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Advancements in Video-Based Insect Tracking: A Bibliometric Analysis to A Short Survey

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ABSTRACT

Video-based insect tracking provides vital insights into insect behavior and ecology, enhancing our understanding of their movements and interactions. Therefore, examining trends in this field over the last few years is essential. This study aims to conduct a bibliometric analysis to unveil the growing interest in video-based insect tracking with a short review based on documents used for bibliometric analysis. To achieve this, 453 documents were extracted from Scopus on 12 June 2023. Only documents in English published between 2010 and 2023, resulting in a dataset of 318 documents, were analyzed. The findings illustrate a consistent growth in video-based insect research over the last years, with a significant peak in 2021, comprising 32 documents. The journal PLOS ONE stands out as the most productive source. The USA exhibited the most significant interest in video-based insect tracking over the last years. Keyword analysis reflects the multidisciplinary nature of insect tracking research. The review demonstrated that video-based insect tracking serves two primary objectives: pose estimation and trajectory information. However, the main challenge in video-based insect tracking is to preserve the identity of multiple individuals in situations involving occlusions or complex interactions.

CCS CONCEPTS

• **Computing methodologies** → **Image processing**.

KEYWORDS

bibliometric analysis, computer vision, insect, video tracking, movement behavior

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1 INTRODUCTION

In recent years, insect tracking through videos has gained significant importance across various domains like agriculture, ecology and robotics. Accurate monitoring and analysis of insect behavior have far-reaching implications, aiding in understanding their ecological roles, interactions with the environment and developing effective pest control strategies [7]. This has driven research towards advanced tracking methods, as traditional manual observation methods are laborious, time-consuming, and error-prone, particularly given the unique challenge posed by small-sized, fast-moving insects with diverse behaviors. Computer vision, image processing, and machine learning techniques have revolutionized the field, enabling automated and precise tracking focusing on determining individual insect trajectories and movement patterns. Such insights reveal valuable information about foraging behavior, mating dynamics, migration patterns, and habitat preferences. Additionally, tracking insects can provide crucial data for studying the spread of vector-borne diseases [37] and assessing the impact of pesticides [33]. Researchers have developed a wide range of methods and algorithms to tackle the challenges in insect tracking. These techniques leverage computer vision algorithms, machine learning models, and sophisticated tracking frameworks to analyze image sequences or videos and extract relevant information about the insect's movement. Tracking algorithms [14, 44] employ various strategies, such as feature extraction, object detection, motion estimation, and trajectory prediction for precise insect monitoring. The field of insect tracking has witnessed a surge in research publications in recent years, indicating the growing interest and recognition of its importance. Researchers from various domains, including computer science, biology, entomology, and engineering, have collaborated to develop innovative solutions and advance our understanding of insect behavior. Then, a comprehensive bibliometric analysis is essential for gauging research trends, identifying influential authors, relevant publications, and uncovering emerging research directions [43]. In this paper, we conduct a comprehensive bibliometric analysis of insect tracking research via video to offer a thorough overview of the field. Our analysis provides insights into

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current research, guides future investigations, and fosters interdisciplinary collaborations. We outline the paper’s structure: Section 2 details the methodology, Section 3 presents analysis outcomes, Section 4 offers a short survey, Section 5 shows a discussion based on our study, and Section 6 provides the conclusion.

2 METHODOLOGY

We follow several steps for the study to conduct a high-quality bibliometric analysis. Each step is essential, from database selection to the selection of criteria for filtering retrieved data.

2.1 Database selection

This paper focuses on the Scopus database. It was chosen as one of the sources for this bibliometric analysis due to its extensive coverage of scholarly literature, inclusion of high-quality journals and conference proceedings, advanced search functionalities, and the ability to extract relevant bibliographic data.

2.2 Search string definition

The database extraction was performed on 12 June 2023. After multiple attempts, the most relevant search string was identified as “(track OR tracking) AND (video OR image) AND insect”. This search string resulted in 453 scientific documents from 1934 to 2023. The term “image” was included in the search string due to the possibility that some authors may interpret a video as a sequence of successive images.

