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METHOD OF REAL-TIME VIDEO STREAM SYNCHRONIZATION IN THE WORKING ENVIRONMENT OF AN APPLE ORCHARD

Monitoring and analyzing the state of harvest in an apple orchard is essential for efficient horticulture. Unmanned aerial vehicles (UAVs) have been increasingly used for this purpose due to their ability to capture high-resolution images and videos of the orchard from different perspectives. However, synchronizing the video streams from multiple UAVs in real-time presents a significant challenge. The traditional controller-worker architecture used for video stream synchronization is prone to latency issues, which can negatively impact the accuracy of the monitoring system. To address this issue, the authors propose a decentralized method using a consensus algorithm that allows the group of UAVs to synchronize their video streams in real time without relying on a centralized controller device. The proposed method also addresses the challenges of limited network connectivity and environmental factors, such as wind and sunlight. The automated system that utilizes the proposed method was tested in an actual apple orchard. The experimental results show that the proposed approach achieves real-time video stream synchronization with minimal latency and high accuracy. As such, the SSIM index varies from 0.79 to 0.92, with an average value of 0.87, and the PSNR index – varies from 22 to 39, which indicates the decent quality of the received information from combined images. Meanwhile, the effectiveness of the developed system with the proposed approach was proven, which is confirmed by a high average value of 82.69% of the reliability indicator of detecting and calculating the number of fruit fruits and a low average level of type I (14.67%) and II (18.33%) errors. Overall, the proposed method provides a more reliable and efficient approach to real-time video stream synchronization in an apple orchard, which can significantly improve the monitoring and management of apple orchards.

Keywords: real-time video stream, synchronization, image stitching, apple orchard, unmanned aerial vehicles, decentralized approach.

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МЕТОД СИНХРОНІЗАЦІЇ ВІДЕОПОТОКІВ В РЕЖИМІ РЕАЛЬНОГО ЧАСУ В РОБОЧОМУ СЕРЕДОВИЩІ ЯБЛУНЕВОГО САДУ

Моніторинг та аналіз стану врожайності в яблуневому саду є важливими для здійснення ефективного садівництва. Безпілотні літальні апарати (БПЛА) усе частіше використовуються для цієї мети завдяки їхній здатності знімати зображення та відео високої роздільної здатності саду з різних ракурсів. Однак синхронізація відеопотоків із кількох БПЛА в реальному часі може спричиняти низку технічних проблем. Так, традиційна архітектура управління групою БПЛА під назвою «контролер-працівник», яка використовується для синхронізації відеопотоку, схильна до проблем із затримкою, що може негативно вплинути на точність системи моніторингу. Тому, для вирішення подібної проблеми, у цій роботі пропонується децентралізований метод із використанням консенсусного алгоритму, який дає змогу групі БПЛА синхронізувати свої відеопотоки в режимі реального часу без огляду на централізований пристрій керування. Запропонований метод також вирішує проблеми обмеженого підключення до мережі та враховує негативний вплив чинників навколишнього середовища, таких як пориви вітру та високу хмарність. Розроблена автоматизована система, що ґрунтується на запропонованому методі, може працювати в середовищах із низьким рівнем підключення та справлятися з проблемами, пов'язаними із чинниками робочого середовища фруктового саду. У результаті проведення експериментальних досліджень над автоматизованою системою встановлено, що запропонований підхід забезпечує синхронізацію відеопотоку в реальному часі з мінімальною затримкою та високою точністю. Зокрема, оцінка синхронізації відеопотоків за індексом SSIM коливається від 0,79 до 0,92 із середнім значенням 0,87, а за індексом PSNR – від 22 до 39, що свідчить про високу ефективність роботи розробленої системи з відеопотоками та високою якістю отриманої інформації з комбінованих зображень. Заразом було доведено ефективність розробленої системи із запропонованим підходом, що підтверджується високим середнім значенням 82,69 % показника достовірності виявлення яблук та низьким середнім рівнем похибок I (14,67 %) та II (18,33 %) роду. Загалом запропонований метод забезпечує більш надійний та ефективний підхід до синхронізації відеопотоку в реальному часі в яблуневому саду, що може значно покращити моніторинг та управління яблуневими садами.

