Information system for analyzing the movement of complexly identifiable objects against a stationary background*

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Abstract
In recent years, increasing number of studies have focused on the detection of moving objects and the identification of static backgrounds. The most common approaches rely on deep learning methods and the creation of extensive databases and test datasets. However, such approaches face challenges related to the configuration of numerous parameters and the complexity of data storage systems.
The proposed method addresses these limitations by restricting frame processing and localizing the search area to isolate the region containing a moving object against a stationary background. In addition, filters are applied to highlight characteristic areas of the static background and the probable location of dynamic objects.
A method and corresponding software have been developed in the MATLAB environment to assess the dynamic behavior of complexly identifiable moving objects against a stationary background, based on the analysis of successive video surveillance frames.
Experimental results demonstrate that the proposed approach offers a high overall performance in identifying the movement trajectories of dynamic objects in static scenes. Furthermore, it shows resilience to variations in dynamic object parameters and environmental changes, effectively distinguishing between moving and stationary objects.

Keywords
video surveillance, moving object detection, data analysis, image processing

1. Introduction

The detection and classification of dynamic objects is a critical task in numerous fields of research [1–4]. In intelligent transportation systems, for instance, the detection of moving objects is a fundamental research direction. Moving objects are identified in real time using appropriate algorithms within intelligent video surveillance systems [5], for detecting anomalous events [6], and in the development of tracking systems [7].

Developing a reliable system for detecting moving objects remains a challenge due to various factors, one of the most prominent being a non-uniform background. The simplest approach involves background subtraction, where the static background model is subtracted from the input image and the resulting pixel differences beyond a defined threshold are treated as foreground. Background subtraction methods are well-suited for static or slowly changing scenes, such as waving tree leaves or water surface movement.

Common techniques for adaptive background modeling include Gaussian Mixture Models (GMM) [8] and Visual Background Extractor (ViBe) [9].

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To enable early intervention, it is important to identify the current position of foreign objects as well as their speed and acceleration [10-13]. However, in video surveillance scenarios where object parameters significantly differ from those of the background, visual identification becomes difficult.

2. Problem statement and proposed method

For the implementation of preventive measures, it is crucial to identify the current position of a foreign object, as well as its speed and acceleration.

When the parameters of the observed object and the general background are not comparable during video surveillance, the object may not be visually identifiable. For example, the surveillance frames in Figure 1 (a) and (b) differ by the presence of an additional element in one of them, shown in Figure 1 (c).

Below, we propose an approach for analyzing the pixel-level images of video frames that allows for the fixation of the current position and movement of objects with complex identification against a stationary background.

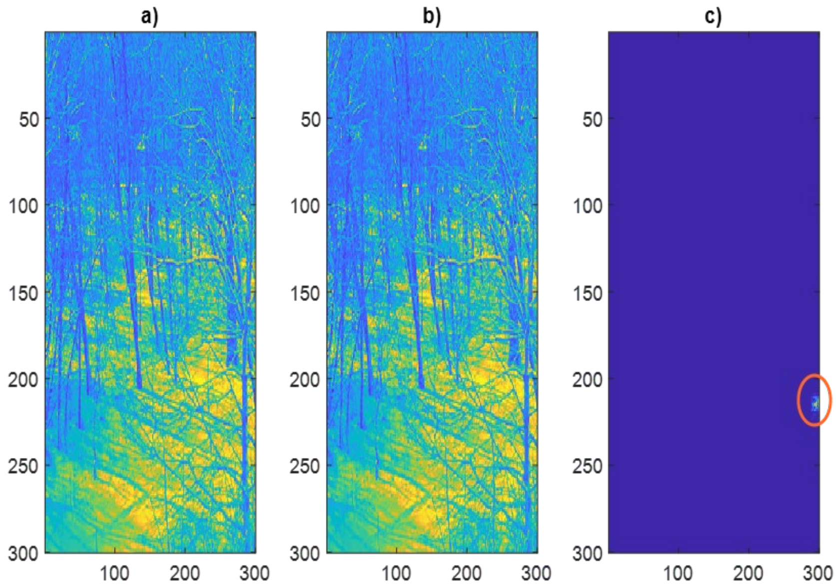

Figure 1: a) background; b) presence of an external object on the background; c) pixel image of the object.