2.3 Tools and software selection

To perform in-depth bibliometric analysis, we utilized the “bibliometrix” [5] package in R Studio [42], along with the “biblioshiny” interface, which is a shiny app providing a web interface for “bibliometrix”. This powerful combination enabled us to extract valuable bibliometric data, including publication trends, citation networks, co-authorship patterns, and keyword analysis. In addition to bibliometrix, we utilized LibreOffice Calc, a spreadsheet program, for data management and organization.

2.4 Criteria definition

To ensure a more comprehensive understanding of the methods and results presented in the documents, we limited our analysis to those published in English. Since the objective of our study is to evaluate trends over the last years, we conduct our analysis on documents produced between 2010 and 2023. No filter was applied to the different document types. The multiple filters applied reduce the number of documents to explore down to 318. The analysis of retained documents reveals that articles comprise approximately 73.90% of the corpus, with conference papers accounting for 19.81% and other document types (such as books and letters) contributing 6.29% to the documents under investigation. This predominance of articles could be attributed to the in-depth nature of research studies often found in articles, whereas conference papers may present more concise or preliminary findings.

2.5 Data Analysis

In this bibliometric analysis, we analyzed several aspects of the literature, including publication trends, to understand the growth

of research in insect tracking. We identified top authors based on parameters such as the h-index and the number of published documents. Additionally, we explored the distribution of publications across different journals and conferences to understand knowledge dissemination channels. Citation analysis allowed us to identify highly cited articles and influential works in the field. We also investigated the involvement of countries, revealing collaborative efforts. Finally, a comprehensive keyword analysis helped identify the main research themes and topics within the insect tracks in the video. To support this bibliometric analysis, a short survey of video insect tracking research will be performed using the documents analyzed for the bibliometric study.

3 RESULTS OF BIBLIOMETRIC ANALYSIS

In this section, we present the results of our bibliometric analysis, which provides valuable insights into the research landscape of insect tracking with images. We analyze vital aspects, including publication trends, citation analysis, keyword analysis, and journal distribution.

3.1 Publication trends

The distribution of scientific productions in insect-based video tracking through figure 1 reveals a notable increase in research output over the years. Between 2010 and 2013, article numbers remained relatively stable, but from 2014 onwards, there was a consistent rise, likely due to technological advancements enabling more sophisticated studies. The slight dip in 2020 was likely due to the COVID-19 pandemic’s disruptions, but research rebounded in 2021 with a significant increase, reaching a peak of 32 publications, which reflects the resumption of activities. The positive trend in the first half of 2023 indicates a promising outlook for future research.

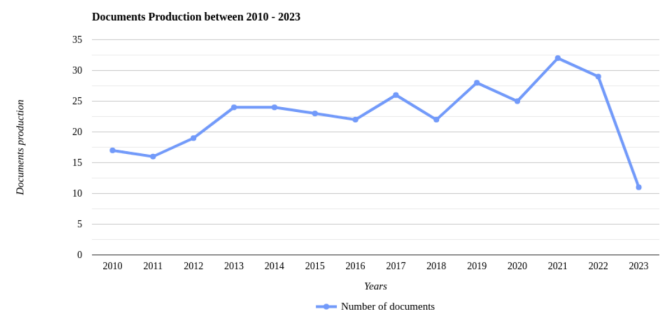


Figure 1: Annual scientific production

3.2 Top authors

The distribution of the most impactful authors through figure 2 in terms of h-index and the number of articles produced provides valuable insights into the contributions of individual researchers in the field of video-based insect tracking from 2010 to 2023. Several authors, such as RA Alzogaray, Anja Brückner, Benjamin Seth Cazoloto, Sam Grainger, Enno Merivee, MUST A, David C. O’Carroll, Steven D. Wiederman, and Eduardo N. Zerba, have achieved an h-index of 4. This indicates that each of these authors has published

at least four articles that have received at least four citations each. These authors have made notable contributions to the field, with a balance between their impact and productivity. Regarding the number of articles produced, O’Carroll and Wiederman stand out with seven publications each, the highest among the authors in the distribution. This highlights their prolific research output in the field of insect tracking. We can observe exciting variations by conducting a cross-analysis of the h-index and the number of articles produced. While some authors with an h-index of 4 have produced fewer articles, others have demonstrated higher productivity. This suggests that the impact of an author’s work is not solely dependent on the number of articles they produce but also on the quality and influence of those articles.

