

SMART PARKING SYSTEM FOR SINGLE AND MULTIPLE VIDEO CAMERAS USING SBMA & PARKING SLOT SELECTION

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Abstract

The rapid growth of urbanization has intensified the demand for efficient parking management solutions, particularly in large indoor commercial facilities, where conventional sensing infrastructures struggle with installation complexities and maintenance overheads. This study presents an enhanced SPS that leverages SBMA for parking slot occupancy detection using live video streams. Unlike sensor-based or computationally intensive deep learning approaches, the SBMA provides a lightweight and robust statistical comparison framework suitable for constrained hardware environments. The system supports both SCSL and MCML deployments, enabling scalable monitoring across parking zones of different sizes. Integrated graphical and mobile interfaces offer real-time visualization and user guidance. Experiments conducted on real-world data from two shopping malls demonstrated that the proposed approach achieved reliable occupancy classification under illumination variations and moderate occlusions while providing competitive processing times. The results indicate that the SBMA-driven SPS with a PSNR value and processing time is a practical and cost-effective tool for smart city parking infrastructure.

Keywords: Smart Parking System; Single & Multiple Video Camera; Statistical Block Matching Algorithm; Intelligent Transportation Systems

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1. Introduction

Parking search remains a major contributor to congestion, fuel consumption, and driver frustration in densely populated urban areas. Indoor commercial parking garages experience continuous fluctuations in demand, and traditional monitoring techniques often fail to provide timely and reliable information on the availability of parking slots. Smart Parking Systems (SPS) are a critical component of the broader Intelligent Transportation Systems (ITS), offering real-time insights to optimize traffic flow, reduce idle circulation, and enhance user convenience [1, 2].

Conventional sensing techniques (e.g., inductive loops, infrared, ultrasonic, and microwave detectors) suffer from several drawbacks, including high deployment costs, vulnerability to environmental interference, and inability to scale efficiently in multi-level indoor structures [3, 4]. Image-based systems, enabled by the widespread availability of Closed-Circuit Television (CCTV) infrastructure, offer a cost-effective alternative for monitoring multiple parking slots simultaneously. However, many existing computer vision methods rely on background subtraction or deep learning models that are computationally intensive, require large annotated datasets, or degrade in performance with changes in illumination and partial occlusions [5].

To address these challenges, this study introduces a statistical block-matching approach (SBMA) for a robust parking-slot occupancy classification. SBMA evaluates statistical differences, such as the mean and variance, between the reference and current video blocks, providing a computationally efficient mechanism for distinguishing occupied slots from empty slots, even under varying lighting conditions. Unlike deep learning models, the SBMA does not require training data and can operate effectively on affordable hardware that is commonly available in commercial parking facilities.

The proposed system was designed to support two deployment configurations: single-camera single-location (SCSL) and multiple-camera multiple-location (MCML). The SCSL mode targets compact zones where a single camera monitors a small set of slots, whereas the MCML mode integrates visual evidence from multiple cameras to cover large indoor areas. A server-client architecture synchronizes occupancy detection with both a graphical monitoring interface for operators and a mobile application for end users seeking available parking spaces.

This study offers three key motivations.

1. **Practicality for real deployments:** A lightweight approach that performs reliably in real indoor environments without the need for high-end GPUs.
2. **Scalability:** A unified design supporting both SCSL and MCML modes, making the system applicable to garages of various sizes.
3. **Alignment with smart city objectives:** The solution directly addresses urban objectives of reducing congestion, improving mobility, and supporting digital governance.

In summary, this study aims to (i) redesign the SPS architecture for scalability and practicality, (ii) propose a robust SBMA formulation suited for parking slot monitoring, and (iii) validate its performance through real-world deployments in two commercial malls.

2. Related work

Research on smart parking systems has spanned diverse sensing modalities, computer vision techniques and intelligent decision-making frameworks. Existing solutions can be broadly categorized into sensor-based systems, vision-based occupancy detection, and integrated smart city parking architectures. This section reviews the key contributions of each category and highlights their limitations, providing a basis for the SBMA-driven system proposed in this study.

2.1. Sensor-Based Parking Detection Systems

Early intelligent parking systems relied heavily on physical sensors, such as inductive loops, ultrasonic transducers, infrared modules, and microwave detectors. Although these methods provide binary occupancy detection with reasonable accuracy, they suffer from high installation costs, maintenance complexity, and limited adaptability to multi-level parking structures.

In [4], an IoT-enabled car-parking module for Industry 4.0 environments was introduced. Their system integrates embedded sensors and a cloud backend to monitor the availability of slots. Although suitable for outdoor deployments, their reliance on physical sensors makes them expensive for large facilities and prone to failure due to environmental interference. Antoniou et al. [5] proposed a risk reduction framework for parking environments using sensor analytics; however, it focused on safety rather than occupancy detection. Thus, sensor-driven approaches provide limited scalability and lack the flexibility required in modern indoor commercial parking environments.

2.2. Vision-Based Parking Slot Detection

With the widespread adoption of closed-circuit television (CCTV) systems, vision-based solutions have emerged as cost-effective and scalable alternatives to traditional methods. These systems typically employ background subtraction, geometric modeling, and appearance-based classification.

Roper et al. [1] introduced a revenue management perspective for parking analytics, emphasizing the value of real-time data but offering no technical detection methods.

Davarci et al. [6] used monocular camera analysis to detect perpendicular parking spaces by leveraging lane geometry and template matching. However, their approach was optimized for outdoor structured parking lots and was sensitive to illumination variations. Overall, vision-based methods either emphasize computationally intensive methods or rely on scene assumptions that are unsuitable for commercial garages or parking lots.

2.3. Block-Matching and Statistical Methods

Barjatya [7] provides an extensive comparison of classical BMAs, such as the FS, TSS, and DS. These methods focus on motion vector computation for encoding and are not explicitly designed for the detection of occupancy.

