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Moving Object Segmentation Using Level Set Algorithm with GWO-KFCM Clustering

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Abstract: Video analytics is widely used to automatically analyze the videos to extract the required information and detect the various events object identification and traffic analysis. The segmentation of the image is referring to extracting the required region from an image. The major objective of the segmentation process is to cluster the images without being affected by the noises. The detection of the moving objects is a challenging task in video analysis due to the dynamic background of the video. The major drawback of the existing Kernel Fuzzy C-Means (KFCM) clustering is initialization of random centroids which increases the execution time to identify the segmented portions. In this research, the Grey Wolf Optimization (GWO) algorithm used to initialize the centroids of required clusters in KFCM and Level Set (LS) Algorithm is used to segment the objects in video sequence. The proposed KFCM-GWO-LS is implemented for moving and static object detection in the videos obtained from SBM-RGBD dataset. For object detection, determining central clusters are important which is performed by using KFCM. GWO helps in finding the best centroids clusters by matching with KFCM. The centroids clusters are segmented by using LS algorithm which undergoes over segmentation problem that is overcome by GWO. As all the three techniques are dependent on one another hybrid of all these techniques obtains better results. The proposed KFCM-GWO-LS is evaluated in terms of Recall, Specificity, Precision and F-measure and the experimental results showed that the proposed method improved the system performance from 0.3 % to 14.35 % compared to existing methods Multi-Sensor Scheduler Algorithm and Statistical Inference Theory model.

Keywords: Dynamic object segmentation, Kernel fuzzy c-means clustering, Level set algorithm, Moving object, Object segmentation, Video analytics.

1 Introduction

Nowadays, the usage of the intelligent video analytics and intelligent video system are significantly increased due to the growing practical requirements like healthcare, transportation, etc. and the video analytics market has 60% compound growth in video systems [1]. The process of obtaining the location and significant information from the image sequences are called as object tracking. The tracking becomes difficult in video analysis when the video has huge amount of rigid objects. Therefore, the robustness of visual tracking is improved to obtain an enhanced tracking performance in video analysis [2]. The unsupervised tasks performed by existing techniques can be broadly categorized into partitioning, hierarchical, destiny and model techniques [3]. An unsupervised foreground - background video object segmentation of the difficult scenes is a challenging task in video analysis. The video analysis system is requiring to develop an efficient technique to separate foreground from background in complex videos for different applications object identification, video compression and security [4].

Generally, the object detection is performed in the context level applications which require the location of the object in each frame [5]. The object detection is considered as challenging step in the video analytics and it is an important process to analyze, track, and match the objects present in the videos [6-

8]. In this study, the DOS scheme is used to segment the object in video and this scheme does not assume any prior knowledge about location and number of objects. This research uses unlabeled videos as input from SBM-RGBD dataset and KFCM and LS Algorithm segment the objects in video sequence and it defines the boundaries of all moving and static objects of the video. GWO algorithm is used to initialize the centroids of required clusters in KFCM and LS Algorithm. KFCM is used for choosing cluster centroids and the Level set algorithm during segmentation degrades the edges that results with over segmentation problem. The over segmentation problem is overcome by using GWO algorithm. The proposed KFCM-GWO-LS experimental results showed that the proposed method improved the system performance from 0.3 % to 14.35 % compared to existing methods Multi-Sensor Scheduler Algorithm and Statistical Inference Theory model.

The organization of this paper is as follows, Section-2 presents a literature survey of recent papers based on object segmentation. In Section-3, a brief explanation of the DOS- Video Analytics scheme is presented and Section-4 shows the comparative experimental result of existing KFCM clustering and proposed DOS-Video Analytic strategies. The conclusion of this paper is made in Section-5.

2 Literature review

Many researchers have suggested several techniques for object segmentation in video analytics. In this scenario, a brief survey of a few significant object segmentation schemes is presented.

Wang [9] implemented a Geodesic Distance (GD)-based scheme to provide a stable and Temporally Consistent Saliency Measurement (TCSM) of the super-pixels. The inter and intra-frame relevancy was used in the undirected graphs to obtain the spatiotemporal saliency. The GD was used on Spatiotemporal Edges (SE) for the intra-frame stimulus and the salient portion of the intra-frame has larger GDs to the background portions. In addition, the Greedy Skeleton Abstraction (GSA) method was utilized to the iteratively select the confident foreground region. But the developed GD based scheme has high computational complexity issues.

Zhang [10] developed the video-based Semantic Object Segmentation (SOS) to improve the detection performance in tagged videos. This SOS method was used to initialize the object tracking by solving the joint assignment issue. The joint assignment constraint was avoided to track the objects from the noisy image frame. Next, the initial object tracks were refined by using the voting-based algorithm which provides the spatiotemporally consistent object segmentations. The pre-processing of SOS segmentation has execution time is 63.11 seconds, which was high when compared to other techniques. However, object segmentation failed to explore multiple weakly labelled videos that lowered the ratio of per-video detections to the segmentations.