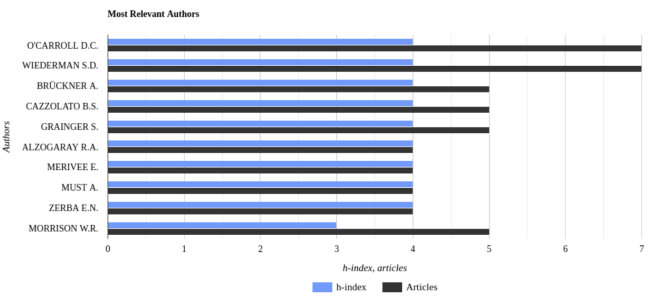


Figure 2: Most Relevant Authors

3.3 Top institutions

The distribution of top institutions in insect tracking research from videos through figure 3 between 2010 and 2023 demonstrates a diverse landscape. The Estonian University of Life Sciences, Universidade Federal de Viçosa, and Weizmann Institute of Science lead with 16 articles, showcasing a solid commitment to the field. Aarhus University closely follows with 15 articles, emphasizing active involvement. Other notable contributors include the University of Sheffield, Lund University, and Yangtze University, with 13, 11, and 11 articles, respectively. This global distribution underscores collaborative, multidisciplinary efforts in understanding insect behavior and movement.

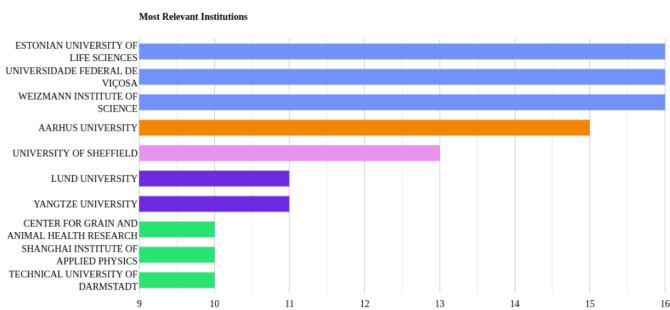


Figure 3: Most Relevant Institutions

3.4 Source analysis

The distribution of the most impactful sources through figure 4 in insect tracking, based on their h-index and the number of articles they have published, reveals exciting insights and highlights the significance of these sources. The Journal of Experimental Biology stands out with the highest h-index of 8, indicating its influential role. This source has also produced 9 articles, demonstrating its consistent contributions to advancing knowledge in insect tracking. PLOS ONE follows closely with an h-index of 7 and the highest number of articles, 13. This suggests a combination of impact and productivity, making PLOS ONE a prominent platform for disseminating research in this field. The cross-analysis of the h-index and the number of articles published by each source allow for a comprehensive evaluation of their impact and productivity. While sources with higher h-indexes are considered more influential regarding citations, the number of articles published indicates the breadth and depth of research the source covers.

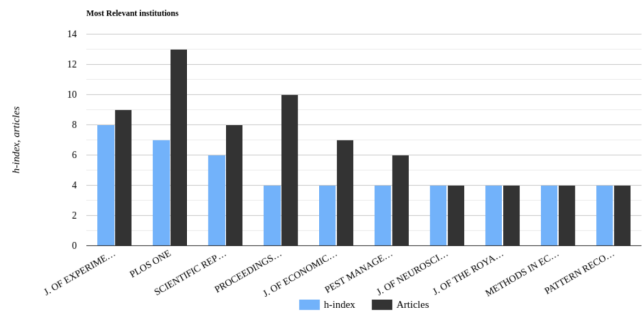


Figure 4: Most Impactful Sources

3.5 Citation analysis

The distribution of the most cited documents through figure 5 reveals key contributions in insect tracking. Paper [31] stands out as the most cited document with 265 citations, demonstrating its significant impact on the research community. References [29] and [36] also exhibit substantial citation counts, indicating their importance in the field. Other notable documents include [9] and [4], which have significantly contributed to the literature with 140 and 138 citations, respectively. These highly cited works reflect their influence and contributions to the field of insect tracking, providing valuable insights and serving as fundamental references for future research in this domain.