Ключові слова: відеопотік у реальному часі, синхронізація, об'єднання зображень, яблуневий сад, безпілотні літальні апарати, децентралізований підхід.

Introduction

Apple orchards often face numerous challenges, including pest infestations, weather changes, disease outbreaks, and labor shortages. These challenges can lead to reduced crop yields, increased costs, and even crop failure [1]. Furthermore, traditional methods of monitoring and managing orchards [2], such as manual inspection, can be time-consuming, labor-intensive, and often yield incomplete or inaccurate information.

To address these challenges, there is a growing need for implementing information technologies in apple orchards. Using technologies such as drones, sensors, and computer vision can provide real-time data on crop health, soil moisture, temperature, and other factors impacting fruit growth and yield [3, 4]. This data can be used to optimize fruit management strategies, such as targeted irrigation, pest control, and automatic detection and calculation of the amount of harvest that may increase fruit yields and reduce costs.

Specifically, monitoring and analyzing the growth and condition of apples in a fruit orchard is essential for effective orchard management. Unmanned aerial vehicles (UAVs) have been increasingly used for this purpose due to their ability to capture high-resolution images and videos of the orchard from different perspectives [4]. However, synchronizing the video streams from multiple UAVs in real-time presents a significant challenge [5].

The problem of real-time video stream synchronization from UAVs in the working environment of an apple orchard is the focus of many recent kinds of research. The main challenge arises from UAVs being in constant motion and subject to various environmental factors, such as wind and sunlight [5, 6]. Weather conditions cause significant variations in the captured video streams, making it difficult to align them accurately in real-time.

Related works

Over the past decade, researchers have proposed several methods for real-time video stream synchronization from UAVs in the working environment of an apple orchard. One approach uses a controller-worker architecture [7], where one UAV is designated as the controller, and the other UAVs are designated as workers [8]. The controller UAV generates a synchronization signal transmitted to the worker UAVs through a wireless connection [9]. The worker UAVs then adjust their internal clocks to match the controller UAV, ensuring that all UAVs are synchronized.

Another approach [10] is to use visual odometry, which is a technique for estimating the motion of a vehicle by analyzing the changes in the images captured by its camera. In other work [11], each UAV is equipped with a visual odometry system that estimates its motion in real time. The estimated motion is then used to align the UAV video streams. One of the challenges in using visual odometry is the accuracy of the motion estimation, which can be affected by various factors such as camera calibration, image noise, and scene complexity. To address this challenge, researchers have proposed various techniques for improving the accuracy of visual odometry, such as using multiple sensors [12] and incorporating deep learning algorithms [13].

Some researchers have also proposed using sensor fusion to synchronize the video streams from multiple UAVs, like in [14]. In another study [15], each UAV has multiple sensors, such as GPS, inertial measurement units, and magnetometers. Such approaches employ advanced algorithms to fuse the sensor data to estimate the position and orientation of each UAV in real time, yet commonly with low accuracy. In this case, the estimated position and orientation are then used to align the video streams captured by the UAVs.

Overall, the problem of real-time video stream synchronization from UAVs in the working environment of an apple orchard is a challenging research problem with significant implications for orchard management. Accurately synchronizing the video streams from multiple UAVs can enable more accurate tracking of the growth and condition of apple trees [16], leading to improved crop yield optimization. Additionally, the proposed methods for real-time video stream synchronization from UAVs have applications beyond apple orchards and can be applied in other dynamic environments where real-time video stream synchronization is essential.

Problem statement

From the literature review, it was observed that traditional approaches to video stream synchronization rely on using a centralized controller-worker architecture [17], where one device acts as a controller, and the other devices act as workers. However, this architecture is prone to latency issues, which can result in delays in video stream synchronization and negatively impact the accuracy of the monitoring system. Additionally, the working environment of an apple orchard presents additional challenges, such as limited network connectivity and environmental factors, such as wind and sunlight, which can further exacerbate latency issues and make real-time video stream synchronization more challenging.

