

Recognizing Objects in Complex Scenes: A Recent Systematic Review

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1. Introduction

The ability to recognize objects within complex scenes [1-6] is a fundamental aspect of human cognition and a longstanding challenge in computer vision in most previous studies. In our increasingly data-driven world, where visual information is abundant and diverse, the development of robust and efficient algorithms for object recognition holds paramount importance across various domains from previous research, including robotics, autonomous systems, healthcare, security, and beyond [7-13]. Objects in natural scenes exhibit substantial variability in appearance, scale, orientation, occlusion, and context, presenting formidable hurdles for accurate recognition. The human visual system effortlessly tackles these challenges, demonstrating an innate capacity to

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identify objects amidst intricate backgrounds, variations in lighting, and diverse environmental conditions.

Replicating this cognitive accomplishment in machines has been a central focus of exploration in the fields of computer vision and artificial intelligence. Traditional approaches to object recognition heavily relied on handcrafted features and predefined models, facing limitations in handling the intricacies of real-world scenes. However, the field experienced a profound shift with the introduction of deep learning, specifically convolutional neural networks (CNNs). This advancement revolutionized object recognition performance by automating the extraction of hierarchical features from raw data which used on existing studies [14-16]. Deep learning models excel in learning intricate patterns and representations, offering promising avenues for addressing the complexities inherent in scene understanding. Despite significant progress, challenges persist in recognizing objects within complex scenes. Factors such as insufficient labeled data, domain shifts, adversarial attacks, and robustness to real-world variations pose persistent hurdles. Additionally, the ethical considerations regarding privacy, biases, and societal implications of object recognition technologies warrant critical attention.

The objective of this article is to examine the latest methodologies, progress, and difficulties associated with the identification of objects in intricate scenes. We delve into the evolution of object recognition techniques, the role of deep learning architectures, recent breakthroughs, and explore avenues for future research. Furthermore, we analyze the implications of object recognition in various applications and underscore the importance of developing robust, ethical, and interpretable models for addressing real-world complexities. Through this comprehensive exploration, our article endeavors to contribute to the broader discourse on advancing object recognition capabilities, fostering innovation, and guiding the development of responsible and impactful technologies for complex scene understanding.

2. Literature Review

In diving into the realm of spotting things in tricky settings, we need to cover a bunch of angles. One big thing to look at is how well methods for detecting 3D objects hold up in wild scenes, especially when it comes to self-driving situations. We want to get into the nitty-gritty of the challenges these methods face, like dealing with funky lighting, bad weather, faraway or tiny objects, and the pressing need for solid and spot-on detection in those kinds of situations [17]. Another avenue to stroll down is checking out how copying the way living things see things could help us pick out features and recognize stuff in complicated scenes. We're talking about getting inspiration from how living eyes and brains work [18].

Understanding and making sense of the environment is crucial when it comes to recognizing objects with limited examples, as highlighted in the concept of contextual cueing and scene context semantics for few-shot learning in object recognition [19]. In real-world scenarios, multiple object tracking (MOT) plays a significant role, helping to handle challenges such as occlusion, similar appearances, and difficulties in detecting small objects. This is particularly important in applications like autonomous driving [20]. Achieving high accuracy and real-time recognition of traffic signs is essential in intelligent transportation systems. To address this, a suggested two-stage approach involves using a lightweight superclass detector and a refinement classifier. This approach relies on prior knowledge of sign locations and sizes, emphasizing the importance of efficient recognition in critical situations [21].

Tracking several objects at once is crucial when dealing with intricate scenes, especially when factors like occlusion, similar appearances, and the challenges of detecting small objects come into play. The application of Multiple Object Tracking (MOT) extends to real-time tracking of multiple objects, with notable relevance in practical scenarios such as autonomous driving [22]. Keeping an eye on multiple objects simultaneously becomes quite important when handling complex scenes. This is especially true when you consider factors like objects hiding behind others, similar looks, and the difficulty of spotting small items. Multiple Object Tracking (MOT) proves its significance in scenarios that require tracking multiple objects in real-time, with practical applications like autonomous driving being particularly noteworthy [23].