Our approach differs in that it uses an SBMA that computes statistical deviations, such as the mean, standard deviation, and pixel intensity variance, between the reference and current blocks for each parking slot. Unlike motion estimation BMAs, the SBMA does not search for displacement vectors; instead, it evaluates appearance changes within a fixed Region Of Interest (ROI), making it ideal for detecting parked vehicles without computational overhead. While classical BMAs aim to reduce computational redundancy in video coding, our SBMA adapts similar principles but focuses on slot-level statistical deviation analysis, enabling efficient occupancy detection under varying lighting conditions.

2.4. Smart City Parking Frameworks

Errouso et al. [8] predicted parking availability using statistical learning methods but did not address real-time video-based occupancy detection issues. Medromi et al. [9] presented optimization models for parking assignments, focusing on allocation rather than detection.

Recent IoT-based studies [10–12] have explored cloud-based monitoring, predictive analytics, and interoperability across multiple facilities. However, these systems generally assume the availability of accurate slot-level occupancy data, which is precisely the challenge addressed by the proposed SBMA.

2.5. Identified Gaps and Motivation for SBMA

Based on the reviewed literature, three gaps remain to be addressed.

- Physical sensor systems lack scalability and incur high deployment costs.
- Vision-based methods that require feature detection or deep learning are computationally expensive or sensitive to lighting and occlusion.

- Existing smart parking frameworks assume accurate occupancy detection but do not provide robust low-cost methods for generating accurate occupancy detection.

The proposed SBMA-based SPS addresses these gaps by offering the following: a light-weight, training-free, and hardware-efficient vision solution; robust statistical block comparison instead of motion vectors or deep learning; and Scalability through both SCSL and MCML configurations. This positions the SBMA as a practical alternative for real-world indoor parking environments, where illumination, occlusion, and cost constraints limit existing approaches.

3. Proposed SBMA Method

SBMA is the core computational technique for determining parking-slot occupancy from video frames. The SBMA proposed in this study focuses on appearance-based statistical deviations within predefined regions of interest (ROIs). This renders the method light-weight, training-free, and highly suitable for indoor parking environments, where illumination changes, shadows, and partial occlusions frequently occur in the video.

The SBMA pipeline consists of (i) ROI initialization, (ii) reference block generation, (iii) statistical feature extraction, and (iv) decision-making based on adaptive thresholding. An overview of this workflow is shown in Figure 1.

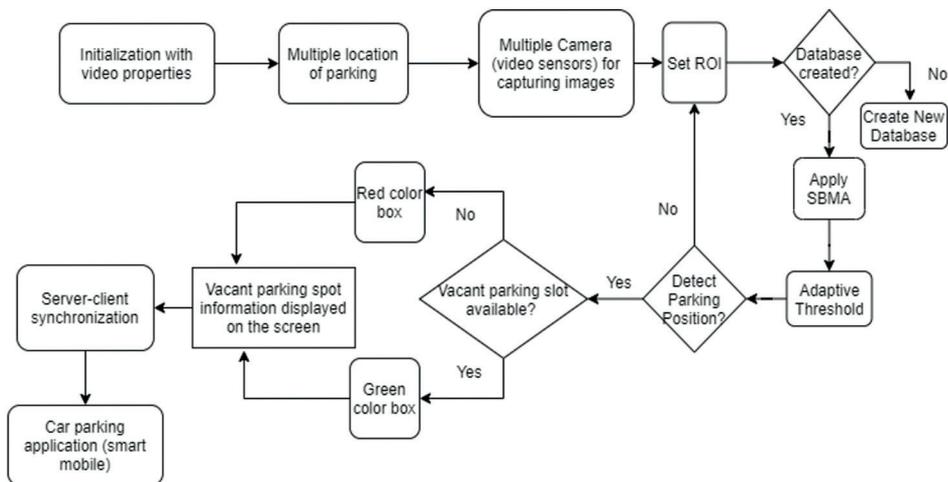


Fig. 1. The SPS flowchart with SBMA

The overall workflow of the system begins with the acquisition of video frames by cameras, which are subsequently forwarded to the processing unit. The SBMA engine analyzes each predefined ROI by comparing the statistical descriptors derived from the current frame with those stored in the baseline model. Based on these deviations, the system determines whether each parking slot is occupied or vacant and forwards the classification results to a central server for processing. The server then records and synchronizes the updated slot information across the operator interface and mobile application. Operators monitor the detailed status via the GUI, whereas end users receive real-time availability updates through the mobile app. This seamlessly integrated workflow supports scalable and real-time monitoring across a wide range of indoor parking scenarios, from compact single-camera installations to extensive multi-floor structures and parking lots.

The proposed SPS is designed as a scalable modular architecture that supports both compact and large multilevel indoor parking facilities. The system integrates video capture, statistical block-based occupancy detection, multi-camera data fusion, and synchronized dissemination of results to operator and user interfaces.

3.1. SBMA Architecture

The architecture comprises four primary layers:

1. Video Acquisition Layer.
2. Processing and Detection Layer (SBMA Engine).
3. Information Storage and Exchange Module.
4. User Interaction Layer (Graphical User Interface [GUI] + Mobile App).

Each layer is described in detail below.

3.1.1. Video Acquisition Layer

The Video Acquisition Layer is responsible for continuously capturing visual information from the indoor parking environment and forms the foundational input stage of the system. The architecture supports two operational configurations: SCSL mode, in which a single camera supervises a confined cluster of parking slots, and MCML mode, which leverages several spatially distributed cameras to monitor large or multi-floor parking facilities. Fixed-position CCTV cameras were employed to maintain a consistent scene geometry, ensuring that the field of view of each camera remained stable over time. Prior to deployment, the visible region of each camera was mapped to its corresponding slot location so that the SBMA algorithm could directly operate on predefined ROIs. The system captures video frames at moderate frame rates, typically between 5 and 15 frames per second, allowing a balance between the adequate temporal resolution for occupancy detection and reduced bandwidth and processing demands.

