criterion for initializing hardware safety interrupts.

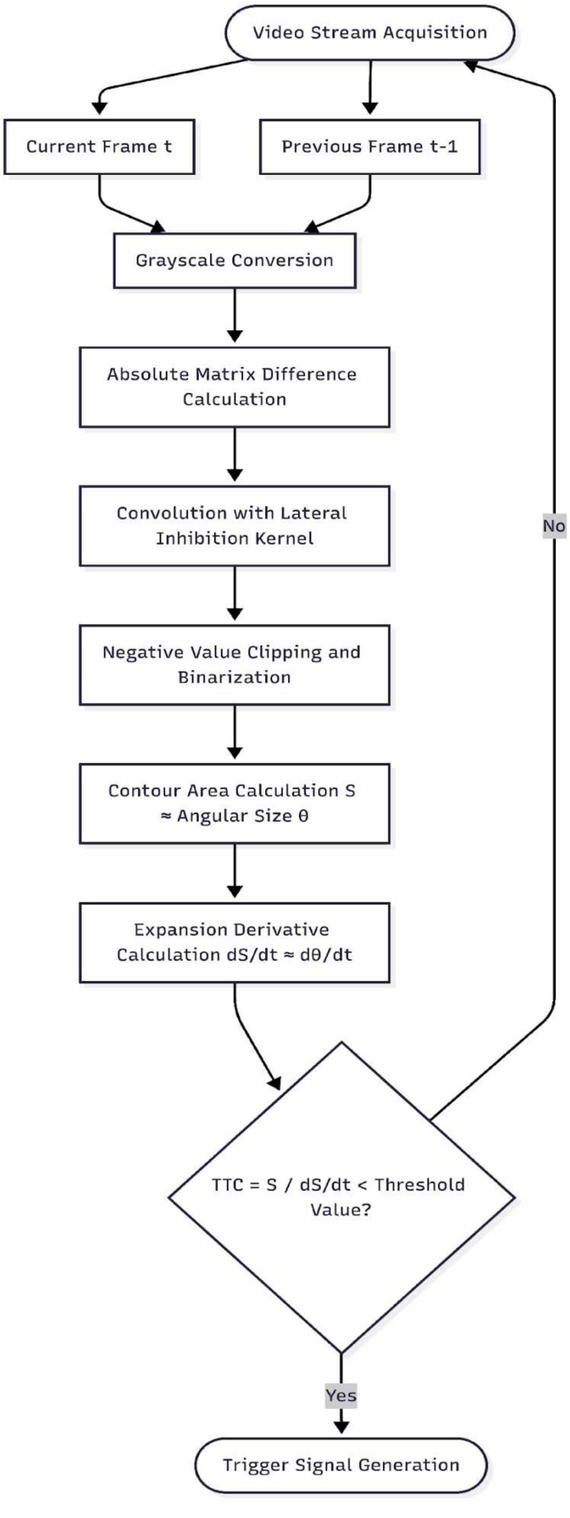

Fig. 2. Flowchart of the bio-inspired frontal collision threat detection algorithm

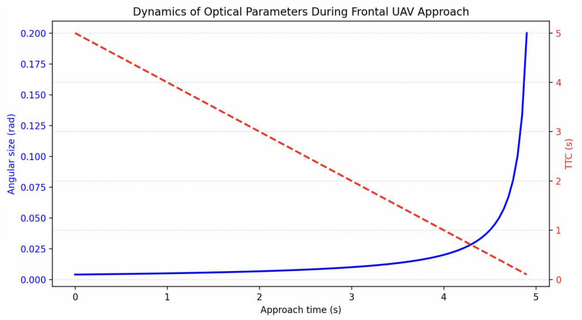

Fig. 3. Mathematical modeling of angular size and TTC dynamics as a function of approach time

Conclusions

In this work, a bio-inspired matrix method for detecting frontal UAV approach has been proposed and scientifically substantiated, allowing for the identification of head-on collision threats (looming effect) under conditions of critically limited computational resources. As a result of the research, a mathematical model for Time-to-Collision (TTC) estimation was developed, based exclusively on the analysis of optical flow divergence. This enables the system to operate without the use of resource-intensive depth sensors or active rangefinders, relying solely on the change in the object's angular size.