Recognizing traffic signs plays a crucial role in making transportation systems smarter. To enhance this process, a proposed two-stage approach suggests combining a lightweight superclass detector with a refinement classifier. This method leverages information about the locations and sizes of signs to create a probability distribution model. To achieve this, Inception and Channel Attention are introduced, aiming to generate multi-scale receptive fields and dynamically adjust channel features [24]. Researchers have extensively explored the impact of scene context on object recognition. For example, a study conducted and published in Frontiers in Psychology revealed that scene context, such as a semantically consistent background, greatly aids in the detection and recognition of objects within natural scenes [25].

Moreover, researchers have delved into the relationship between scene and object processing through different approaches. One such method is the scene-object congruity paradigm, which assesses how contextual processing influences object recognition [26]. Another paper delves into the phenomenon of visual crowding, wherein peripheral object recognition is hindered by surrounding objects in computer-generated real-world scenarios. The results reveal instances of crowding affecting features, object components, and entire objects, underscoring its pivotal role as a constraint on conscious visual perception [27].

In general, blending these methods can enhance the identification of objects in intricate surroundings. Conducting a thorough review of existing literature on these methods can shed light on the latest advancements and possible avenues for future research.

3. Methodology

3.1 Identification

Three key phases in the systematic review process were utilized to select a substantial volume of relevant publications for this study. Initially, keywords were selected, and related terms were sought using thesauri, dictionaries, encyclopedias, and prior research. Search strings for Scopus and WoS were then developed (refer to Table 1), incorporating all relevant keywords. A total of 1600 publications pertinent to the present study were successfully gathered from both databases during the initial stage of the systematic review process.

Table 1

The search string	
Scopus	TITLE ((recogni* OR detect OR classifi* OR identif* OR cluster* OR predict*) AND (object OR
	image OR item OR piece) AND ("complex scenes" OR noise OR overlap OR flip OR blur)) AND (
	LIMIT-TO (PUBYEAR, 2023)) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE,
	$"English"$)
World of Science	TI=(recogni* OR detect OR classifi* OR identif* OR cluster* OR predict*) AND (object OR image)
	AND ("complex scenes" OR noise OR overlap OR blur)

3.2 Screening

The initial step in the screening process involves a meticulous examination of the pool of potentially pertinent research materials to identify content that aligns with the predetermined research questions. Common criteria employed in this phase include filtering research items based on the categorization of recognizing objects in complex scenes. During this stage, any duplicates among the gathered papers are systematically eliminated. A total of 1536 publications were excluded during the initial screening phase, while the subsequent phase evaluated 64 papers according to distinct inclusion and exclusion criteria established for this study (refer to Table 2). The primary criterion for selection was the literature (research papers), as it serves as the principal source of practical recommendations, encompassing reviews, meta-syntheses, meta-analyses, books, book series, chapters, and conference proceedings not covered in the latest study. Furthermore, the review exclusively focused on English-language publications from the year 2023. Importantly, it should be emphasized that no publications were rejected solely based on duplication criteria.

3.3 Eligibility

During the eligibility assessment phase, a collection of 50 articles was gathered. Rigorous examination was conducted on the titles and crucial content of each article to ensure alignment with the inclusion criteria, in accordance with the present research objectives. Subsequently, 25 reports were eliminated from consideration, as they did not meet the criteria of being strictly scientific articles based on empirical evidence. Therefore, 25 articles are retained for further review, as indicated in Figure 1.

