ADAPTIVE MULTI-KERNEL BACKGROUND SUBTRACTION USING FUZZY LOGIC FOR ROBUST OBJECT DETECTION IN COMPLEX SCENES

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Abstract

This research introduces an adaptive background subtraction method utilizing Fuzzy Logic. The approach dynamically adjusts to factors such as illumination variations, scene complexity, and motion dynamics, ensuring the optimal model selection. By leveraging Fuzzy rules, various background subtraction models are managed in real-time, and parameters are updated adaptively. The proposed method enhances stability and accuracy in object detection systems. Experimental results demonstrate that the Fuzzy Logic-based background subtraction technique exhibits greater flexibility and efficiency compared to conventional and deep learning-based methods.

Keywords: Fuzzy Logic, Adaptive Background Subtraction, Object Detection, Multi-Kernel Approach

Introduction

Real-time object detection is a crucial domain in computer vision, encompassing a broad spectrum of applications, including video surveillance systems, autonomous vehicles, human-computer interaction, and industrial automation [1, 2, 3]. A fundamental phase in object detection is background subtraction.

Conventional background subtraction techniques, such as the Gaussian Mixture Model (GMM), Median Filtering, and Optical Flow, perform well under specific conditions; however, they encounter notable difficulties in complex and dynamic environments [4, 5]. In such cases, these methods tend to produce a high rate of false positives (FP) and false negatives (FN) [6].

The primary challenges faced by modern object detection systems include:

- Varying conditions between day and night, artificial lighting changes, shadows, and reflections can cause detection errors.
- Elements such as fluctuating water, wind-driven objects, reflections from vehicle lights, and other dynamic factors complicate background stability.
- Rapid object motion and size variations due to perspective pose challenges for traditional methods in accurate object recognition.
- Many object detection techniques demand substantial computational power, leading to performance constraints in real-time applications.

To overcome these obstacles, adaptive background subtraction methods leveraging Fuzzy Logic can be introduced. Fuzzy Logic provides an effective framework for modeling object and background variability in real-world conditions, thereby improving object detection accuracy.

In this paper, a Fuzzy Logic-based adaptive background subtraction method is introduced as a novel approach to overcoming existing challenges in real-time object detection. Traditional background subtraction techniques depend on static rules, limiting their effectiveness in handling varying illumination, complex scenes, and dynamic backgrounds. The proposed method addresses these constraints by implementing an adaptive system that considers multiple parameters.

The key contributions of this paper are as follows:

Fuzzy Logic-Based Background Subtraction – Unlike conventional methods, the proposed approach selects the background model dynamically based on illumination levels, motion dynamics, and scene complexity.

Multi-Kernel Background Models – Assesses the suitability of various background subtraction techniques such as MOG2, KNN, and GMM for different scenes and automatically selects the most optimal model.

Adaptive Handling of Illumination and Scene Complexity – Adjusts the background model in real time based on lighting variations and object movement characteristics within the scene.

Optimized Real-Time Object Detection Approach – Reduces computational overhead, ensuring more efficient utilization of GPU and CPU resources.

The primary objective of this research is to develop a Fuzzy Logic-based adaptive background subtraction technique and assess its performance in real-world applications. The aim is to improve the accuracy and speed of object detection by addressing the following challenges:

- Designing a background model resilient to illumination changes.
- Enhancing accuracy in distinguishing objects from the background in dynamic environments.
- Developing a fast and optimized method suitable for real-time processing.

The proposed method can be applied across various domains, including industrial automation, video surveillance systems, autonomous vehicles, and artificial intelligence-based object recognition systems. The effectiveness of the approach has been evaluated and validated.

Application of Fuzzy Logic in Background Subtraction

Fuzzy Logic is employed to adapt to uncertain and dynamic environments, in contrast to traditional methods that depend on rigid rules. Instead of binary classification, a pixel's probability of belonging to the background or an object is assigned a value between 0 and 1 [7, 9, 11]. Methods such as the Gaussian Membership Function, Triangular Membership Function, and Trapezoidal Membership Function are utilized. Fuzzy logic-based systems determine the background model by taking into account scene complexity, illumination levels, and object motion [5].

Advantages:

- Adapts effectively to dynamic illumination changes.
- Better manages transition regions between background and objects [4].
- Provides an improved framework for adaptive background subtraction.

A potential drawback is that integrating Fuzzy Logic with deep learning methods may increase computational load.

We have briefly outlined the working principles, advantages, and disadvantages of traditional methods, deep learning approaches, and fuzzy logic-based models in the domain of background subtraction and object detection. In this paper, our objective is to develop an adaptive background subtraction method by leveraging the strengths of these approaches.

Traditional and deep learning-based methods in background subtraction and object detection have various limitations. In dynamic environments, factors such as illumination changes, scene complexity, and object variability reduce the effectiveness of existing techniques. To address these challenges, we propose a method that integrates a multi-kernel approach with fuzzy logic-based background subtraction.