Therefore, there is a need for a new method of real-time video stream synchronization in the working environment of an apple orchard that can effectively address the challenges posed by multiple UAVs and environmental factors. This method should be reliable, efficient, and able to synchronize video streams in real-time with minimal latency while also being able to operate in low-connectivity environments and handle the challenges posed by environmental factors. Such a method would significantly improve the monitoring and management of apple orchards, allowing for more accurate and efficient decision-making.

Method of real-time video stream synchronization

The automated multi-level system proposed for detecting and calculating the number of similar structural objects by a group of UAVs utilizes multiple hardware devices to capture video sequences of the target objects. This unique feature enables the system to efficiently process and analyze a large number of video streams in real time. The proposed system can be used in various applications, such as monitoring agricultural fields, detecting structural damage in buildings, and assessing disaster areas.

Synchronizing video streams from multiple UAVs can be complicated due to various factors, such as the type of video cameras used, speed differences in receiving video streams, and distorted or missing video streams. Differences in flight characteristics and video capture methods between UAVs from different manufacturers can also negatively affect the detection quality and accuracy of structural object calculations. To address these problems, this study proposes a new method for real-time video stream synchronization. The method involves merging video sequences obtained from each drone in a group during an operational mission into a single image of a fruit tree to prevent issues with receiving video sequences. The proposed method is implemented through several software blocks combined into a single information system to create a behavioral signature, detect, and calculate the number of structural objects representing apples on trees. The method is depicted in fig. 1.