Fig. 1. Flow diagram of the proposed searching study [28]

3.4 Data Abstraction and Analysis

An integrative analysis served as a key assessment approach in this research, focusing on the examination and synthesis of various research designs, particularly quantitative methods. The objective of this proficient investigation was to pinpoint pertinent topics and subtopics. The initial phase of data collection marked the commencement of theme development. Figure 1 illustrates how the authors meticulously scrutinized a compilation of 25 publications, extracting assertions and materials pertinent to the study's themes. Subsequently, the authors assessed prevailing studies concerning the recognition of objects in intricate scenes. The investigation delves into the methodologies and research findings across all studies. Collaborating with co-authors, the authors formulated themes grounded in the study's contextual evidence. A log meticulously documented analyses, perspectives, puzzles, and other relevant thoughts during the data interpretation process. Ultimately, a comparative analysis was conducted to identify any inconsistencies in theme development. Any conceptual discrepancies were discussed among the authors, and the resulting themes underwent refinement to ensure coherence. Two experts in image processing, cognitive computation and artificial intelligence, conducted the analysis selection, verifying the validity of identified issues. The expert review phase established the domain validity, ensuring clarity, significance, and appropriateness for each subtheme.

4. Results

Numerous studies have made noteworthy contributions in these domains, collectively advancing techniques for noise identification and removal, noise-resistant image classification, and novel approaches for robust image analysis.

4.1 Theme 1: Image Noise Identification and Removal Techniques

Four different types of noise filters are proposed based on modifying linear cellular automata (LCA), offering efficient noise reduction at various levels of noise density. These filters leverage the asynchronous operation of the LCA model, which enhances computational efficiency [29]. In the field of image segmentation (Figure 2), a method called kernel fuzzy clustering (KFPKL) stands out for its ability to handle noise, uncertainty, and complex structures in images. It has shown superior performance on both synthetic image datasets and brain MRI datasets [30]. Additionally, improved filters for synthetic aperture radar (SAR) noise, including an enhanced Lee sigma filter, outperform standard filters, achieving impressive levels of noise reduction on virtual SAR datasets [31].

In the domain of deep learning, a two-stage approach to denoising images achieves excellent accuracy across different types of noise [32]. Another method, the PFLWCM-CIM algorithm, uses fuzzy clustering to segment noisy images, incorporating image patches and a special metric called correntropy induced metric (CIM) [33]. Furthermore, a novel approach to fuzzy clustering for image segmentation, the PFLWCM-CIM algorithm, focuses on using image patches instead of individual pixels, which helps preserve local image details. It also introduces a new metric that combines image patches and CIM [34]. Moreover, a new type of neural network, the Gaussian-Noise Convolutional Neural Network (GN-CNN), is introduced for identifying noise variations in scanning electron microscope (SEM) images [35]. For removing salt-and-pepper noise, the supervised hierarchical clustering filter (SHCF) shows promising results, especially on images with many black and white pixels [36]. Lastly, an adaptive neurofuzzy estimation method is used to predict denoising performance in color images by analyzing speckle noise distribution, highlighting the effectiveness of the ALOHA filter [37]. Table 3 presents the previous research findings for Theme 1.

Table 3

Table 3. Continued

Table 3. Continued

The research article findings based on the proposed searching criterion: Theme 1

4.2 Theme 2: Image Classification and Recognition under Noise

This study introduces a new way to classify hyperspectral images that's better than older methods. It adds a special module to handle noise and cleans up the images using a special framework. The result is a more accurate way to tell things apart in real-world datasets [38]. When it comes to spotting breast cancer, using a method based on Muduli *et al*.'s [39] work gives impressive results: 93.2% accuracy in telling benign from malignant lesions. This suggests that using single-slice DBT could be even better than mammograms for screening [40]. Another study suggests a new method for spotting kidney problems by dealing with noisy labels. By doing this, it can beat other methods in spotting glomerular lesions, which could be helpful for diagnosing kidney issues [41]. In the world of intelligent transport systems, a new way to fuse audio and visual features is helping to classify vehicles more accurately, even in bad weather [42].