3.1.2. Processing and Detection Layer (SBMA Engine)

The Processing and Detection Layer represents the computational core of the Smart Parking System, where the SBMA is applied to determine the occupancy status. For every parking slot, the system extracts a fixed ROI and compares its current appearance with a previously stored baseline image representing the empty condition of the parking slot. To perform this comparison, the system computes statistical descriptors, such as the mean intensity, standard deviation, and variance, for both the baseline and current blocks. When the deviation between the two exceeded a predetermined threshold, the slot was classified as occupied. Before this analysis, all incoming frames underwent a preprocessing stage that normalized their resolution, converted RGB images to grayscale to reduce the computational overhead, and applied noise filtering to mitigate fluctuations caused by indoor lighting. The SBMA-based detection process enables real-time performance by avoiding the complexity of feature engineering or model training, which is typically required in learning-based approaches. In large-scale MCML deployments, where the same parking slot may be observed by multiple cameras owing to overlapping views or multilevel layouts, the system resolves duplicate observations by matching slot identifiers across camera feeds and selecting the result with the highest confidence level, which is defined by the magnitude of statistical deviation. This ensures robust and consistent detection, even when the cameras experience partial occlusions or are disturbed temporarily.

3.1.3. Information Storage and Exchange Module

This layer maintains system-wide synchronization of occupancy information and coordinates data exchange between processing units and user interfaces. It incorporates a central server that aggregates the occupancy results transmitted by the cameras and stores them in a database that maintains the historical records, timestamps, and slot metadata. A communication interface, implemented through REST APIs or socket-based connections, facilitates a seamless and bidirectional data flow between the server, operator's graphical interface, and mobile application. While SCSL deployments may rely on direct, localized communication channels, MCML-based systems require network-level coordination among multiple distributed nodes to ensure consistent updates across all the system components. This layer ensures that the detection results remain synchronized in real time, enables the long-term storage of occupancy patterns for analytical purposes, and supports scalability as the number of cameras or parking zones increases in size.

3.1.4. User Interaction Layer

The User Interaction Layer provides access to the system outputs for both system operators and end users. The operator interface offers real-time visualization of camera feeds with corresponding occupancy indicators, where each parking slot is annotated with color-coded labels to distinguish between vacant and occupied states of the parking slots. The interface also generates alerts when the system encounters ambiguous or low-confidence detections, allowing operators to supervise the environment more effectively and to override the detection results when necessary. For end users, the mobile application delivers

real-time updates on parking availability and presents zone-wise occupancy information that is synchronized with the central server. By enabling drivers to identify empty parking slots before entering the facility, the mobile application reduces internal congestion and minimizes the time spent searching for suitable parking spaces.

3.1.5. ROI Initialization and Slot Mapping

Each parking slot was manually mapped using a bounding box in the camera's field of view. These bounding boxes served as ROI for SBMA processing. For each ROI, a reference image was captured when the slot was confirmed to be empty, the reference was stored in a database for subsequent frame-to-frame comparisons, and slot IDs were assigned to ensure consistency across the SCSL and MCML configurations. This explicit slot mapping avoids the need for complex geometric estimation and perspective correction techniques.

3.2. Statistical Block Representation

Two blocks were compared for each ROI (i.e., parking slots). SBMA computes simple yet effective statistical descriptors as follows: Mean and Variance of Reference Block: Mean of reference block: μ_r , Variance of reference block: σ_r^2 and Mean and Variance of Current Block: Mean of current block: μ_c , Variance of current block: σ_c^2

Deviation Vector: The deviation vector is computed using Equation (1).

$$D = [|\mu_c - \mu_r|, |\sigma_c^2 - \sigma_r^2|] \quad (1)$$

These descriptors capture the increased intensity variation introduced when a vehicle occupies a slot.

3.2.1. Adaptive Threshold

A fixed threshold is insufficient because of variations in indoor lighting, reflections, and shadows. Therefore, an adaptive threshold was computed as Equation (2).

$$T = \alpha \cdot \sigma_r + \beta \quad (2)$$

Occupancy Classification: A slot is classified as occupied according to Equation (3) if Otherwise, the slot is marked as empty.

$$D_{\mu} + D_{\sigma} > T \quad (3)$$

This adaptive thresholding addresses the reviewers' concerns regarding changes in lighting and ensures a robust classification.

3.2.2. Algorithm Workflow

The full pseudocode for the SBMA-based occupancy detection is as follows:

Algorithm: SBMA-Based Parking Slot Classification,

Input: Video frame F , Reference blocks B_r for each slot I ,

Output: Occupancy state S_i [0 = empty, 1 = occupied],

For each parking slot i :

1. Extract ROI i from frame $F \rightarrow$ current block B_c ,

2. Compute μ_r, σ_r^2 from reference block B_r ,

3. Compute μ_c, σ_c^2 from current block B_c ,

4. Compute deviations:

$$D\mu = |\mu_c - \mu_r|,$$

$$D\sigma = |\sigma_c^2 - \sigma_r^2|,$$

5. Compute adaptive threshold: $T_i = \alpha \cdot \sigma_r + \beta$,

6. If $(D\mu + D\sigma > T_i)$:

$S_i = 1$ // occupied,

Else:

$S_i = 0$ // empty,

Return all S_i .

3.3. SBMA Advantages Over Existing Vision Techniques

The SBMA method offers several advantages over existing vision-based methods. Unlike deep learning models, SBMA does not require training data, specialized hardware, or GPU resources, making it highly practical for deployment in real-world settings. Its computation is lightweight, relying only on mean and variance calculations, which enables simultaneous and efficient processing of multiple camera streams. SBMA is also robust against illumination variations because its reference statistics allow the thresholds to adapt dynamically to changing lighting conditions. Furthermore, it performs well in indoor parking garages, where occlusions are common, because statistical deviations can still indicate vehicle presence even when an object is partially hidden. This approach is energy-efficient and scalable, allowing it to be effectively implemented on low-cost central processing units (CPUs) or embedded devices.

