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Research Article

Dynamic Background Subtraction in Moving Object Detection on Modified FCM-CS Algorithm

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Abstract:

This study uses deep learning for background subtraction in video surveillance. Scanned images often have unwanted background elements, making it difficult to separate objects from their backgrounds accurately. This affects how items are distinguished from their backgrounds. To solve this problem, this article introduces a model called the Improved Fuzzy C Means Cosine Similarity (FCM-CS). This model is designed to identify moving foreground objects in surveillance camera footage and address the associated challenges. The effectiveness of this model is evaluated against the current state-of-the-art, validating its performance. The results demonstrate the remarkable performance of the model on the CDnet2014 dataset.

Keywords: Deep Learning, Fuzzy Histogram, Object Detection, Threshold.
Dataset Link: -

1. Introduction

Dynamic background subtraction plays a crucial role in moving object detection for various applications, including video surveillance and computer vision. The accurate identification and isolation of moving objects can be challenging due to dynamic backgrounds, which introduce complexities into traditional algorithms [1]. The technique of background removal is commonly employed to extract foreground targets from video sequences [2] .

In many surveillance scenarios, diverse background subtraction models have been utilized to tackle various challenges [3]. Dynamic backgrounds present challenges such as variations in lighting conditions, sudden changes in scene elements, and unpredictable movements, which can impact the reliability of moving object detection algorithms. Existing approaches, such as the Fuzzy C Means Cosine Similarity (FCM-CS) algorithm, may require enhancements to effectively address these challenges. Background modelling is frequently used in applications like video surveillance, optical motion capture, human-computer interaction, and content-based video coding to model the background and detect moving objects [4].

Predicting the dynamic backdrop and recognizing objects in a noisy environment are computationally demanding tasks in the visual surveillance model [5]. In a video surveillance system, background subtraction is an essential process. It allows for the recognition and segmentation of moving objects by distinguishing them from the background in video frames. Creating a representation model facilitates the removal of the background from subsequent frames. Each pixel is compared to a set of thresholds for foreground detection and classified accordingly. There are various techniques for background modelling, such as simple background modelling, statistical background modelling, fuzzy background modelling, and background estimation. Traditional background removal techniques, such as the Gaussian mixture model (GMM), kernel density estimation (KDE), and ViBe, have been proposed.

The Gaussian Mixture Model has been widely used in many studies. However, it lacks sensitivity in adapting to persistent changes in moving objects. To address this, we propose a novel approach to background modelling using the FCM-CS algorithm with a dynamic threshold and noise indicator. In this work, we utilized three state-of-the-art cascade processes: (i) background initialization, which generates the initial background image using multiple video frames; (ii) background modelling, which creates a scene for comparison with the current frame; and (iii) background maintenance, which updates the background model based on the prior scene, the foreground mask, and the current scene in response to frequent changes.

The manuscript is written according to the following sequence. The introduction and literature review sections comprise the introduction and literature analysis, respectively. Section three offers an in-depth explanation of the proposed model and approach. Section 4 delves into the results and discussion of this study, focusing particularly on the performance evaluation experiments. Lastly, Section 5 offers the concluding remarks of the work.

2. Method:

Literature Review

Background subtraction models have been developed and implemented in video surveillance systems for many years. Previous research has focused on basic models, such as median, histogram, and mean, which use a threshold difference between the current image and the generated model to determine if a pixel is background or foreground [6]–[10]. There are also mathematical models, which can be parametric or non-parametric. An example of a parametric model is the Gaussian Mixture Model (GMM) [11].

Non-parametric models include algorithms like the Self-Balanced Sensitivity Segmenter (SuBSENSE) [12], Visual Background Extractor (ViBe) [13], and Kernel Density Estimation (KDE) [14]. Clustering models, such as the Codebook model [15] and the K-means algorithm [16]–[19], identify a pixel as foreground based on its color intensity value. Filter models estimate the pixel value based on its historical intensity. Examples of filters include the Wiener filter [20], [21], the Tchebychev filter [22]–[26], the Correntropy filter [27], and the Kalman filter [28].