Considering the image as a set of pixels defined by their position and intensity, we assign to each element the coordinate values *i, j* and the intensity level p_{ij}.

To the image as a whole, we associate a conditional "center of mass," analogously to the center of mass of material objects distributed on a plane.

If the size of the selected image for analysis is (m, n) pixels, the abscissa of its "center of mass" can be calculated as:

$$XC = \frac{\sum_{i=1}^{l} X_i P_i}{\sum_{i=1}^{l} P_i} \tag{1}$$

where

$$X_i = \frac{\sum_{j=1}^{l} j\, p_{ij}}{\sum_{j=1}^{l} p_{ij}}, P_i = \sum_{j=1}^{l} p_{ij} \tag{2}$$

and the ordinate as:

$$YC = \frac{\sum_{j=1}^{m} Y_j P_j}{\sum_{j=1}^{m} P_j} \tag{3}$$

where

$$Y_j = \frac{\sum_{i=1}^{m} i\, p_{ij}}{\sum_{i=1}^{m} p_{ij}}, P_j = \sum_{i=1}^{m} p_{ij} \tag{4}$$

Thus, for the case shown in Fig. 1(c), we obtain: XC= 295.9176 pix., YC= 214.8757 pix.

Accordingly, by observing the displacement of a given object against a stationary background, we can track the change in the position of its "center of mass" in the pixel image, which results from the difference between the current frame and the background frame.

3. Case study

When monitoring the movement of the object shown in Figure 1 (c) against the background in Figure 1 (a), we obtain a sequence of frames similar to Figure 1 (b), in which the localization of the object is problematic.

The result of applying the developed software based on the proposed method is shown in Figure 2.

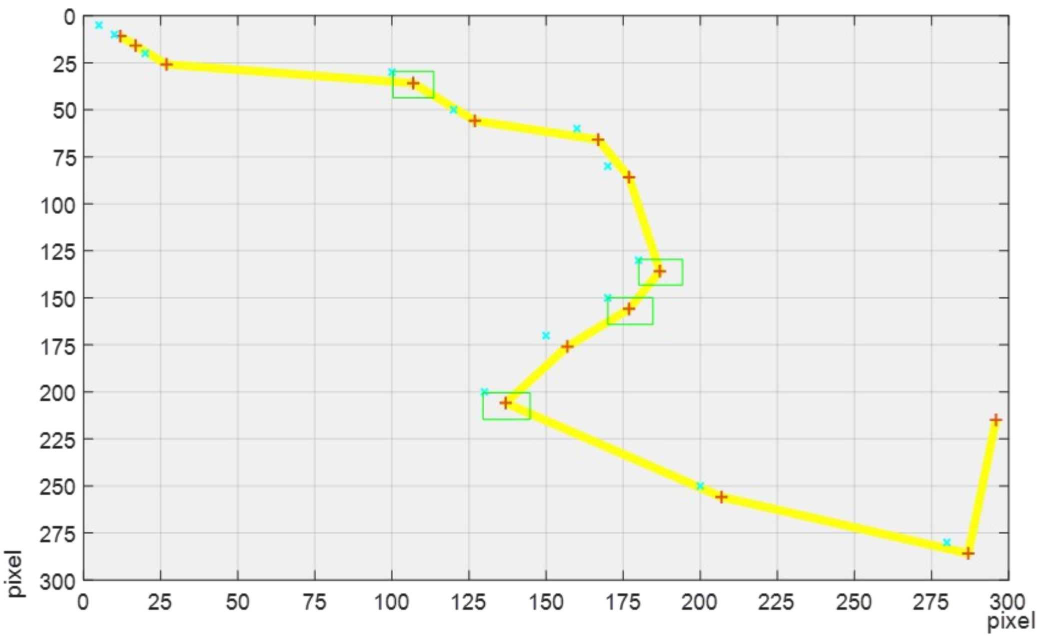

Figure 2: Trajectory of the detected foreign object's movement during the observation period.

During the analysis of 14 consecutive frames sized (300×300) pixels, the computed positions of the "center of mass" are marked with red dots, the object boundaries on the general background are outlined in green, and the trajectory of movement is shown as a yellow line.