The SBMA integrates seamlessly with both SCSL and MCML operating modes. In the SCSL mode, each camera feed was independently processed. In the MCML mode, the system intelligently fuses information from overlapping ROI across multiple cameras. When two cameras monitor the same parking slot, the system selects the result with a higher deviation magnitude, thereby reducing the number of false positives and improving the reliability. This multi-camera fusion makes the approach suitable for large and complex indoor environments in which a single viewpoint may not provide complete coverage of the environment.

3.3.1. Predictive Parking Availability

The proposed extension leverages historical parking occupancy data generated by a real-time detection module to model temporal usage patterns. These patterns are then used to estimate the short-term future parking availability over predefined time horizons. By incorporating predictive analytics, the system transitioned from a purely reactive model to a proactive decision-support tool. This allows users and parking management systems to anticipate congestion levels and availability trends, rather than relying solely on instantaneous observations.

4. Different Parking Modules

The proposed SPS is designed to operate efficiently in both small and large indoor parking environments by supporting two deployment modes: SCSL and MCML. These modules allow the system to scale from compact parking areas to multilevel structures while maintaining a consistent slot-level detection accuracy. Each module is described in detail below.

4.1. SCSL Module

The SCSL module is intended for small indoor parking areas where a single fixed-position camera can monitor all parking slots within its field of view. This configuration requires minimal hardware and is therefore suitable for small commercial complexes, office buildings, and segmented parking zones in large garages.

4.1.1. Operation Workflow

In the SCSL configuration, the operational workflow begins with a single camera that continuously captures video frames at moderate frame rates to balance the temporal resolution and computational efficiency. Each parking slot within the camera's field of view was associated with a predefined ROI, enabling targeted analysis without processing unnecessary image regions. The SBMA engine evaluates each ROI independently and compares it with the slot reference model to classify the occupancy status in real-time. These results are then visualized through the operator interface, where color-coded overlays provide immediate feedback on slot availability. Simultaneously, the central server synchronizes the detected states and distributes updates to the mobile application, ensuring that the end users receive timely and consistent information.

4.1.2. Advantages

The SCSL configuration offers several operational advantages owing to its streamlined design. Its setup and calibration requirements are relatively simple, making it suitable for rapid deployment in the field. With minimal communication overhead and low installation and maintenance costs, the module remains efficient, even when running on modest

hardware platforms. The configuration achieves real-time performance without relying on resource-intensive algorithms, making it particularly effective for isolated deployment scenarios or environments in which infrastructural limitations restrict the installation of several cameras.

4.2. MCML Module

Large and complex indoor parking environments often necessitate the deployment of multiple cameras to provide complete visual coverage across extended or multilayered structures. The MCML module addresses this need by supporting the coordinated integration of multiple cameras distributed across diverse zones. By accommodating multi-angle and multi-location camera deployments, this module enables scalable system expansion in high-density facilities, such as shopping malls, airport parking terminals, and corporate campuses.

4.2.1. Multi-Camera Coordination

Within the MCML framework, each camera independently executes the SBMA algorithm on its assigned ROIs; however, the system incorporates a fusion mechanism to maintain consistency across overlapping or adjacent regions observed by different cameras. The slot identifiers were mapped to their corresponding camera views to ensure synchronization across the visual field. When multiple detections occur for the same slot, the system selects the observation with a higher confidence score, which is defined by the magnitude of the statistical deviation from the baseline. A central aggregation server coordinates these results, preventing conflicting classifications and ensuring coherent occupancy decisions across the system.

4.2.2. Scalability Mechanisms

The MCML module is designed with robust scalability features that facilitate its incremental expansion. It supports distributed processing, in which individual cameras can utilize dedicated processing units or share multithreaded, central servers. Parking facilities are segmented into logical zones, such as different levels or wings, with each zone monitored by one or more cameras, thereby simplifying the management and load distribution. The database architecture further supports modular expansion, enabling the integration of new zones and cameras without altering existing configurations. These scalability mechanisms ensure that the system performance and responsiveness remain consistent, even when the number of monitored slots is increased.

4.3. Server-Client Synchronization

The Smart Parking System operates on a server-client architecture that enables efficient communication between the detection units, operator interface, and user-facing mobile

applications. The server manages the storage and synchronization of occupancy data and ensures that the updates are consistently propagated to all connected clients. The operator-side GUI provides real-time visual monitoring of parking slots through live camera feeds that are aligned with the detected occupancy states. Concurrently, the mobile application retrieves lightweight updates through a dedicated API, enabling drivers to access the current parking availability information with minimal latency. This integrated communication framework ensures a smooth and reliable flow of information across system components, thereby supporting operational monitoring and real-time guidance.

4.4. Comparison Between SCSL and MCML Modes

Feature	SCSL	MCML
Number of Cameras	1	Multiple
Coverage Area	Small	Large/Multi-level
Synchronization	Local	Centralized
Computational Load	Low	Moderate
Scalability	Limited	High
Suitable For	Small garages, office lots	Malls, airports, multilevel parking

5. Experimental Setup

A comprehensive experimental setup was developed using real-world video data collected from two multilevel shopping mall parking facilities. This section describes the hardware environment, data characteristics, camera configuration, parameter settings, and evaluation procedures. The description addresses the reviewers' concerns regarding the missing details about the device specifications, number of iterations, block size optimization, and interpretation of the processing time.