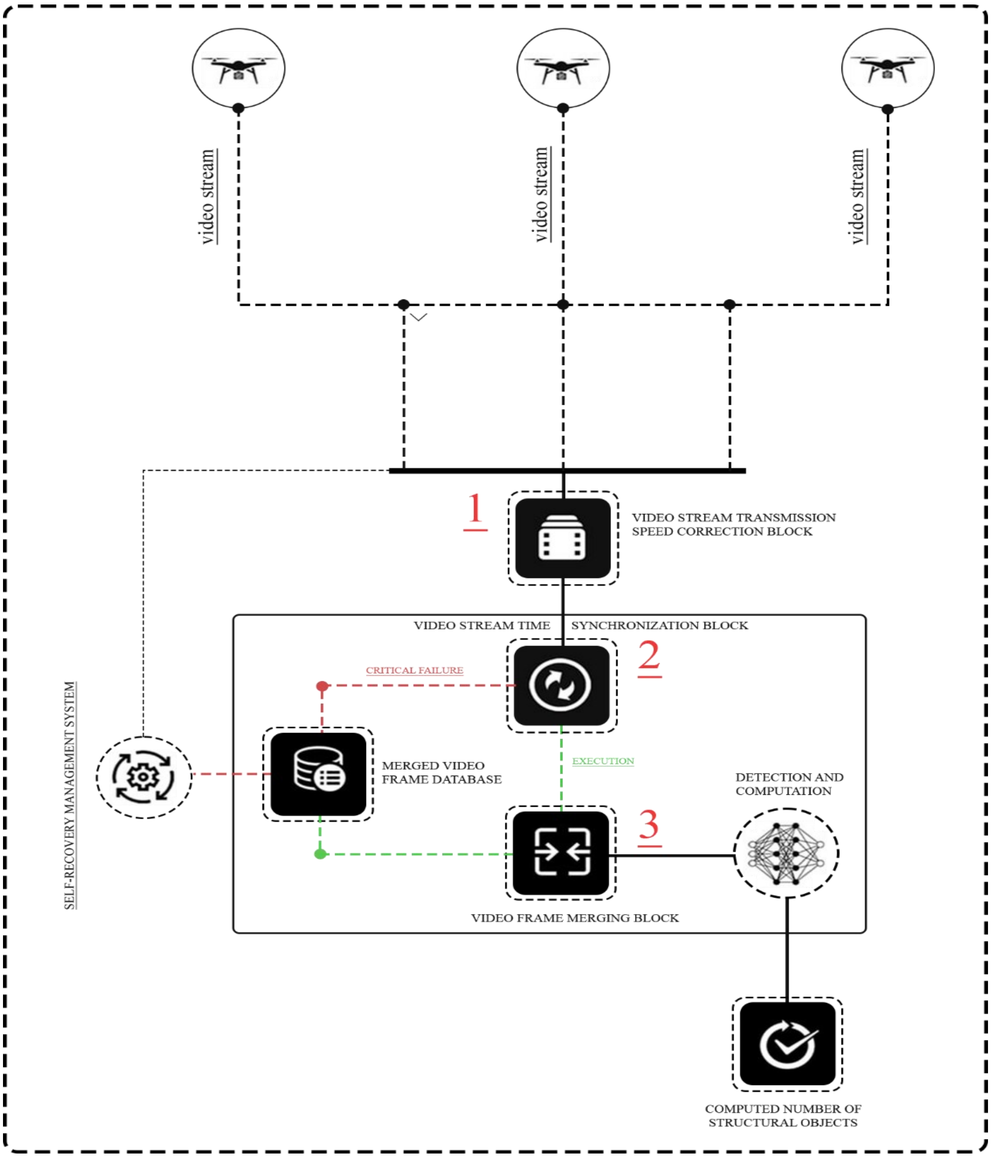

Fig. 1. The scheme of the method of real-time synchronization of video streams

The method consists of the following main components:

1. ***Block 1***: unit for adjusting the speed of transmission of video streams. While conducting a software mission in the working area, the group of UAVs generates video sequences that are transmitted over the network to the detection software module. However, these sequences enter the module at different times, which can be due to several factors, such as fluctuations in the network connection, the type of cameras used by the UAVs, and the speed at which the drones move in the working area, among others.

Given the characteristics of the video stream flow in the work environment, the speed adjustment unit constructs a software framework that incorporates mechanisms to process the transmission speed of video streams and establishes the functionality of halting and receiving a video stream. When the block for adjusting the transmission speed of a video stream transitions to the «waiting» state, it guarantees the reception of all video streams from each UAV simultaneously.

The block’s generated software structure includes the following features [18]: 1) an identifier specific to the drone, 2) bytes set of the video frame, 3) the video sequence’s frame rate, 4) the time of the speed correction block receiving the video frame from the drone, and 5) coding format of the video frame. When block completes its task, it transitions to the «execution» state and delivers the generated multiple program structures to the next execution block.

2. ***Block 2***: synchronization of video streams in time. The functioning of this block is based on the quantity of program structure sets received from the preceding block responsible for the speed correction of video streams. Initially, the video stream synchronization block inspects the number of program structure sets and processes the following scenarios accordingly:

2.1. A critical state is triggered if the number of program structure sets received by the synchronization block does not match the number of drones. The block then generates a request to retrieve the most recently saved program structure from the database of merged video frames. If the database contains the requested program structure, it is sent to the self-recovery module upon request. However, if the requested program structure is not in the database, a critical request is immediately issued to terminate the operation since it suggests that the UAV group failed to complete its mission. First, the video frame fusion unit checks the equivalence of the generation time of a set of program data structures. Performing a characteristic time check ensures the integrity of the generated data while creating one program data structure.

2.2. If video streams are successfully synchronized, the behavioral signature transitions to the "video sequence storyboarding" state. However, each drone may have different hardware that encodes video frames differently. Therefore, to ensure the unit can detect and calculate structural objects, the frames are converted into a single software format as an image. A derivative unit is developed that decodes the video frames into the required system format and creates program structures. The decoding time is recorded and added to the structure. As a result, the output of this block is a set of program structures that act as input data for the next block, which merges the video frames.

3. ***Block 3***: Unit for merging video frames. To ensure that the software objects used by the neural network have accurate geometric parameters, video frames captured by drones at various heights and angles are transformed using algebraic image transformation algorithms. The video cameras used by drones from different manufacturers have varying capture widths, and the weather conditions in the working environment can affect the camera's stability and distort the visual area. The dynamic nature of the working environment means that weather conditions and wind gusts can change during the UAV group's mission. Fig. 2 shows a diagram of the execution process of the video frame fusion block.