From the resulting trajectory, we can estimate discrete values of instantaneous velocity and acceleration. The magnitude of the velocity vector is calculated as:

$$V_{i+1} = \sqrt{V_{xi+1}^2 + V_{yi+1}^2} \tag{5}$$

where

$$V_{xi+1} = \frac{x_{i+1} - x_i}{\Delta_t} V_{yi+1} = \frac{y_{i+1} - y_i}{\Delta_t} \tag{6}$$

where Δ_t – is the time interval between adjacent frames.

The change in velocity magnitude during the object's observation interval shown in Figure 2 is illustrated in Figure 3.

The computed discrete values are marked with red dots. A continuous change, represented by the dashed blue line, is obtained through spline approximation of the discrete data.

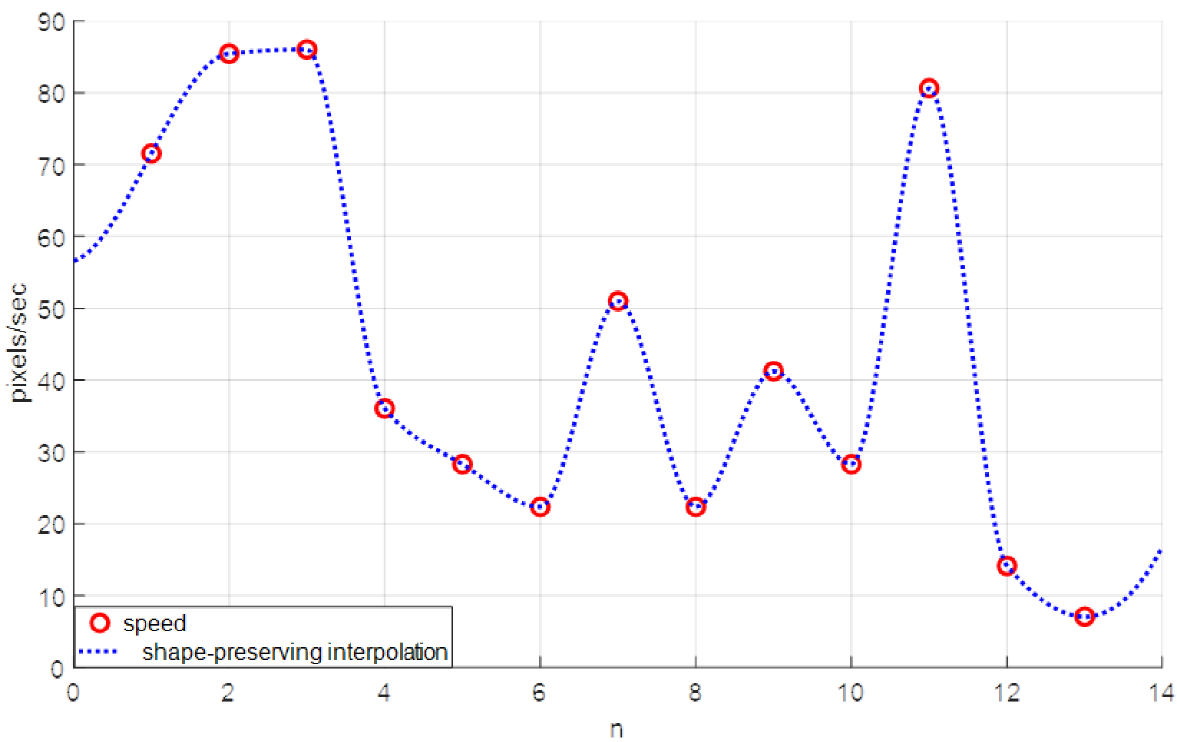

Figure 3: Change in the velocity magnitude of the observed object during the tracking stage.

The components of the acceleration vector magnitude are calculated similarly:

$$A_{xi+1} = \frac{V_{xi+1} - V_{xi}}{\Delta_t} A_{yi+1} = \frac{V_{yi+1} - V_{yi}}{\Delta_t} \tag{7}$$

The change in the magnitude of acceleration during the observation interval of the object shown in Figure 2 is presented in Figure 4.

The calculated discrete values are indicated with red markers. The continuous variation, represented by the dashed blue curve, is obtained using spline approximation of the discrete dependency.