3.6 Relevant countries

The analysis of countries’ scientific production and citation in insect tracking through figure 6 and 7 reveals significant findings. The United States leads in scientific output (331 documents and 1629 citations), indicating its robust research influence. Figure 2 also shows that the USA has established substantial collaborations with countries such as the United Kingdom, Canada, Brazil, Netherlands, and Germany, highlighting the importance of international cooperation in advancing insect tracking research using images or videos. These collaborations reflect shared research interests,

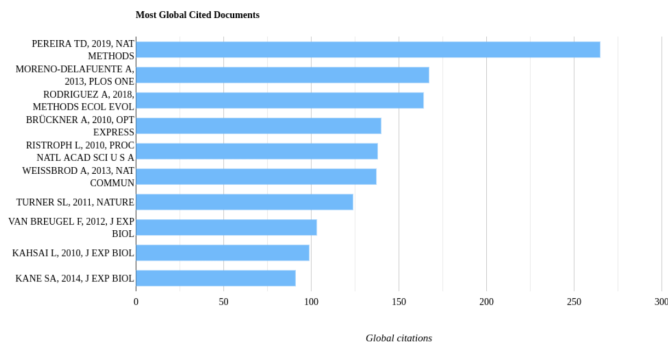


Figure 5: Most Global Cited Documents

complementary expertise, and a robust scientific network. An interesting observation is that China has more research documents than Germany and France but receives fewer citations, possibly due to a regional focus, publication practices, language barriers, or variations in the visibility and accessibility of research outputs. United Kingdom has a significant citation relative to its production, which indicates a strong impact. However, it is essential to note that citation counts alone do not fully reflect research quality or impact, as factors like research relevance, methodology, and contributions also matter and can vary by country. Moreover, citation patterns can vary depending on the research culture, publication practices, and language preferences in different countries.

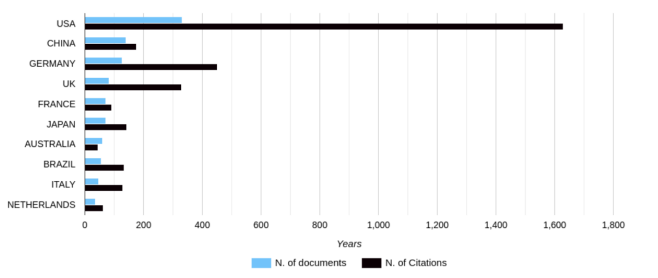


Figure 6: Most Relevant Countries

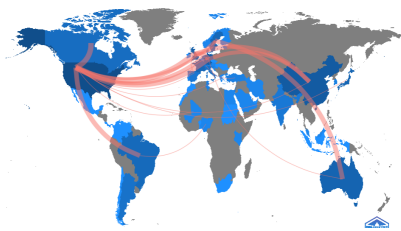


Figure 7: Countries Collaboration World Map

3.7 Keyword analysis

Analyzing the most frequent keywords (Figure 3) reveals key focus areas in insect tracking research. Terms like “video recording” and

“image processing” highlight the importance of visual data analysis and computational techniques. “Automation” and “robotics” indicate technology integration for automated tracking. Keywords such as “flight animal”, “flying” and “movement” reflect the interest in insect locomotion and flight mechanics. “Insecticide” suggests pest control re- search. “Computer vision”, “algorithms” and “deep learning” show the use of artificial intelligence for tracking. “Social behavior” and “feeding behavior” indicate studies on insect interactions and sensory perception. These keywords reflect the multidisciplinary nature of insect tracking research across biology, computer science, and behavioral studies.

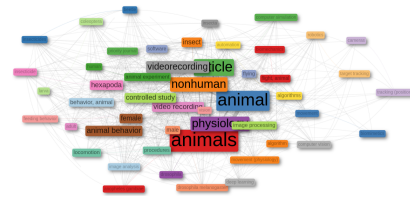


Figure 8: Keyword Map

4 SHORT SURVEY

Insect tracking methods have witnessed substantial advancements, driven by integrating computer vision, sensor technologies, and innovative algorithms. Video-based tracking has been employed to study various insect species, including fruit flies, drosophila, dragonflies and damselflies, mosquitoes, and more. This section comprehensively reviews various tracking techniques employed in entomological research, providing insights into their strengths, limitations, and applications.