Application of the Multi-Kernel Approach

Traditional background subtraction techniques rely on a single model for object detection. However, in real-world scenarios, their effectiveness diminishes due to scene variability. For instance, the Gaussian Mixture Model (GMM) may misclassify shadows as objects in complex environments, whereas the K-Nearest Neighbors (KNN) method has a high likelihood of producing false positives in regions with significant motion [8, 9].

To overcome these limitations, we introduce a multi-kernel background subtraction approach. This method runs multiple background subtraction techniques in parallel and dynamically selects the most optimal background model based on scene characteristics. By leveraging multiple statistical and machine learning-based models, the multi-kernel approach enhances accuracy and reliability [3, 6].

Key Principles of the Multi-Kernel Approach:

- Multiple background subtraction methods (e.g., MOG2, KNN, GMM) are executed simultaneously.
- The most suitable model is dynamically selected based on scene complexity and illumination conditions.
- The background model is continuously updated in real-time to adapt to environmental changes. This results in improved accuracy and robustness compared to single-model approaches.

Advantages of the Multi-Kernel Approach:

- Effectiveness in Dynamic Scenes – If one model struggles with illumination changes, other models compensate.
- High Accuracy with Combined Models – The most appropriate model is chosen based on diverse scene characteristics.
- Real-World Adaptation – The optimal background model is determined for various objects and scene conditions, enhancing overall detection reliability.

Adaptive Background Subtraction using Fuzzy Logic and Multi-Kernel Integration

Traditional background subtraction methods employ a strict classification approach, categorizing pixels as either background (0) or object (1). However, in real-world scenarios, this rigid classification often results in inaccuracies. In contrast, Fuzzy Logic-based background subtraction determines the probability of a pixel belonging to the background or an object by using smooth transitions with values ranging between 0 and 1 [9].

Fuzzy Logic-based systems incorporate multiple variables to facilitate adaptive decision-making in dynamic environments. These variables include:

- Lighting Conditions – Different background models are applied depending on whether the scene is dark or overly bright. Lighting is assessed using histogram analysis and brightness statistics.
- Scene Complexity – The number of objects and edge details in the scene are considered. Complexity is evaluated using Canny Edge Detection and ORB/SIFT Feature Extraction methods.
- Motion Complexity – The intensity of object movement in the scene is measured using Optical Flow and Frame Differencing techniques.

Stages of Fuzzy Logic-Based Systems

Fuzzy Membership Function – The probability of background and object classification is determined using the Gaussian Membership Function:

$$\mu(x) = e^{-\frac{(x-c)^2}{2\sigma^2}}$$

Here, c represents the mean value, and σ denotes the standard deviation.

Model Selection Based on Fuzzy Rules:

If the lighting is stable and the scene is simple → GMM is used.

If the lighting varies and the scene is complex → KNN is applied.

If there is high motion in the scene → MOG2 is selected.

Fuzzy Output and Adaptive Updating:

As each new frame is processed, Fuzzy membership functions are updated, and the optimal background model is dynamically selected.

Advantages of Fuzzy Logic:

- The background model is selected based on scene conditions.
- Ensures reliable performance in both bright and dark environments.
- Evaluates the probability of each pixel belonging to the background or an object, reducing abrupt misclassifications.

The multi-kernel approach further enhances object detection accuracy by integrating multiple background models. Fuzzy Logic ensures that the most suitable background model is selected by taking into account illumination variations, scene complexity, and motion dynamics.

Fuzzy Logic-based background subtraction methods improve object detection accuracy by making adaptive decisions based on varying scene conditions. A key advantage of this approach is its ability to select the most suitable model and dynamically update parameters using Fuzzy rules.

The performance of a background subtraction system is highly dependent on illumination conditions, scene complexity, and motion intensity. Since a single background model may not always yield optimal results across different environments [10], our approach focuses on achieving the best possible performance by dynamically selecting the most appropriate background subtraction method based on Fuzzy Logic.

Experimental Evaluation and Performance Analysis

For a comparative analysis of object detection and background subtraction methods, both widely used international datasets and a custom-created dataset were utilized.

Used Datasets:

CDNet 2014 (Change Detection Dataset) - A dataset comprising real-world scenes with various background changes. Evaluation of object detection efficiency in both static and dynamic background conditions.

VisDrone (Vision Meets Drone Dataset) - A dataset containing videos captured by drones. Assessment of the method’s robustness in scenarios involving a moving camera and highly dynamic backgrounds.

Custom Video Dataset (Our Own Dataset) - A collection of videos featuring diverse real-world scenes, including outdoor environments, low-light conditions, and crowded areas. Examination of the proposed fuzzy logic-based system’s adaptive performance across different environmental conditions.

The results demonstrate that the Fuzzy Adaptive Multi-Kernel background subtraction method achieves high accuracy and speed, surpassing traditional approaches. This method recorded the highest values in Precision (0.92), Recall (0.84), and IoU (0.80), indicating its superior performance.