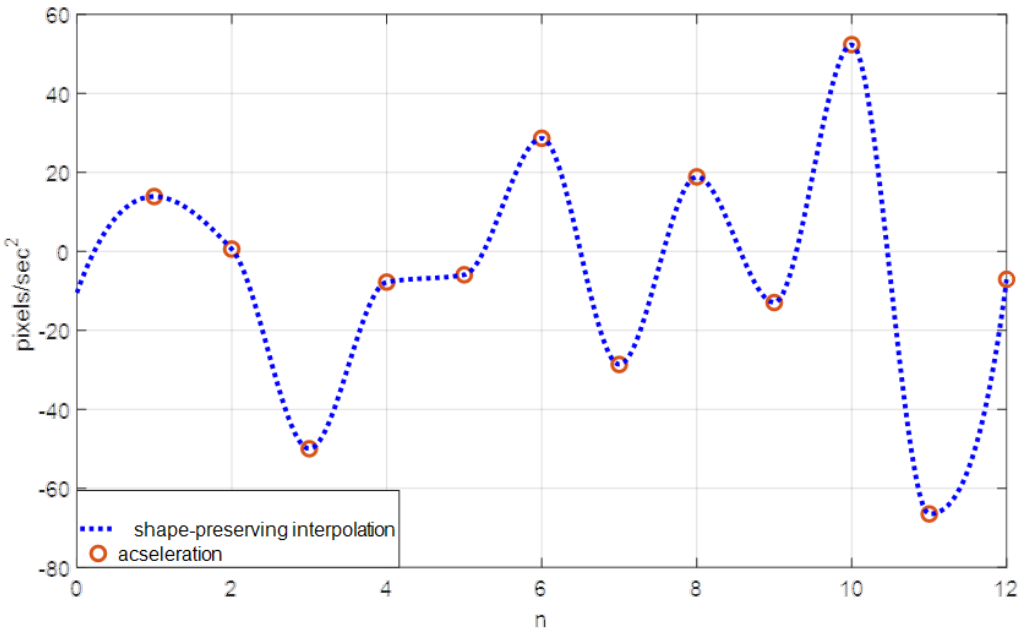

Figure 4: Change in acceleration of the observed object during tracking.

To adequately assess the state of the object at time moments between available video frames, in addition to the magnitudes of the velocity and acceleration vectors, it is also important to determine their directions. The direction of motion — i.e., the argument of the velocity vector — is calculated as:

$$\varphi_{Vi+1} = \tan^{-1}\frac{V_{xi+1}}{V_{yi+1}} \tag{8}$$

and the argument of the acceleration vector magnitude is calculated as:

$$\varphi_{Ai+1} = \tan^{-1}\frac{A_{xi+1}}{A_{yi+1}} \tag{9}$$

Thus, the movement of the detected object during the observation interval, shown in Figure 2, is accompanied by changes in its velocity and acceleration vectors, as illustrated in Figure 5. The object's positions in the video frames are marked with red dots. Velocity vectors at specific moments are shown in blue, while acceleration vectors are shown in green.

4. Influence of random noise on video frames

The accuracy of determining the current position of the observed object may be affected by random noise superimposed on the working frames.

As shown in Figure 6 and Figure 7, the effect depends on both the dimensions of the working fields and the comparative evaluation of the overall intensity level of the pixel image of the tracked object versus the noise level in the analyzed frame:

$$Q = \frac{\sum_{i=1}^{k}\sum_{j=1}^{n} p_{object\,ij}}{\sum_{i=1}^{m}\sum_{j=1}^{l} p_{noise\,ij}} \tag{10}$$

where $p_{object\,ij}$ – are the pixel intensities of the object image of size $(k \times n)$, and $p_{noise\,ij}$ – are the pixel intensities of the noise in the working frame.

Figure 6 presents an example of the trajectory shift (red line) compared to the one obtained without noise (yellow line) for parameters: k = 16, n = 12, m = 300, l = 300, Q = 6.05%.