There's also progress in radar technology. A new method helps radar systems work better by reducing noise in the data they collect [43]. This could make radar systems cheaper and more effective. In medicine, a new system can clean up blurry X-ray images without needing to take the Xrays again. This could make diagnosing medical issues faster and easier [44]. In the field of braininspired machine learning, researchers are finding that connections in the brain can help improve how machines recognize things, especially in noisy conditions [45]. For studying yeast growth, a new algorithm called BABY helps measure how fast individual cells grow, which could give insights into how microbes work [46]. And finally, a new method using deep learning (Figure 3) can tell apart normal and noisy QR codes, helping to improve information retrieval [47]. Table 4 shows the previous research findings for Theme 2.

Fig. 3. Outline of the developed deep learning [40]

Table 4

Table 4. Continued

Table 4. Continued

Table 4. Continued

The research article findings based on the proposed searching criterion: Theme 2

4.3 Theme 3: Innovative Models and Approaches for Noise-Robust Image Analysis

Machine learning models can struggle with noisy data, leading to degraded performance. To tackle this, researchers use metalearning (Figure 4), a method that predicts how different types of noise affect model accuracy. This study digs into how noise affects performance for different categories, using advanced simulation techniques. They found that metalearning accurately predicts how well a model will perform based on the type of noise it encounters [48]. In image processing, fuzzy clustering algorithms like C-means often struggle with noisy images. A new method improves this by combining different types of information to better segment noisy images, outperforming other methods [49].

Fig. 4. The process for training and evaluating of the metamodels (a) Training process (b) Evaluation process [48]

For image classification, traditional deep learning models can be sensitive to noise, while spiking neural networks (SNNs) are more robust. A new kind of neural network, the Spiking Quantum Neural Network (SQNN), blends classical and quantum computing to handle noisy images better than other models [50]. There's also a new theory for recognizing objects in blurry images without having to first unblur them. This theory, developed using advanced mathematical techniques, outperforms traditional methods [51]. In hyperspectral image classification, a new method combines different techniques to improve accuracy, especially in noisy environments. This could be useful for tasks like

remote sensing [52]. Lastly, a new model excels at identifying the source of digital images in social media networks, achieving impressive accuracy rates [53]. The research article findings based on the proposed search criteria are listed in Table 5.

Table 5

Table 5. Continued

The research article findings based on the proposed searching criterion: Theme 3

5. Conclusions

The discoveries within three main themes highlight some exciting advancements in image processing and analysis. Theme 1 introduces us to remarkable filters like the Extended Lee-sigma filter and the SHCF. These filters excel in tasks such as SAR image processing by effectively reducing high-density noise. Moreover, the PFLWCM-CIM algorithm stands out as a significant innovation for

picture segmentation in noisy environments. In Theme 2, progress in image classification and recognition is evident, with models like LVINet and single-slice DBT demonstrating impressive accuracy. This progress holds promise for enhancing medical imaging diagnoses. Lastly, Theme 3 focuses on new models and approaches that improve image analysis in noisy conditions. Techniques such as metalearning for predicting class performance and the SQNN model surpassing established networks across diverse datasets are noteworthy advancements. These findings collectively push the boundaries of image processing, offering promising solutions for real-world applications.

In conclusion, the field of object recognition in complex scenes is continuously evolving due to advancements in deep learning, biomimetic techniques, contextual cueing, and scene context semantics. Despite significant progress, challenges persist, such as detecting 3D objects in adverse conditions and learning with limited examples. However, innovative methods like biomimetic visual transformation and contextual cueing show potential in overcoming these challenges. Moreover, prioritizing ethical considerations regarding privacy, biases, and societal impacts is crucial for responsible technology development and deployment. Looking ahead, concerted efforts towards creating interpretable, robust, and ethically sound models will be essential for unlocking the full potential of object recognition across various domains. Through continued research and collaboration, we can address these challenges and drive the field towards more impactful and socially conscious advancements.

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