In addition, machine learning models, including support vector machines (SVM) [30], deep learning, neural networks, and convolutional neural networks (CNN) [18], have become cutting-edge approaches. However, these models are not yet suitable for real-time applications due to the extensive processing time required [31]–[33].

In the context of background subtraction, a hard computation classification has been widely used. This classification binary classifies a pixel as background or foreground. However, inaccuracies in this classification can significantly affect the reliability of the background model. Therefore, the fuzzy model has gained popularity as a soft computing classification method. It addresses the uncertainty of a pixel's value and produces better results in dynamic scenes, shadows, and lighting variations [34]. In fuzzy models, items on the boundaries of different classes are assigned membership degrees between 0 and 1 to represent their partial membership.

Fuzzy models can address the ambiguity, inconsistency, and imprecision inherent in data. Several algorithms exemplify this model, such as the Fuzzy Choquet Integral [35]–[37], the Fuzzy Sugeno Integral [38], and Fuzzy C-Means (FCM) [39], [40].

Materials and Methods

In this section, we will discuss the detailed illustration of the proposed work.

Prior to conducting the experimentation, several data pre-processing steps were implemented. These steps included data cleaning to ensure the integrity of the dataset and prevent any issues during the training or evaluation processes. Format standardization was also performed to ensure consistency in all file formats and address any inconsistencies within the dataset. Additionally, the data was labelled to assess the model's performance on unseen data and prevent overfitting.

The modified algorithm underwent a training process using CDnet2014. The data consisted of frames labelled as either containing a dynamic background or not. The images were resized to a consistent resolution, and the pixel values were normalized, ensuring uniformity, and facilitating the model's ability to generalize well across the dataset. Subsequently, the algorithm was tested on the same dataset.

The proposed work on background subtraction is depicted through a flow diagram of the proposed framework. Figure 1 highlights the proposed FCM-CS phase of the pipelined background subtraction. The training phase involves gathering data from multiple input video frames to construct the background model. The foreground detection phase, consisting of per-pixel cosine similarity and per-pixel smart thresholding, is represented by two sections of code. The background maintenance phase comprises background model updates and noise indicator updates. Finally, the post-processing stage involves generating the foreground mask output after applying all final modifications.

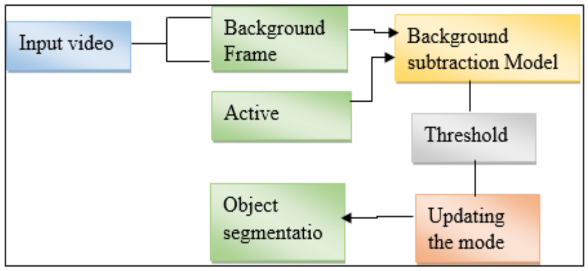


Figure 1. General workflow diagram of the improved FCM-CS model

The FCM-CS model utilizes the RGB color space and calculates fuzzy histograms for each pixel value in the red, green, and blue channels. Fuzziness reduces color variation in the dynamic background, enhancing the detection of moving foreground targets. This is the reason why fuzzy color histograms are used instead of conventional color histograms.

Therefore, fuzzy color histograms (FCH) are employed in place of conventional color histograms (CCH). In CCH, each pixel is closely associated with one histogram interval (bin), leading to abrupt changes in adjacent pixel values. In contrast, FCH assigns a degree of membership to each pixel for every histogram interval (bin), resulting in a smooth and continuous merging of neighboring pixels into the background model. By determining the membership value of each pixel to the cluster center, the FCM algorithm calculates the FCH, which is then utilized for the intended purpose. FCM is a well-established fuzzy clustering model in the field of soft computing. The magnitude (G) of the depth gradients, as given by Equation 1, can be utilized to extract the ROI borders from the depth image.

$$G = \sqrt{\left(\frac{\partial I'}{\partial x}\right)^2 + \left(\frac{\partial I'}{\partial y}\right)^2} \quad (1)$$

where I' is the depth image corresponding to the Extracted from the field of view image, and $(\partial I' / \partial x)$ and $(\partial I' / \partial y)$ are the depth gradients of I along the x and y directions, respectively. The G image was binarized using the otsu method, converting each pixel to a value of 1 or 0, the pixel membership value, the cluster center determined using FCM, where the median value is used as a center, and the fuzzification coefficient number. G is the total number of bins (histogram intervals), which is set to 16 intervals. Where, each pixel membership to the cluster center is computed.