Additionally, the computational load of the proposed method is lower compared to MOG2 and GMM, while still ensuring better accuracy and adaptability. Due to its high FPS performance, the method is well-suited for real-time object detection.

A key advantage of the Fuzzy Logic-based approach is its adaptive nature - unlike other methods, it automatically analyzes illumination conditions and background complexity and adjusts dynamically. The system utilizes Fuzzy Membership functions to handle illumination variations, ensuring stable detection.

Key Findings from Tests:

Illumination Variations: Traditional methods often misclassify objects under shadows and lighting changes, whereas the Fuzzy Logic-based system maintains more consistent results.

Dynamic Background Handling: In real-world scenarios, backgrounds are often not static (e.g., moving tree leaves, rippling water, crowded areas). The Fuzzy Logic-based method successfully analyzes dynamic background changes and provides stable results.

Test Results

Static Lighting Conditions: All methods produce stable results.

Sudden Lighting Changes (e.g., day-night transitions, vehicle headlights): The Fuzzy Adaptive Multi-Kernel method maintains over 90% object detection accuracy.

Shadows and Light Reflections: MOG2 and KNN misclassify objects as background, whereas the Fuzzy Logic-based method effectively distinguishes shadows.

Static Background Conditions: All methods achieve 85%+ accuracy.

Dynamic Background Conditions (e.g., tree leaves moving in the wind):

MOG2, KNN, and GMM misclassify parts of objects as background, leading to a decrease in Recall.

Fuzzy Adaptive Multi-Kernel evaluates motion intensity, extracts the background more accurately, and maintains Recall > 0.84.

Fuzzy Adaptive Multi-Kernel Background Subtraction outperforms traditional background subtraction methods in terms of accuracy, speed, and stability.

Key Advantages:

- Higher Accuracy (Precision = 0.92, IoU = 0.80)
- Adaptive Response to lighting variations and background complexity
- Optimized Computational Load (FPS = 55, RAM usage = 1.5 GB)
- Robust Performance in challenging scenes and real-world environments

Conclusion

The Fuzzy Adaptive Multi-Kernel Background Subtraction method demonstrates exceptional performance in dynamic and complex environments, ensuring high accuracy while optimizing computational efficiency. Unlike traditional background subtraction techniques that rely on static models, this approach dynamically adapts to changing illumination conditions, scene complexity, and motion dynamics. By incorporating Fuzzy Logic, the method continuously selects the most suitable background model based on real-time environmental conditions, significantly improving object detection accuracy. This adaptability allows the system to effectively handle challenges such as shadows, reflections, and sudden lighting changes, which often degrade performance in conventional methods.

In addition to its robust detection capabilities, the method also mitigates background motion challenges. By leveraging a multi-kernel approach, it ensures that multiple background models work in parallel to achieve higher precision and recall rates. Furthermore, the optimized computational framework reduces processing load, allowing the system to maintain high FPS performance while consuming minimal resources. These advantages make the Fuzzy Adaptive Multi-Kernel approach particularly well-suited for real-time applications.

Comparison of Different Background Subtraction Methods:

Method	Precision ↑	Recall ↑	F1-score ↑	IoU ↑	FPS ↑	Computational Load ↓
MOG2	0.85	0.72	0.78	0.68	**50 FPS**	**Medium**
KNN	0.87	0.74	0.80	0.70	35 FPS	High
GMM	0.82	0.76	0.79	0.69	40 FPS	Medium
Fuzzy-GMM	**0.90**	**0.81**	**0.85**	**0.78**	45 FPS	Medium
Fuzzy Adaptive Multi-Kernel	**0.92**	**0.84**	**0.88**	**0.80**	**55 FPS**	**Low**

Challenging Cases and Advantages of the Fuzzy Logic-Based Method:

Challenging Scene	Limitations of Traditional Methods	Advantages of Fuzzy Adaptive Multi-Kernel
Fog or low-visibility objects	Objects are not fully detected (Recall < 0.7)	Accuracy is improved using Fuzzy membership functions (Recall > 0.82)
Light reflections and mirrors	Objects are misclassified (FP increases)	Lighting is adjusted using Fuzzy membership functions
Overlapping multiple objects	Object contours are not fully identified	Multi-kernel approach effectively separates objects
Moving background (crowds, rippling water, etc.)	Objects blend with the background (IoU < 0.7)	Fuzzy rules enhance object recognition (IoU > 0.78)

Real-Time Test Results (Computational Load vs. Performance):

Method	CPU Load ↓	GPU Load ↓	RAM Usage ↓	FPS ↑
MOG2	Medium	Low	1.2 GB	50 FPS
KNN	High	Medium	2.5 GB	35 FPS
GMM	Medium	Medium	2.0 GB	40 FPS
Fuzzy-GMM	Medium	Medium	2.0 GB	45 FPS
Fuzzy Adaptive Multi-Kernel	Low	Medium	1.5 GB	55 FPS

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