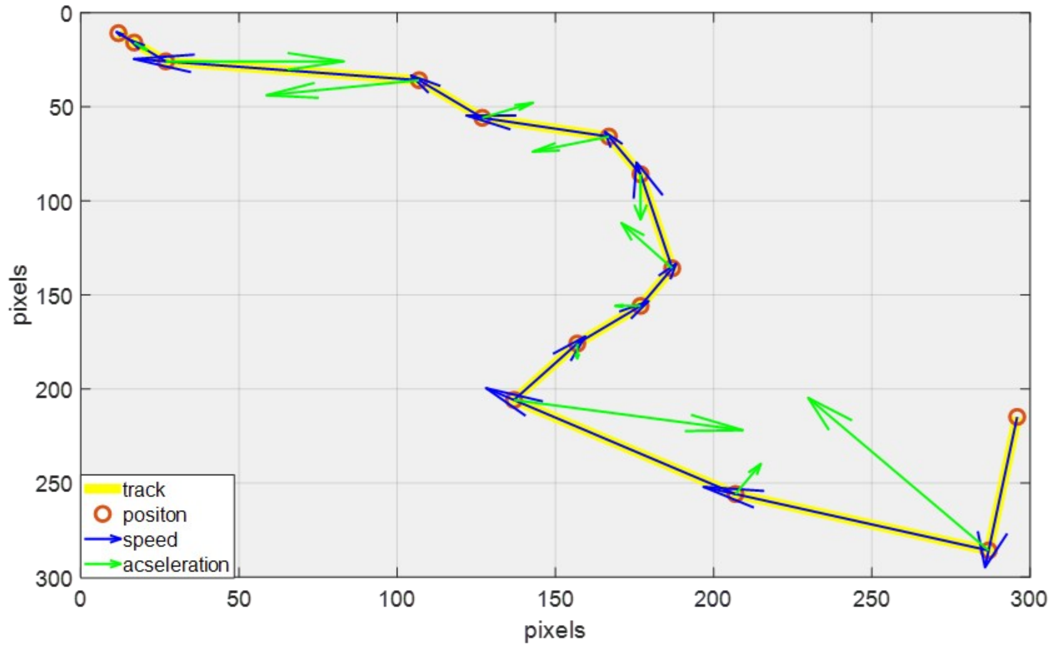

Figure 5: Changes in velocity and acceleration vectors of the observed object during tracking.