4.1 Methods for insect tracking

Historically, *manual tracking* has been a fundamental approach for observing insect behavior. Researchers emphasized the importance of meticulous visual observations in understanding insect movement patterns. However, manual tracking is time-consuming, subjective, and often impractical for large-scale studies. Transitioning to more advanced techniques, *Physical Marker Tracking* involves affixing reflective dots onto insects to enable automated tracking [41]. This method ensures precise position determination even under challenging conditions. However, the attachment of markers may inadvertently modify insect behavior, potentially introducing biases. *Acoustic Sensors based tracking* represents an innovative avenue for capturing sounds emitted during various insect activities [17]. This approach is efficient for insects emitting distinct acoustic signals, like mating calls. However, it may have limitations in cases where visual confirmation is essential. In the realm of *Radio Frequency Tracking*, the attachment of radio transmitters to insects, coupled with the use of receivers to trace movements via radio signals, has demonstrated effectiveness [19]. This technique enables continuous monitoring over expansive areas. However, its implementation mandates a network of receivers and antennas, making it resource-intensive. In a non-invasive avenue, *Chemical Marker Tracking* has gained prominence by employing harmless chemicals to mark insects for tracking purposes [16]. This method

facilitates inconspicuous monitoring without direct physical interaction. Nevertheless, chemical marking could influence insect behavior and elicit ecological concerns. Most of the previously mentioned methods are largely invasive and can disrupt the natural behavior of insects. With sophisticated cameras and highly effective image processing algorithms emerging, a noticeable shift towards *video-based tracking* methods has been observed. This method utilizes camera systems and image analysis software for automated insect monitoring. However, processing large video datasets can be computationally intensive. In our bibliometric analysis, a clear pattern emerges in video-based insect tracking, with studies typically falling into two distinct categories, each with specific objectives and methodologies. One category involves precise *pose estimation* of insects by tracking their anatomical features. At the same time, the other focuses on providing *trajectory information* of insects from sequential images to reveal movement patterns.

4.2 Pose Estimation

Pose estimation, in this context, refers to determining an insect's spatial configuration or posture at any given moment within a video sequence. Accurate pose estimation enhances our ability to comprehend complex behaviors, such as mating rituals, flight patterns, and interactions within insect populations. To this end, some frameworks [39, 38] are proposed to automatically track bees' antennae, mandibles, and proboscis. This framework incorporates information about their kinematics, shape, order, and temporal correlation between neighboring frames. Similarly, a framework [27] was developed to detect the positions of 32 key points on a bee. In [18], they present an approach for continuously estimating poses in small articulated animals, utilizing multi-view video sequences. This method includes several key components, like the derivation of an initial skeleton model, the extraction of root and extremity points, and the computation of joint kinematics using the Forward and Backward Reaching Inverse Kinematics (FABRIK) algorithm [1]. Another work presents a model-based method for pose-estimation of free-flying fruit flies from multi-view high-speed videos [3]. A deep learning method was used to predict the positions of fruit flies body parts in image sequences [31]. Three-dimensional techniques were also applied, as exemplified in [20], which showcases an open-source toolkit designed for robust markerless 3D pose estimation of insects. Pose estimation proves to be the most challenging task in insect tracking based on video. While it has received less attention, there is substantial room for enhancing existing methodologies. In recent years, pose estimation models have become more specialized and tailored to the unique characteristics of different insect species. For instance, methods designed for tracking bees may differ from those used for tracking mosquitoes or butterflies due to size, shape, and behavior variations. Additionally, ongoing research explores the integration of 3D pose estimation techniques, which provide richer information about insect orientation and movement in three-dimensional space.

4.3 Trajectory information

Insect trajectory analysis, vital for behavioral and ecological research, can be categorized into two scenarios: single target and

multiple target tracking. In single-target tracking, researchers focus on monitoring an individual insect's movements and behaviors in detail, suitable for understanding specific insects like pollinators or disease vectors. Precision is crucial in data collection and analysis. Conversely, multiple target tracking involves monitoring and analyzing several insects in a scene simultaneously, providing insights into group dynamics, swarm behaviors, and collective insect movements. It is valuable for studying social behaviors and community-level interactions. Four steps were required for multiple target tracking: acquisition, background and foreground modeling, insect recognition and trajectory generation.