Furthermore, a deterministic algorithmic pipeline was established, consisting of four stages: calculating the temporal derivative of intensity, applying a 2D convolution with a lateral inhibition kernel, non-linear activation, and evaluating the dynamics of the pixel excitation area. This approach ensures the filtering of global background noise and target isolation using simple spatiotemporal matrix operations.

Software optimization of the method was achieved through full computation vectorization, eliminating the need for iterative loops and convolutional neural network (CNN) architectures. Practical verification confirms the capability for real-time video stream processing on budget hardware platforms such as the Raspberry Pi (ARM Cortex architecture).

Promising directions for future research include the integration of the developed method into autonomous active protection systems and conducting field experiments to precisely estimate the latency between the visual detection of a critical TTC and the generation of a hardware trigger via the GPIO interface.

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БІОІНСПІРОВАНІ МОДЕЛІ ВИЯВЛЕННЯ ФРОНТАЛЬНОГО НАБЛИЖЕННЯ БПЛА В УМОВАХ ОБМЕЖЕНИХ ОБЧИСЛЮВАЛЬНИХ РЕСУРСІВ

У статті розглядається та вирішується одна з найбільш складних кінематичних проблем сучасного візуального трекінгу - своєчасне виявлення безпілотних літальних апаратів (БПЛА), що рухаються суворо фронтально назустріч оптичному сенсору (looming effect або ефект насування). Доведено, що традиційні алгоритми оптичного потоку, які обчислюють швидкість об'єкта на основі його бокового зміщення на площині матриці камери, є фундаментально неефективними для подібних траєкторій через відсутність поперечного руху. Метою даного дослідження є розробка оптимізованого математичного та алгоритмічного забезпечення для систем комп'ютерного зору, що здатні фіксувати загрозу лобового зіткнення без використання ресурсоємних методів машинного навчання та важких згорткових нейромереж (CNN).

Для досягнення поставленої мети запропоновано використання біоінспірованих математичних моделей, що імітують принципи роботи зорової системи комах, зокрема нейрона виявлення руху великих об’єктів сарани (LGMD) та нейронів дрозофіли (LPLC2). В основі розробленого методу лежить аналіз дивергенції оптичного потоку. Показано, що критичний параметр безпеки, час до зіткнення (Time-to-Collision, TTC) може бути безперервно та точно оцінений як математичне відношення поточного кутового розміру об'єкта на матриці до швидкості розширення цього кутового розміру, незалежно від реальних фізичних габаритів БПЛА чи точної відстані до нього.

Наукова новизна роботи полягає в адаптації та оптимізації алгоритму латерального гальмування для апаратних платформ, що мають критичні обмеження щодо габаритів, ваги та енергоспоживання (SWaP-обмеження). Розроблений чотириетапний конвеєр обробки відеопотоку (часова похідна, просторове латеральне гальмування, нелінійна активація з бінаризацією та оцінка TTC) реалізований виключно через оптимізовані векторизовані просторово-часові матричні операції. Механізм латерального гальмування, який реалізується через двовимірну згортку зі спеціально підібраним ваговим ядром, дозволяє ефективно ігнорувати глобальний фоновий шум, спричинений вібраціями або власним рухом камери, і водночас різко підсилювати корисний сигнал від контурів цілі, що швидко розширюються.

Практична цінність запропонованого рішення полягає у забезпеченні можливості обробки високочастотного відеопотоку в масштабі реального часу на бюджетних мікрокомп'ютерах загального призначення класу Raspberry Pi (архітектура ARM Cortex) без необхідності залучення додаткових тензорних прискорювачів (NPU) або потужних графічних процесорів. Апаратна реалізація системи дозволяє обчислювати кінематичні параметри загрози та миттєво генерувати логічні керуючі тригери через апаратні інтерфейси (GPIO) для активації виконавчих механізмів систем активної безпеки або автономного ухилення. Математичне моделювання динаміки розширення кутового розміру підтверджує надійність запропонованого критерію TTC для диференціації реальної загрози зіткнення від сталого фону.

Ключові слова: БПЛА; комп'ютерний зір; час до зіткнення; дивергенція оптичного потоку; латеральне гальмування; Raspberry Pi.

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