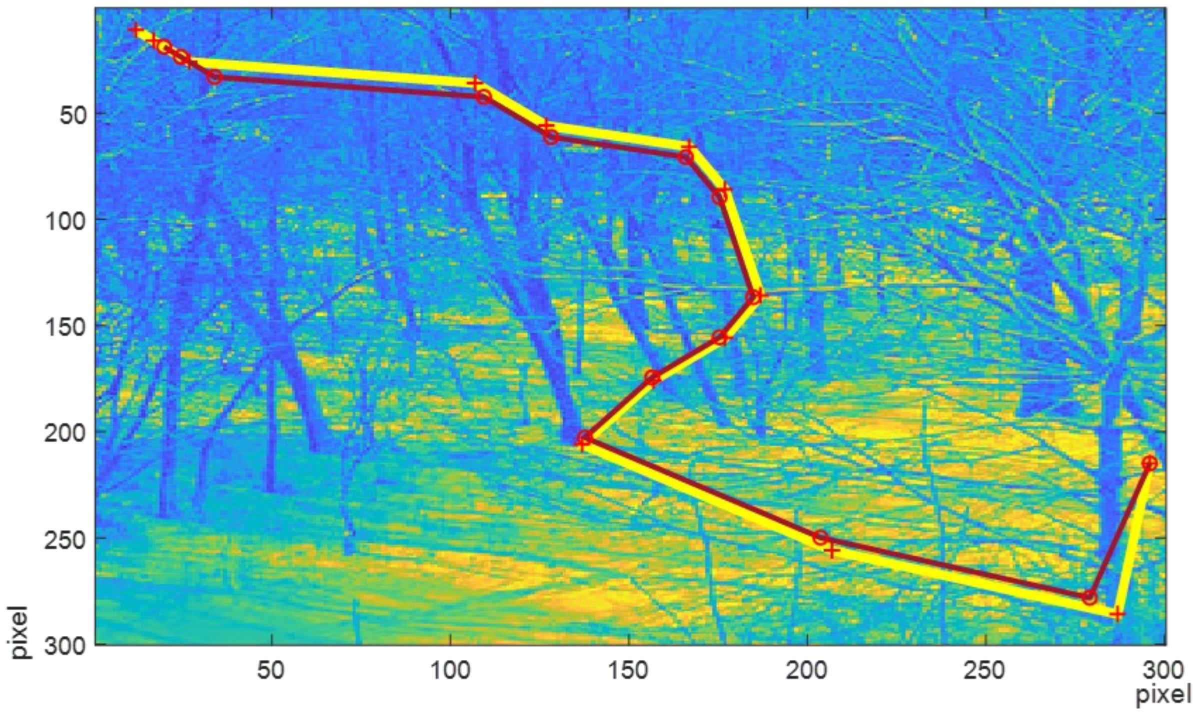

Figure 6: Deviation of the observed object's motion trajectory under random noise conditions with Q = 6.05%.

Figure 7 shows the results of applying the method under similar conditions, but with all observation frames distorted by random noise at Q = 60.5%.

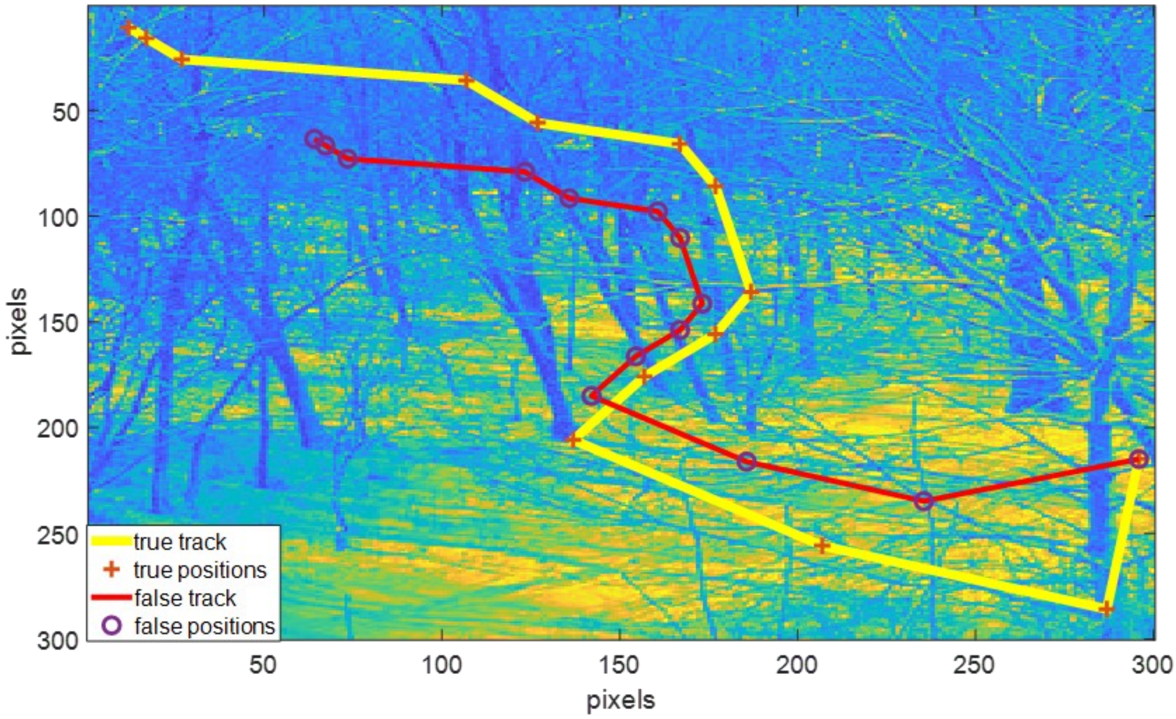

Figure 7: Deviation of the observed object's motion trajectory under random noise conditions with Q = 60.5%.

5. Conclusions

Moving object detection plays a pivotal role in video surveillance and computer vision systems. Traditional trajectory identification methods often fail in accurately isolating the background, especially in the presence of noise. Deep learning-based approaches partially solve this issue but are often too complex and resource-intensive for real-time video surveillance systems.

In this work, we propose a method and implement a software tool in MATLAB to evaluate the dynamic behavior of complexly identifiable moving objects using live video frames. We also investigate the impact of random image noise on observation outcomes.

The proposed method combines the strengths of object detection models with background modeling techniques. Experimental results indicate that this method performs well with complex dynamic objects, even in noisy visual environments.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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