4.3.1 Acquisition. The acquisition is a pivotal step in video-based insect tracking, laying the foundation for subsequent image processing and analysis. Researchers utilize two primary methods for video acquisition: offline and online [30]. The offline approach analyzes a pre-recorded video sequence, enabling extensive computational analysis and frame-by-frame processing. This method is advantageous for complex tracking algorithms that require access to past and future frames and for handling vast amounts of data. This is evident in the work of [23], which involves performing offline processing on video sequences captured at 120 fps for phlebotominae tracking. In contrast, the online method involves real-time analysis of a live video stream from cameras, ensuring immediate monitoring of insect behaviors. Online tracking demands real-time processing to match the camera frame rate and minimize data loss, making it suitable for relatively more uncomplicated tracking algorithms. As an illustration, [6] employed a camera system coupled with a Jetson Nano computer, which performs real-time classification and insect tracking at 0.33 frames per second. This highlights the low real-time data processing rate. Key factors, such as frame rate and camera resolution, are pivotal for accurate and reliable insect tracking data acquisition. Higher frame rates are essential for capturing fast movements, while lower rates suffice for slower behaviors. Camera resolution is crucial for detecting and recognizing small insects. In most cases, 20 to 30 fps at 720p to 1080p resolution is enough to achieve good results on insects such as bees, ants, sandflies, and many other insect pollinators [36, 40, 15, 34]. It is also recommended to ensure that each organism to track consists of at least 50 pixels within a video [36, 32].

4.3.2 Background and Foreground Modeling. Accurate tracking of insects in videos requires an effective separation between the background and foreground elements. The primary objective is to differentiate between static and dynamic elements within a scene, enabling the identification and tracking of insects against a changing background. Various approaches are employed to model the background in insect tracking. One of the most common techniques involves statistical methods, like Gaussian Mixture Models (GMMs), which learn the statistical distribution of pixel intensities over time. In [23, 22, 24], they used the GMM method for modeling the background and the detection of foreground objects. After that, they applied mathematical morphology operations to filter the foreground and retain only the areas corresponding to sandflies. Indeed, further advancements in insect tracking harness the power of machine learning techniques, including the K-Nearest Neighbors (K-NN) algorithm, to enhance the modeling of background and foreground

components. For example, [35] uses a K-NN background subtractor, and then a median filter and an erosion-based morphological filter are applied to the segmented image to remove noise for honeybee tracking. The work [21] also developed a tracker based on background detection and connected regions with a K-NN model. The methods mentioned previously are considered dynamic approaches because they can adapt to changes in lighting over time. However, some studies opt for more straightforward static methods [15, 32, 8]. For example, they create a reference background image by performing an average or a median of initial pixel frames before insects appear. Then, subsequent images are subtracted from this reference background to highlight the foreground objects. The choice between dynamic and static tracking methods depends on tracking needs and lighting conditions. Dynamic methods adapt to changing light but are computationally intensive. Static methods are lightweight and work well in stable lighting but may struggle in variable lighting. Despite the effectiveness of background modeling techniques, challenges persist, including rapid and unpredictable lighting variations, occlusions, and robustness concerns for complex backgrounds like vegetation. Additionally, selecting optimal parameters, model adaptation, and real-time performance remain challenging.