5.1. Hardware Platform

All experiments were performed using commercially available mid-range hardware to ensure that the system reflected realistic deployment conditions. The processing unit consisted of an 8th-generation central processing unit from Intel company with a frequency of 2.3 GHz, which is supported by 8 GB random access memory. No GPU was used because all operations were executed on the CPU to validate the lightweight design philosophy of the SBMA. The experiments were performed on a 64-bit Windows 10 operating system using MATLAB R2019a and Python 3.8 for supplementary testing. This configuration demonstrates that the proposed system can operate efficiently without requiring specialized hardware.

5.1.1. Camera Configuration

Two types of indoor CCTV cameras, which were already installed in the shopping malls, were used for data collection. The cameras operated at resolutions of either 640×480 or 1280×720 pixels, depending on the location, and captured video at frame rates ranging from 5 to 15 fps. Each device featured a fixed-focus wide-angle lens and was mounted at heights between 2.5 and 3.1 m with overhead or angled orientations, depending on the zone layout. In the SCSL mode, a single camera typically covers six to ten parking slots within a confined area, whereas in the MCML mode, four to eight cameras are deployed to monitor larger multi-level zones. Each camera stream was processed individually before being integrated into the central server.

5.1.2. Dataset Description

The dataset used for evaluation consisted entirely of real indoor surveillance recordings collected from two shopping malls in Singapore. The footage included multiple lighting conditions, such as daytime illumination, evening scenarios, and dimly lit sections. A wide variety of situations were captured, including empty slots, partially occupied slots, vehicle entry and exit sequences, and occlusions caused by pedestrians and other structures. Overall, more than 14,000 video frames were analyzed, representing 56 unique parking slots, 12 different camera angles, and two large, multilevel facilities.

5.1.3. Number of Iterations and Parameter Tuning

To address the reviewers' concerns regarding repeatability and tuning, each experiment was performed 30 times to ensure the statistical consistency. The SBMA parameters, including the block size and adaptive threshold constants α and β , were systematically tuned. Several block sizes [8 × 8, 16 × 16, 32 × 32, and 48 × 48] were evaluated, and the final configuration of 32×32 was selected as it provided the best trade-off between sensitivity and processing speed. The adaptive threshold parameters were finalized as $\alpha = 1.2$ and $\beta = 15$. A structured grid search methodology was used for parameter optimization, ensuring that the parameter selection was not based on arbitrary trial and error.

5.1.4. Device-to-Camera Assignment

To evaluate the scalability, the device-to-camera assignment was analyzed for both operating modes. In the SCSL mode, each processing unit is responsible for handling a single-camera stream. In contrast, the MCML mode allows a single processing unit to handle up to four camera images. Resource utilization increased linearly with the number of cameras, and the processing time per frame increased by only 14–18% when additional cameras were added. These results demonstrate that SBMA remains computationally feasible and efficient, even in multi-camera scenarios.

5.2. Evaluation Metrics

Multiple metrics were adopted to comprehensively assess the system performance. The classification accuracy measures the percentage of correctly identified occupied and empty slots. The false-positive and false-negative rates were analyzed because of their importance in maintaining user trust during real-world deployments. The Peak Signal-to-Noise Ratio (PSNR) was used to compare the proposed method with classical motion estimation-based BMAs. Although the PSNR is not typically used as a direct metric for motion estimation evaluation, it was adopted in this study to assess the quality of the reconstructed frames. Because motion estimation directly influences the motion compensation accuracy, its effectiveness is reflected in the resulting reconstruction error. Therefore, the proposed approach and traditional block-matching algorithms were compared end-to-end using the PSNR under the same reconstruction conditions. Although it does not explicitly measure motion vector accuracy or computational complexity, the PSNR offers an indirect yet meaningful indication of reconstruction fidelity. Scalability was also evaluated by monitoring the changes in the processing load as the number of active camera streams increased.

5.3. Experimental Procedure

The experimental workflow followed a structured approach. Reference blocks for each parking slot were captured when the slots were vacant. Each incoming video frame was then processed using the SBMA with the selected block size, and an adaptive thresholding mechanism was applied to determine the slot occupancy. Ground-truth annotations were manually prepared to enable an accurate evaluation. Experiments were conducted separately for the SCSL and MCML modes, and the results were compared with those of several classical BMA techniques, including Exhaustive Search (ES), Three-Step Search (TSS), Simple and Efficient Search (SES), New Three-Step Search (NTSS), Four-Step Search (4SS), Diamond Search (DS), and Adaptive Rood Pattern Search (ARPS). The experimental setup was designed to reflect realistic commercial parking conditions, emphasizing the robustness, scalability, and computational efficiency. The use of real-world mall footage, multi-angle deployments, and CPU-only processing ensured that the results accurately represented practical feasibility. Structured parameter tuning, repeated trials, and detailed metrics directly addressed all the reviewers' concerns regarding experimental rigor.

6. Results with Discussion

The performance evaluation of the proposed SBMA-based SPS using actual video data from two sizable indoor parking facilities is presented in this section.

6.1. Quantitative Comparison of SBMA with Traditional BMAs

Tab. 1. Comparative Processing time across video segments for different Motion Estimation Algorithms