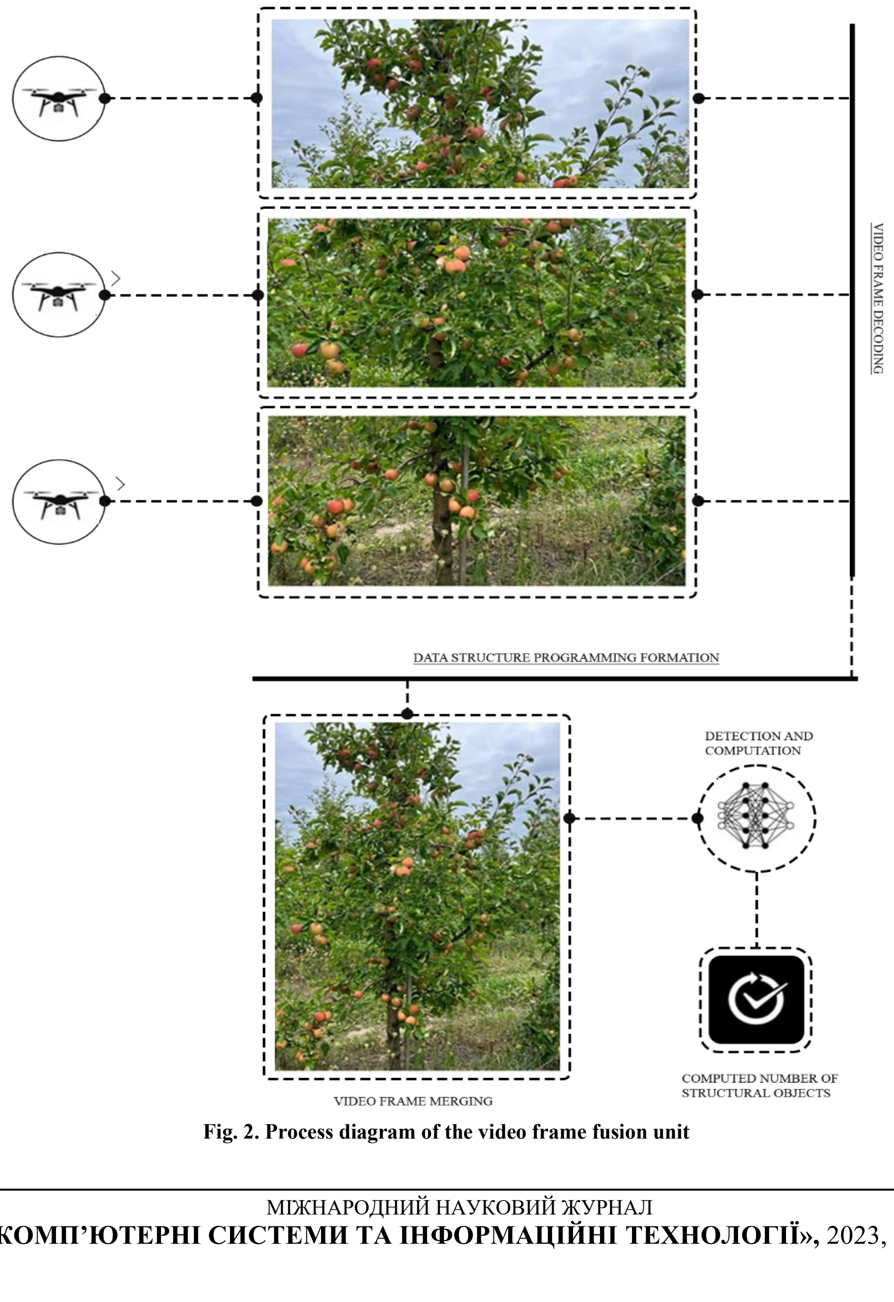

Fig. 2. Process diagram of the video frame fusion unit

The video frames undergo further transformation through the following steps:

Step 1: The interlaced video frame represented by a set of bytes is converted into a file. The software mechanisms then check the file's metadata, including file type, geometry, color space, resolution, and channel depth, by determining the file's signatures.

1.1) The set of images obtained in Step 1 is then corrected for rotation angle using an affine transformation, resulting in transformed video frames with coinciding geometric feature values.

1.2) The converted images are then sent to the software merge function.

Step 2: The corrected images are merged into a single image by fusing them.

2.1) The merged image may contain graphical artifacts, such as overexposed or underexposed areas and varying depth of field between frames. To address this issue, a software filter defined in the system is applied to mask the transitions between the frames. This filtering ensures that the merged video frames appear as a single image without noticeable transitions and with transparent edges.