4.3.3 Insect Recognition. Following successful foreground and background separation, the next critical step in video-based insect tracking is insect recognition, which is essential for preserving individual identities, especially when tracking multiple species. However, this step becomes optional in controlled environments with a single species. Recognizing insects involves various techniques, from traditional methods to advanced deep learning, contributing to tracking accuracy and reliability. Traditional methods often involve feature extraction techniques like color histogram [13], feature fingerprints [32], and Scale-Invariant Feature Transform (SIFT) [28]. These methods focus on extracting relevant features from the insect's appearance, such as texture, shape, and edges, allowing for subsequent classification. However, these techniques can encounter challenges with variations in insect appearance due to factors like lighting changes and occlusions. Recent advancements in deep learning have introduced Convolutional Neural Networks (CNNs) as a powerful tool for insect recognition. This is reflected in the significance of pre-trained models, such as YOLO (You Only Look Once) and ResNet (Residual Neural Network), in insect recognition cannot be overstated. These models, preloaded with a vast amount of diverse data, exhibit remarkable capabilities in extracting intricate features from images. YOLO, for instance, offers real-time object detection and classification, enabling accurate identification of insects even in complex scenes. On the other hand, ResNet's deep architecture facilitates the extraction of intricate hierarchical features, making it exceptionally adept at discerning subtle differences among insect species. In [35], they try to recognize honeybees after insect segmentation using a deep learning model YOLOv2. The paper [6] designed a system to recognize and track 8 insect species using a deep learning model based on YOLOv3, which shows a good performance. In [11], a model based on ResNet was trained for ant detection before trajectory prediction. However, it can also happen that some researchers decide to build their deep-learning models from scratch to have a model that specifically meets the

needs of the work. For example, the second main step of anTraX algorithm [15] consists of tracklet classification, in which identifiable single-insect tracklets are labeled with a specific ID by a pre-trained CNN model. In contrast, other tracklets are marked as unidentified single-insect tracklets. The work [8] proposes a designed system to attract moths (Lepidoptera) and insects at night and automatically capture images based on a motion for tracking. However, moths must be recognized among other insects for counting. For this task, a CNN model classification was trained for ten classes, including seven moth species and other insects. A key challenge in insect recognition is the variability in appearance due to species, life stages, and environmental conditions. Robust recognition models that handle such variations are essential, especially considering occlusions, cluttered backgrounds, and changing lighting conditions. Investigating innovative deep learning frameworks, such as the YOLO model, known for its rapid and diverse object identification capabilities [12], presents a potential solution for enhancing the efficiency of insect tracking in lengthy video sequences.

4.3.4 Trajectory Generation. One common technique involves linking the detected insect positions across consecutive frames to create trajectories. This method is efficient and well-suited for single-target tracking scenarios. The predominant method employed to address multiple insect tracking is the Kalman filter for trajectory enhancement, predicting an insect's next-frame position based on motion dynamics and probabilistic modeling and often combined with the Hungarian algorithm for accurate position estimation. The Kalman filter has frequently demonstrated its effectiveness in tracking humans in complex conditions [26] and has also found several applications in tracking insects. In [23], they used the Kalman filter to predict insect position, and then they assigned each detected phlebotominae to each track using the Hungarian assignment algorithm. Kalman filter also performs well to generate a trajectory for ants [11], drosophila [40], and mosquitos [2]. In some instances, the Hungarian algorithm is employed independently to generate trajectories by finding the most optimal consecutive positions for an insect between two images. For example, in [8], the position and size of individual insects were estimated for each frame, enabling tracking through the optimal assignment of insects between consecutive frames. The Hungarian algorithm was employed, where the cost function encompassed a weighted combination of distance and area between matched bounding boxes in the preceding and current frames. In [6], a similar approach was also employed, utilizing only the Hungarian algorithm to enable real-time lightweight processing for insect tracking. Nevertheless, when dealing with objects having non-linear state transition and observation models, an extended Kalman filter is employed to provide more precise predictions for insect tracking. Particle filters are also used to deal with non-linear problems [10]; however, as the number of particles increases, the computational complexity increases exponentially. The Kalman filter and other similar methods encounter limitations when applied to insect-tracking situations involving occlusions or interactions between multiple insects. This constraint arises from their inability to maintain object identities, relying solely on spatial data for trajectory matching [30]. A typical example of an illustration where these techniques fail is when two insects' cross paths and change direction after a collision. When this situation occurs, the algorithm

temporarily loses track of the insects. The primary challenge currently faced in the trajectory-generation stage is maintaining the identity of multiple individuals (identity preservation) following an occlusion. To address this challenge, some studies undertake manual corrections [40]. Other works perform a texture analysis to analyze insects' similarity between occlusions [32]. In [15], they combine color tags to mark individuals, more sophisticated CNN models, and a graph-based approach. An exciting study explored ant head direction information to preserve ant identity in crossover and touching scenarios [40]. A method like the Particle-Kalman Filter (PKF), which combines the Kalman filter and particle filters, has proven highly effective in tracking objects such as humans and vehicles in occlusion scenarios [25] and holds the potential for adaptation to insect tracking. The trajectory generation in insect tracking from video data presents challenges and future opportunities. One major challenge involves preserving the identity of multiple insects during occlusions or interactions, which impacts trajectory accuracy. Current methods face difficulties maintaining consistent tracking when objects cross paths or change directions due to collisions, resulting in brief tracking losses. Future research may focus on advanced techniques such as deep learning to improve identity preservation and trajectory accuracy.