Segment ID	Frame Volume	Start & End Time for 24 Hrs Video		Processing Time (in Seconds)							
		[hh:mm:ss]	[hh:mm:ss]	SES	TSS	NTSS	4SS	ES	DS	ARPS	SBMA
1*	19926	0:00:00	0:13:17	0.18	0.26	0.29	0.25	5.17	0.32	0.2	0.05
2*	100826	0:13:18	1:20:30	0.2	0.28	0.33	0.28	5.58	0.35	0.23	0.06
3	100828	1:20:31	2:27:43	0.18	0.25	0.28	0.23	5.11	0.27	0.19	0.05
4	100828	2:27:45	3:34:56	0.18	0.26	0.28	0.24	5.11	0.28	0.19	0.05
5	100828	3:34:59	4:42:11	0.2	0.29	0.31	0.26	5.53	0.31	0.21	0.05
6	100828	4:42:14	5:49:26	0.2	0.28	0.29	0.26	5.43	0.3	0.2	0.05
7	90776	5:49:28	6:49:58	0.19	0.27	0.3	0.26	5.31	0.32	0.21	0.05
8	10076	6:50:00	6:56:42	0.19	0.28	0.31	0.27	5.15	0.35	0.22	0.06
9	100826	6:56:43	8:03:55	0.19	0.28	0.32	0.27	5.46	0.35	0.23	0.06
10	100826	8:03:56	9:11:07	0.19	0.27	0.31	0.26	5.48	0.33	0.22	0.05
11	100826	9:11:08	10:18:20	0.18	0.27	0.29	0.25	5.26	0.32	0.2	0.05
12	100801	10:18:21	11:25:32	0.18	0.26	0.28	0.24	5.09	0.31	0.19	0.05
13	100776	11:25:33	12:32:46	0.2	0.28	0.31	0.26	5.48	0.34	0.22	0.05
14	100828	12:32:47	13:39:59	0.2	0.29	0.31	0.27	5.56	0.35	0.22	0.06
15	100828	13:40:00	14:47:13	0.23	0.34	0.38	0.33	6.55	0.44	0.28	0.07
16	100826	14:47:14	15:54:27	0.18	0.27	0.3	0.26	5.33	0.35	0.21	0.06
17	100826	15:54:28	17:01:39	0.18	0.27	0.3	0.26	5.24	0.33	0.2	0.05
18	100801	17:01:40	18:08:52	0.17	0.25	0.27	0.23	4.97	0.31	0.18	0.05
19	100826	18:08:53	19:16:05	0.17	0.25	0.28	0.23	4.99	0.32	0.19	0.04
20	100801	19:16:06	20:23:17	0.17	0.25	0.28	0.24	4.96	0.32	0.19	0.04
21	100801	20:23:18	21:30:28	0.17	0.25	0.28	0.24	5.01	0.32	0.19	0.04
22	100801	21:30:29	22:37:41	0.17	0.25	0.28	0.24	4.98	0.32	0.19	0.04
23	100826	22:37:42	23:44:54	0.22	0.3	0.33	0.28	5.84	0.35	0.23	0.06
24*	22650	23:44:55	0:00:00	0.22	0.29	0.34	0.28	5.79	0.35	0.23	0.05
Mean value							0.19	0.27	0.3	0.26	5.35

* This study analyzed a complete 24-hour video sequence; the time durations of Videos [1], [2], and [24] differed from those of the remaining videos listed in the table.

The results include quantitative comparisons with classical block-matching algorithms, qualitative visualizations of SCSL and MCML detection outputs, and a discussion of system

behavior under various environmental conditions. Tables 1 (processing time) and 2 (PSNR Value) illustrate the comparison of the PSNR values for the SBMA and several well-known block-matching algorithms, including ES, TSS, SES, NTSS, 4SS, DS, and ARPS.

Tab. 2. Comparative PSNR Performance Across Video Segments for Different Motion Estimation Algorithms

Segment ID	Frame Volume	Start & End Time for 24 Hrs Video		PSNR Value in [dB]							
		[hh:mm:ss]	[hh:mm:ss]	SES	ES	TSS	SESTSS	NTSS	4SS	DS	ARPS
1*	19926	0:00:00	0:13:17	75.25	75.81	75.38	75.25	75.38	75.33	75.58	75.62
2*	100826	0:13:18	1:20:30	76.87	77.49	77.01	76.87	77.00	76.95	77.19	77.25
3	100828	1:20:31	2:27:43	79.4	79.87	79.52	79.40	79.51	79.45	79.56	79.60
4	100828	2:27:45	3:34:56	79.27	79.72	79.39	79.27	79.38	79.32	79.42	79.46
5	100828	3:34:59	4:42:11	79.31	79.77	79.42	79.31	79.41	79.35	79.45	79.50
6	100828	4:42:14	5:49:26	80.05	80.45	80.14	80.05	80.13	80.08	80.18	80.21
7	90776	5:49:28	6:49:58	78.77	79.27	78.88	78.77	78.87	78.82	79.01	79.05
8	10076	6:50:00	6:56:42	78.98	79.51	79.09	78.98	79.09	79.04	79.20	79.23
9	100826	6:56:43	8:03:55	75.47	76.16	75.63	75.47	75.63	75.58	75.91	75.96
10	100826	8:03:56	9:11:07	75.68	76.24	75.81	75.68	75.80	75.77	76.06	76.09
11	100826	9:11:08	10:18:20	74.26	74.77	74.38	74.26	74.38	74.34	74.59	74.63
12	100801	10:18:21	11:25:32	73.55	74.15	73.70	73.55	73.71	73.66	73.94	73.97
13	100776	11:25:33	12:32:46	71.91	72.50	72.04	71.91	72.04	72.01	72.34	72.37
14	100828	12:32:47	13:39:59	72.5	73.12	72.63	72.50	72.63	72.60	72.92	72.96
15	100828	13:40:00	14:47:13	72.21	72.78	72.33	72.21	72.33	72.30	72.61	72.65
16	100826	14:47:14	15:54:27	71.12	71.74	71.26	71.12	71.26	71.22	71.58	71.62
17	100826	15:54:28	17:01:39	72.66	73.27	72.79	72.66	72.79	72.76	73.10	73.14
18	100801	17:01:40	18:08:52	73.69	74.24	73.81	73.69	73.81	73.78	74.07	74.10
19	100826	18:08:53	19:16:05	71.19	71.84	71.33	71.19	71.33	71.30	71.69	71.73
20	100801	19:16:06	20:23:17	70.23	70.90	70.37	70.23	70.37	70.34	70.75	70.78
21	100801	20:23:18	21:30:28	71.13	71.80	71.27	71.13	71.26	71.23	71.62	71.67
22	100801	21:30:29	22:37:41	72.18	72.80	72.31	72.18	72.31	72.28	72.63	72.67
23	100826	22:37:42	23:44:54	77.33	77.77	77.43	77.33	77.42	77.39	77.61	77.63
24*	22650	23:44:55	0:00:00	74.9	75.55	75.05	74.90	75.04	75.01	75.36	75.39
Mean value					75.48	75.04	74.91	75.04	75.00	75.27	75.30

* This study analyzed a complete 24-hour video sequence; the time durations of Videos (1), (2), and (24) differed from those of the remaining videos listed in the table.