2.2) The software compression engine receives the filtered video frames.

2.3) The video frame compression process involves an affine transformation that relies on the geometric transformation parameters of the neural network algorithms' input data. Since the video frames captured by the UAVs are rectangular, the compression mechanism converts them to a square shape for maximum efficiency in detecting and calculating the number of structural objects. This step results in a set of video frames ready for merging.

2.4) The set of prepared video frames from step 2.3) is then passed to the software fusion function.

2.5. Merging multiple video frames into one complete image produces a matrix-type object program data structure. Each element of the matrix corresponds to the color code value of a single graphic pixel. This matrix forms a continuous representation of a fruit tree, where all the single video frames from different drones combine into one image.

2.6) The data obtained in step 2.5) is then stored in the internal database of merged video frames.

2.7) The matrix software data structure is sent to the software module responsible for detecting and calculating the number of structural objects with similar characteristics.

The successful execution of the video frame fusion block results in a program data structure represented by a matrix of color codes. The fusion unit incorporates a functionality element that stores merged video frames in the internal database, which ensures system integrity in the event of a critical failure. The video frame fusion unit uses image conversion mechanisms to automatically process all video streams received during the UAV group's program mission. The system can identify critical failures that distort the data structure's integrity and store them in an error log to prevent their use as input parameters for further processing. Therefore, the video stream synchronization component ensures data integrity and prevents the system from processing distorted information.

Experimental results

The structural similarity index (SSIM) and the peak visual signal-to-noise ratio (PSNR) index [19] were used to evaluate the effectiveness of the real-time video stream synchronization method that is proposed in this work.

The SSIM index is formalized as follows

$$\mathrm{SSIM} = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)}, \tag{1}$$

where μ_x and μ_y are the mean values of pixels in the input and merged images, respectively, σ_x^2 and $\sigma_и^2$ are the standard deviations of pixels in the input and merged images, respectively, σ_{xy} is the covariance between pixels in both images, C_1 and C_2 are constant values that allow stabilizing the resulting value of the formula.

The PSNR index is formalized by the formula

$$PSNR = 10\log_{10}\left(\frac{MAX_I^2}{MSE}\right), \tag{2}$$

where MAX_I is the maximum pixel value in the original image *I*;

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left[I(i,j) - K(i,j)\right]^2,$$

where *I* is a set of three original images of total $m \times n$ pixels, *K* is the $m \times n$ merged images.

Achieving the efficiency of video stream synchronization according to (1) consists of obtaining a value from 0.5 to 1, considered a high-efficiency value; at the same time, an SSIM value in the range of 0 to 0.49 indicates ineffective synchronization. Formula (2) represents the degree of quality of the image obtained because of the merging operation; the value of the PSNR index is calculated as the ratio between the maximum possible power of the visual signal and the noise present in the image; the higher the value, the better the quality of the received image.

Table 1 shows the results of the video stream synchronization module of the automated system implementing the corresponding method for a stream of 12 consecutive groups of video frames randomly selected for testing; each group contains three video frames obtained from three UAVs, which are further combined into one image.

Table 1

The study outcomes of the efficiency of the video stream synchronization method achieved by the UAV group.

Index of a merged image	SSIM	PSNR	Index of a merged image	SSIM	PSNR
1	0.90	35.20	7	0.86	31.43
2	0.45	27.22	8	0.47	27.87
3	0.72	37.50	9	0.90	30.12
4	0.85	29.11	10	0.83	31.54
5	0.87	36.90	11	0.52	28.91
6	0.91	39.10	12	0.86	30.36

From table 1, SSIM performance ranges from 0.79 to 0.92, with an average value of 0.87. At the same time, images for which the value of the SSIM index is less than 0.50 are considered distorted by the system. Currently, those merged images with a PSNR index value greater than 30 are considered high quality; at the same time, PSNR values less than 30 indicate low image quality, which may be caused by external factors of the working environment (strong gusts of wind, precipitation, etc.).

If the current image has an SSIM index value less than 0.50, and the SSIM index value is less than 30, then this image will be considered distorted by the system and will therefore be discarded and will not go to the next module of detecting and calculating the number of structural objects.