5 DISCUSSION

Our study highlights the 2010-2013 evolution in video-based insect tracking, aiding insect behavior researchers in future planning and decision-making. Through our analysis, we demonstrate the continuous growth of this field, resilient even in the face of global disruptions such as the COVID-19 pandemic. We have also illustrated the high research activity in video tracking insects, with a strong presence from countries like the United States. Furthermore, our study highlights the multidisciplinary nature of this research domain, encompassing biology, artificial intelligence, insect behavioral studies, image processing, etc. Our comprehensive review shows the evolution of insect tracking methods, emphasizing the shift from labor-intensive manual observation to sophisticated video-based techniques. It covers various tracking methods, including physical markers, acoustics, radio frequency, chemical markers, and video-based tracking. The latter has revolutionized insect monitoring, particularly in precise pose estimation and trajectory extraction. Pose estimation frameworks leverage kinematics for anatomical feature tracking, while trajectory analysis distinguishes between single-target and multiple-target tracking. The trajectory extraction process involves crucial steps such as acquisition (offline and online), background modeling (dynamic and static), insect recognition (traditional and deep learning-based), and trajectory generation (Kalman filter, Hungarian algorithm, particle filters). Table 1 summarizes trajectory information extraction methods. Our study reveals several challenges in advancing video-based insect tracking, and promising directions emerge. Preserving the identity of multiple individuals, especially in complex interactions or occlusions, remains a challenge in trajectory generation. Real-time tracking is crucial for ecological studies, requiring a balance between computational efficiency and accuracy. Incorporating machine learning and deep learning methods show potential for improved recognition, robust tracking, and adaptability to environmental variations. Open-access

datasets and benchmarking standards can promote collaboration and algorithm evaluation. Field experiments in real-world conditions are vital for validating tracking methodologies.

Table 1: Summary of trajectory information extraction methods

Tracking steps	Commonly used methods	Additional parameters / methods
Acquisition	Online; Offline	Camera resolution: 720p to 1080p Frames per second: 20 to 30
Background, Foreground Modeling	Gaussian Mixture Model; K-Nearest Neighbors; Reference background; Pixel-based averaging or median model;	Morphological filter (opening, erosion, dilatation) to eliminate isolated pixel
Insect Recognition	Color histogram; Scale-Invariant Feature Transform; Feature fingerprints; Speeded-Up Robust Features; Deep Learning (CNN, YOLO, ResNet)	No
Trajectory Generation	Kalman Filter; Hungarian algorithm; Particles Filter; Optical flow;	For identity preservation: graph-based approach; color tags; head direction

6 CONCLUSION

In summary, our study combines a thorough bibliometric analysis with a concise review of the current state of video-based insect tracking. The research output in this field, totaling over 300 publications between 2010 and 2013, underscores its growing significance. Despite disruptions from the COVID-19 pandemic in 2020, research publications in video-based insect tracking maintained steady growth. The United States has emerged as a leader in this area, and machine learning plays a pivotal role. Our study highlights that video-based insect tracking primarily addresses pose estimation and trajectory information, with greater emphasis on the latter due to its enthusiasm. The main challenge lies in preserving the identity of multiple insects, particularly during occlusions or intricate interactions. Additional challenges include real-time tracking and adapting to environmental variations. Considering the limitations of our bibliometric analysis, it's important to recognize that our search string's specificity may have led to the exclusion of some pertinent documents. In future research, a broader approach could involve combining multiple search strings to ensure the inclusion of a wider range of publications. Additionally, this study focused exclusively on the Scopus database; however, expanding our scope to include documents retrieved from the Web of Science database is a promising avenue for further investigation.

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