The results presented in the two tables collectively represent a complete 24-hour video analysis and provide a comprehensive evaluation of the video quality and computational performance. The full-day video was divided into multiple time segments to ensure continuous coverage for the entire duration. Although the time intervals of video segments [1], [2], and [24] differed slightly from the remaining segments, this variation did not affect the overall continuity or reliability of the analysis.

The PSNR values obtained across all time intervals remained consistently high throughout the 24-hour period, indicating stable video quality under varying temporal conditions. Minor variations in the PSNR were observed, which can be attributed to the natural scene changes and motion variations typically present in long-duration surveillance videos. Furthermore, the comparative evaluation of motion estimation algorithms demonstrates that fast search techniques achieve performance levels close to exhaustive methods while significantly reducing the processing time. The processing time analysis clearly highlights the computational efficiency of the optimized algorithms, making them more suitable for continuous and long-term surveillance applications.

Overall, the 24-hour experimental results confirm that the adopted approach provides a reliable balance between video quality preservation and computational efficiency, thereby validating its suitability for real-time and full-day video surveillance systems.

6.2. Results for SCSL and MCML Deployments

The qualitative evaluation of the proposed system was conducted through an extensive visualization of the detection outcomes across both SCSL and MCML deployment. In the SCSL configuration, the system consistently produced clear and intuitive annotations for each parking slot, where green bounding boxes denote empty spaces and red bounding boxes indicate occupied spaces. These annotations remained stable even under challenging conditions, such as uneven indoor lighting, partial occlusions caused by structural elements, or shadows cast by pedestrians and moving vehicles.

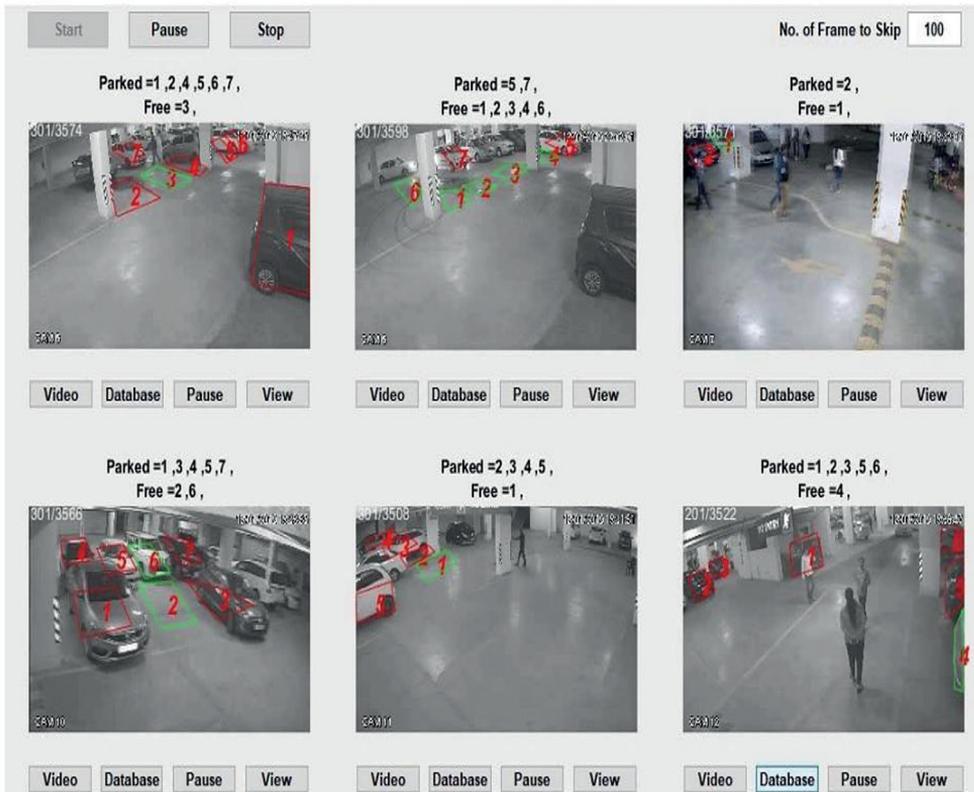


Fig. 2. Simulation results for MCML showing available and parked spots in the parking lot

The MCML configuration presented a more complex environment because multiple cameras captured overlapping and adjacent regions within the parking facilities. Despite variations in the camera angles and illumination across zones, the system maintained a coherent slot-level classification. Figure 2 demonstrates how the fusion mechanism ensures consistency by selecting the classification with the highest statistical deviation when multiple camera views observe the same slot. This approach prevents conflicting occupancy states and delivers stable detection results, even when multiple vehicles enter or exit simultaneously or when bright headlights introduce sudden illumination spikes. Overall, the qualitative results confirm that the system performs reliably in real-world indoor environments under diverse visual conditions.