In this work, the membership degree for each pixel is calculated only once and stored in the Levels matrix, which has a size of 256. Subsequently, the current pixel membership can be associated with the corresponding value calculated in this level matrix. The cluster center is then computed by determining the median value in each of the 16 intervals resulting from dividing the 256-color range [0-255] into equal bins. The overlap ratio R between Ip and Iq is computed by averaging the magnitude of the inlier vectors along the x and y directions. This ratio is determined under the assumption that there is no change in working distance between the target structure and the digital camera mounted on the moving object.

$$R = \frac{100 \times (h - \mu) \times (1 - \pi)}{h \times w} \quad (2)$$

where h is the Height and w is Width, the inlier vectors' averaged magnitude along the x and y directions, R was calculated, the optimal image that satisfies the predefined threshold of R was determined. To decide whether a pixel is foreground or background the current pixel is examined to measure the nearness of this current pixel membership to the correspondent background model pixel (fuzzy histogram background model). To do so, the cosine similarity (CS) measurement is utilized in this work, it can be defined as the division between the dot product of two vectors and the product of Euclidean norms as in equation (3) and equation (4), Cosine similarity measures the similarity between two vectors or more and the output is bounded between the [0,1]. Cosine similarity is invoked over other similarity measurements because it provides the best closeness values between two vectors. In this work cosine similarity is required to compute the closeness between each pixel membership value and the fuzzy histogram background model for cosine similarity as follows:

$$\cos(\theta) = \frac{M \times FCH}{|M| \times |FCH|} \tag{3}$$

$$\cos(\theta) = \frac{\sum_{i=1}^{J} M_1 \times FCH_1}{\sqrt{\sum_{i=1}^{J} M_1^2} \times \sqrt{\sum_{i=1}^{J} FCH_1^2}} \tag{4}$$

Where Mi represents the membership value for the current pixel and FCHi represents the fuzzy histogram for the corresponding current pixel in the background model, J denotes the total number of pixels. The cosine similarity is calculated for all pixels within the 16 bins across three channels. A new approach is adopted to detect the moving foreground object based on a threshold. It has been observed that static background regions require higher thresholds to facilitate the detection of foreground objects. Conversely, dynamic background regions require lower thresholds to avoid false-positive detections of moving background elements as foreground objects. Therefore, a proposed noise indicator (nu) is employed as a measure of dynamic behavior. Higher values at a pixel indicate the presence of a dynamic background or actual foreground. **Figure 2** below illustrates frame samples along with their corresponding noise indicators.

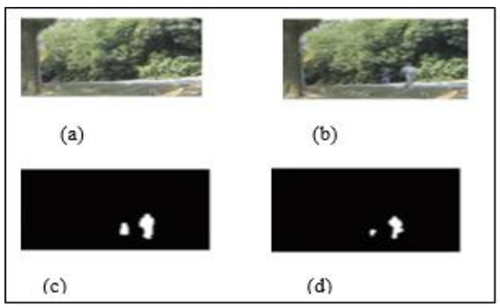


Figure 2. The noise indicator for each corresponding sample

The approach hence increases the threshold where noise is low and decreases it where noise is high. The median value of nu is used across the frame to decide what values of nu may be considered as low or high. Finally, the threshold is clipped to stay in the range between the minimum threshold value and the maximum threshold [T_MIN, T_MAX], as values lower than minimum threshold T_MIN disallow detection of foreground, and values above maximum threshold T_MAX induce many false positive foreground detections. The range T_MIN and T_MAX is fixed to 0.05 for the T_MIN and 0.25 for the T_MAX, the values are selected because of extensive trails. **Figure 3** demonstrates the flowchart explaining the flow of calculating the smart threshold. Once threshold is obtained the model proceed in evaluating each channel to obtain the foreground pixels using the following FP^c is the pixel evaluation per channel.