In order to evaluate the practical validity of the proposed method, we applied an object detector [20] to the merged images to identify and classify apples that appear on the trees. A comparison of the estimates of the types I and II errors obtained by the UAV group during experiments under different weather conditions is shown in fig. 3.

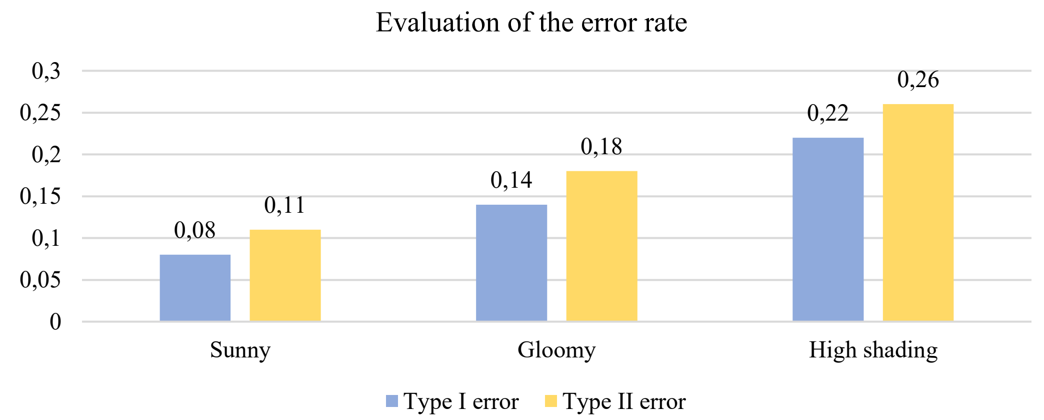

Fig. 3. Comparing the evaluation of errors made by the UAV group in various weather conditions

Fig. 3 demonstrates that the quality of fruit recognition in natural conditions is heavily influenced by weather factors and the presence of shading caused by other trees in the target work zones. These factors, in combination with visual noise such as leaves and tree branches, make it challenging to identify and track target objects in real-time dynamics. This is mainly due to the limited coverage angle of UAV cameras.

The conducted experiments confirmed the effectiveness of using a group of UAVs as part of an automated system for flying over an orchard in various weather conditions. The results showed that under sunny and overcast conditions with soft shade, the system had high accuracy and reliability with type I and II errors at 8% and 11%, respectively; under sunny conditions, and 14% and 18%, respectively; under cloudy weather. However, the errors were higher at 22% and 26% under highly shaded conditions, respectively. It is important to note that the presence of visual noise in the orchard, such as fruits being covered by leaves and branches, means that the UAV group and the automated system cannot achieve 100% efficiency in natural conditions, which is a promising area for further research.

An experimental study was conducted to evaluate the effectiveness of the developed automated system in detecting and calculating the number of fruits in natural conditions. The evaluation criteria included: a) the E index to determine the effectiveness of automatic route determination for the UAV group, b) the accuracy indicators for fruit detection and type I and II errors, and c) the indicators for the effectiveness of real-time synchronization of video frames SSIM and PSNR. The results of the experiments showed that the developed automated system is efficient, as evidenced by a high-reliability indicator of 82.69% on average for detecting and calculating the number of fruits.

Conclusions

The developed automated system with the proposed method can detect and count apples in real time in an orchard. Specifically, the system can receive multiple video frames in real-time from several UAV cameras, synchronize these video frames with each other into one informational data structure, and optimize image quality to improve the detection of apples. The system's video stream synchronization is evaluated based on the SSIM index, which ranges from 0.79 to 0.92 with an average value of 0.87, and the PSNR index, which ranges from 22 to 39. These results indicate the system's high efficiency with video streams and the decent quality of the information received from combined images. Moreover, the effectiveness of the developed automated system was confirmed by a high average value of 82.69% of the reliability indicator of detecting and calculating the number of fruit fruits and a low average level of type I (14.67%) and II (18.33%) errors.

Further research will be conducted to explore the potential of integrating deep learning algorithms into the system to improve the accuracy and efficiency of image processing.

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