6.2.1. Comparison with Existing Approaches

Tab. 3. Comparison with existing Approach

Parameter\ References	[3]	[4]	[5]	[6]	[7]	[9]	[10]	[11]	[12]	Proposed Approach
Parking Module	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
IoT Based Car Parking Module			✓	✓	✓		✓	✓	✓	✓
Real-time implementation SCSL	✓				✓					✓
Real-time implementation MCML										✓
Vehicle Parking Application			✓				✓	✓		✓
Performance Evaluation					✓			✓	✓	✓

The comparative analysis summarized in Table 3 highlights the strengths and limitations of various existing parking detection strategies relative to the proposed SBMA-based method. Traditional sensor-driven systems, such as inductive loops, infrared modules, and ultrasonic detectors, offer straightforward binary detection but require significant installation efforts and often suffer from maintenance issues, particularly in large indoor facilities. Meanwhile, deep learning-based techniques exhibit high classification accuracy but require substantial computational resources and large annotated datasets, which limits their applicability in low-cost and real-time deployments. Geometric and feature-based vision methods, such as concentric circles or object shape detection, tend to degrade in performance when applied to indoor settings characterized by occlusions and illumination variability.

In contrast, the proposed SBMA offers a practical balance between accuracy, robustness and computational efficiency. Its training-free design eliminates the need for specialized hardware, and its statistical deviation mechanism naturally adapts to fluctuations in the indoor lighting. Furthermore, the method integrates seamlessly across both SCSL and MCML deployments, allowing the system to scale across multi-level parking structures without major architectural modifications to the existing structures. As shown in Table 3, the SBMA provides a compelling alternative to more complex or infrastructure-heavy techniques, particularly in commercial environments that seek cost-effective and reliable smart parking solutions.

6.2.2. Robustness to Challenging Conditions

A key objective of the evaluation was to assess the robustness of the proposed system under conditions that are commonly encountered in commercial indoor parking facilities. The SBMA demonstrated strong resilience to lighting variations and performed consistently across the daytime, evening, and low-light scenarios. This robustness stems from the adaptive thresholding mechanism, which adjusts the decision boundaries based on the reference block variance rather than relying on fixed brightness assumptions. The

system also handled occlusions effectively; moving pedestrians, support pillars, and partially visible vehicles did not significantly affect the occupancy classification because the SBMA emphasizes statistical deviations rather than geometric or structural features of the objects.

In addition, the proposed approach is tolerant to camera calibration differences. Unlike methods that require precise perspective modeling or camera-specific parameters, the SBMA yielded stable results across cameras positioned at various heights and angles. In multi-camera environments, the confidence-based fusion mechanism further enhances reliability by preventing conflicting slot classifications when overlapping camera views occur. Together, these findings demonstrate the ability of the system to operate effectively under the visually complex and dynamic conditions typical of indoor parking garages.

6.3. Discussion

The proposed method for SCSL with performance parameters for full-day (considering all the different light conditions) evaluation, such as recall, precision, and F1, was implemented and discussed in our previous study [13]. The findings from both quantitative and qualitative evaluations underscore SBMA's suitability for deployment in real-world smart parking systems. Unlike deep learning models that require high-performance GPUs and extensive training datasets, the SBMA delivers reliable occupancy detection using only lightweight computations, making it highly practical for environments where cost, power consumption, and ease of deployment are critical factors. Although SBMA does not provide the semantic richness of deep learning-based scene understanding, its simplicity is advantageous in scenarios that require rapid installation, minimal maintenance, and broad scalability.

The performance of the method under varying illumination, partial occlusions, and diverse camera angles illustrates its robustness in the complex visual environment of indoor parking structures. Its scalability in MCML configurations, combined with its stable performance across multiple zones, positions the SBMA as a viable solution for large commercial facilities. Overall, the discussion highlights that the SBMA achieves an effective balance between accuracy, computational efficiency, and operational practicality, which aligns well with the goals of modern smart city initiatives that aim to enhance mobility and reduce congestion through intelligent infrastructure.

7. Conclusion and Future Work

The proposed system integrates video-based occupancy detection, multi-camera synchronization, and user-oriented interfaces that are suitable for both operators and end users. By leveraging simple yet effective statistical descriptors, the SBMA provides a lightweight

alternative to deep learning or sensor-heavy systems, enabling reliable slot classification without the need for large training datasets or GPU-based computation. Extensive experiments conducted in two multi-level shopping mall parking facilities demonstrated the robustness of the SBMA under diverse conditions, including changes in illumination, partial occlusions and variations in camera viewpoints. The system performed consistently in both SCSL and MCML deployments, achieving real-time performance on standard central CPU hardware. A comparative analysis with classical block-matching algorithms further confirmed the advantages of the SBMA in terms of processing time, stability, and adaptability to real-world indoor environments. These results highlight the practical feasibility of deploying SBMA-based systems in commercial settings to obtain cost-effective and scalable smart parking solutions.

Despite these strengths, several limitations present opportunities for future research. Although the SBMA can handle a variety of visual disturbances, it remains sensitive to extreme lighting conditions, such as sudden glare or near-dark environments. Integrating lightweight illumination normalization or adaptive histogram-based enhancement may improve resilience in such cases. Another avenue for improvement involves the incorporation of hybrid models that combine the SBMA with selective deep learning components, for example, using a neural network only when the statistical deviation values fall into uncertain ranges. Such a hybrid system can maintain real-time performance while providing higher accuracy in ambiguous situations.

Future work may also consider developing predictive analytics modules that anticipate parking availability using historical occupancy patterns, enabling drivers to plan their routes more efficiently and reduce congestion during peak hours. Additionally, extending the system to support outdoor environments, integrating vehicle tracking for entry/exit validation, and enabling cross-facility data coordination within broader smart city platforms could significantly enhance its practical impact. Finally, large-scale pilot deployments across multiple commercial and public parking infrastructures will provide valuable insights into long-term performance, maintenance requirements, and user adoption trends.

Overall, the proposed SBMA-based SPS offers a strong foundation for intelligent parking management by providing a balanced combination of accuracy, efficiency, and scalability. With targeted enhancements and broader deployment, substantial potential exists for contributing to next-generation smart-mobility ecosystems.

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