$$FP^c = \begin{cases} 1, if\ CS(M_p, FCH) < smart\ threshold(T) \\ 0, Otherwise \end{cases} \tag{5}$$

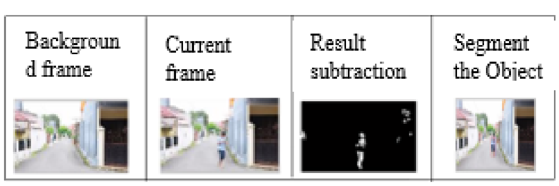


Figure 3. The FP^c from the CDnet 2014 Dataset Videos

Model Updating

The background model is updated adaptively according to Equation 6:

$$FCH^{k+1} = FR^{f}\, FCH^{k} + (1 - FR^{f})(1{-}\propto)FCH^{k} {+}\propto M(p_{k+1}) \tag{6}$$

Where $k = 1, 2, \dots .. N, FR^{f}$ is the final output, the background model is only updated when the final output is not foreground, the update will be according to the current background model, the current membership value, and the updating rate α which is set to 0.011 based on large scale testing. The nu value starts with 0 and gets updated using the current and the previous foreground predictions. Two indicators are used, the blink indicator and background mask. Blinking indicator (xor) is true at pixels where prediction for this frame is different from that for the previous frame while, background mask (bgm) is the inverse of the foreground mask, obtained after post-processing phase of foreground mask, as this mask is obtained after post-processing, this is a certainty that this is a true foreground (fg), and to avoid incrementing nu the first time a pixel is classified as fg, the blink variable is kept on only where bgm is True.

In this method of noise updating, the exponential smoothing of noise across frames is used. The updated noise indicator is obtained by adding the 75% of the current noise indicator and the value of 0.25 only when the pixel is blinking and is a part of the background mask (xor AND bgm).

3. Results and Discussion

In this section, we provide a detailed explanation of our methodology for dynamic background subtraction in moving object detection. The core of our approach involves modifying the FCM-CS algorithm. We will now outline the key aspects of its implementation.

For our training and testing data, we utilize the CDnet2014 dataset, which consists of frames labeled with information about the presence or absence of a dynamic background. The modified FCM-CS algorithm undergoes an extensive training process using this prepared dataset. The goal is to teach the model how to effectively distinguish between dynamic backgrounds and foreground objects. Subsequently, the trained algorithm is rigorously tested on the same dataset to evaluate its performance in dynamic background subtraction. Evaluation metrics such as precision, recall, and F1 score are used to measure the accuracy and effectiveness of the model.

Our implementation incorporates a comprehensive framework for dynamic background subtraction, with a specific focus on the proposed modifications to the FCM-CS algorithm.

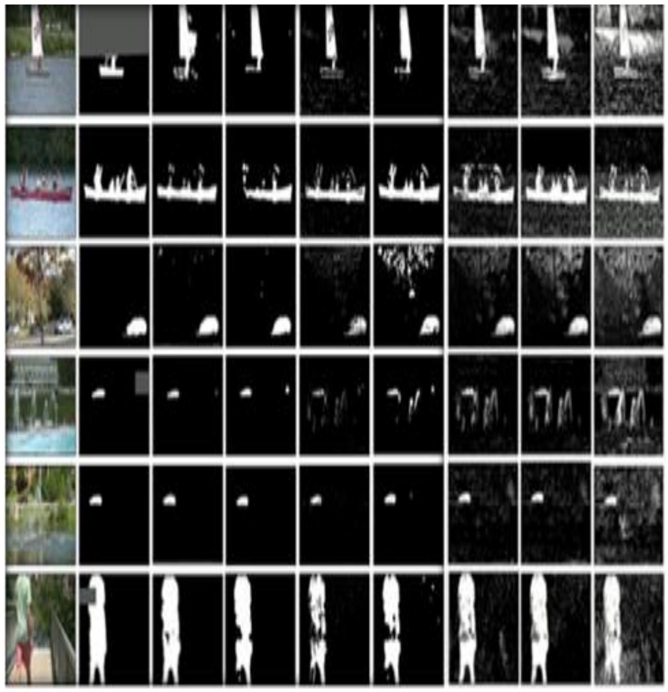
To visually represent the workflow of our proposed framework and the stages involved in dynamic background subtraction, we have created a flow diagram. **Figure 4** highlights a specific phase of the pipelined background subtraction process, demonstrating the effectiveness of the modified FCM-CS algorithm.

Both the six benchmark models and the FCM-CS models have been applied to scenes with challenging, dynamic backgrounds. To evaluate the performance of our model, we have used the CD Net 2014 dataset. Table 1 provides the Accuracy metric, which indicates whether a pixel should be classified as a foreground or background pixel. The average performance of the proposed FCM-CS model is compared against that of the well-known benchmark models in **Table 1**.

Table 1. Average Performance Metrics Results of Applying Background Subtraction Models

Model	Accuracy	Precision	Recall	F1	FPR	FNR	PWC
SuBSENSE	0.99	0.61	0.73	0.80	0.00	0.26	0.40
ViBe	0.99	0.19	0.56	0.52	0.01	0.44	1.38
LOBSTER	0.98	0.34	0.73	0.62	0.02	0.27	1.91
GMM	0.97	0.13	0.74	0.43	0.02	0.26	2.61
KNN	0.96	0.12	0.85	0.45	0.04	0.15	3.62
Codebook	0.88	0.05	0.83	0.22	0.12	0.18	12.2
Proposed	0.99	0.92	0.66	0.83	0.00	0.34	0.26

Based on the table, the proposed model, FCM-CS, achieved an accuracy of 0.997, precision of 0.92, F-Measure (F1) of 0.83, and overall accuracy that surpasses other models. These findings demonstrate a significant improvement over all the videos in the CDnet 2014 dataset. For a visual assessment of the proposed model's performance, refer to **Figure 4**, displaying the background subtraction results on the CDnet 2014 dataset.



(a) (b) (c) (d) (e) (f) g) (h) (i)

Figure 4. The visual comparison (a) original scene (b) ground-truth (c) The proposed FCM-CS foreground mask (d) SuBSENSE foreground mask (e) ViBe foreground mask (f) LOBSTER foreground mask (g) GMM foreground mask (h) KNN foreground mask (i) Codebook foreground mask

4. Conclusion

In conclusion, the exploration of dynamic background subtraction for moving object detection using the modified FCM-CS algorithm has resulted in significant advancements in the field. Through meticulous implementation and testing, notable results have been achieved, as demonstrated in Table 1. The modification of the FCM-CS algorithm has played a crucial role in improving the model's ability to accurately distinguish dynamic backgrounds and foreground objects.

The comprehensive training process, along with rigorous testing on the CDnet2014 dataset, demonstrates the effectiveness of the approach in dynamic background subtraction.

Evaluation metrics such as precision, recall, and F1 score provide quantitative evidence of the model's accuracy and effectiveness in identifying moving objects against varying backgrounds. Furthermore, the proposed framework seamlessly integrates into the existing landscape of moving object detection, demonstrating its versatility in handling dynamic backgrounds in different scenarios. The visual representation in Figure 1 highlights a specific phase of the background subtraction process, offering a clear and intuitive illustration of the proposed methodology.

In summary, this work presents a robust and advanced solution for dynamic background subtraction, laying the foundation for improved moving object detection in diverse real-world applications. The modified FCM-CS algorithm, with its enhanced capabilities, significantly contributes to the evolving landscape of computer vision and object detection techniques.

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