Jyothi [11] implemented an intellectual three step Content-Based Medical Image Retrieval (CBMIR), which recovered the related images from a substantial medicinal dataset to help the radiologist in detecting tumor images. The CBMIR method used the segmentation strategy to recognize the irregular images at various orientation by using higher order steerable filter at 10-iterations. Finally, the performance of the retrieval system was improved by the subjective feedback approach, but the execution of a segmentation strategy was affected by the moments feature thereby increased the computation time for the execution.

Wang [12] developed Video Salient Object Detection through Fully Convolutional Networks. The developed deep video saliency model used both spatial and temporal saliency cues, produced accurate spatiotemporal saliency estimation. The developed augmentation technique simulated video training data from image datasets enabled the network to learn diverse saliency information and prevented over fitting with the limited number of training videos. However, the model underwent over-fitting problem as high similarities of scenes were present within the same video.

Ammar [13] developed Deep Detector Classifier (DeepDC) for moving objects segmentation and classification in video surveillance. The developed DeepDC employed and validated Deep Sphere, identified the anomalous cases in spatial and temporal context performed foreground objects segmentation. However, the deep neural networks trained vast quantities of labelled data and were difficult to apply deep models to datasets with limited labels.

Rasoulidanesh [14] developed a novel change detection algorithm that was used in star network configuration. The model performed tasks to detect changes in the depth signal. The foreground segmentation, background detection, target detection and monitoring the tracked tasks are performed. The approach decreased the power consumption overall in the system and also reduced the computational overheads. However, identifying the object with distinct sensor was failed to achieve with respect to multi-subject tracking.

Muthu [15] developed motion segmentation using Selective object based sampling and

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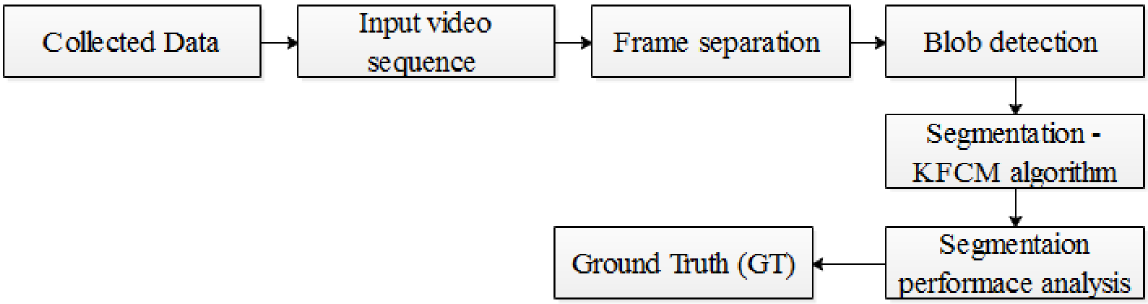

Figure. 1 Block diagram of the KFCM-GWO-LS method

correspondence matching that overcame the problem of over segmentation occurred in the moving parts of different objects. The developed model identified objects with similar motions thereby characterized motion using a statistical inference theory to assess similarities. However, the limitation was that the model ceased to track moving objects that remain stationary for a few frames.

To overcome the aforementioned limitations, the KFCM-GWO-LS method is implemented to improve the performance of the image segmentation process.

1. KFCM-GWO-LS methodology

Nowadays, several segmentation algorithms have been implemented along with a number of evaluation criteria to segment the object from the video. The segmentation of the moving object in the image order plays a significant role in video processing and analysis. In this study, the KFCM algorithm is used to effectively segment the objects from the video sequences and the block diagram of the proposed KFCM-GWO-LS method is shown in Fig.1. The proposed KFCM-GWO-LS method is used for ordinary segmentation detection and it consists of four major phases such as data collection, frame separation, blob detection, and segmentation process. The brief explanation about the proposed KFCM-GWO-LS method is described in the following section.

1.1 Blob detection

In the initial phase of the object segmentation, video sequences are collected from the SBM-RGBD dataset. After the acquisition of datasets, the frame isolation or separation is done for the object segmentation process. Next to frame isolation, the blob detection process is done to obtain a specific region of interest to perform further operation like the object segmentation. The major aim of the blob detection is to find regions in a digital image with different properties such as color, brightness, and surrounding regions. The presence of object and parts of objects are represented by the blob portion which is obtained in the object segmentation application [16]. Each blob regions exist in the vertical and horizontal directions until the entire blob region is enclosed in a rectangular box. In the proposed KFCM-GWO-LS method, the blob detection system mainly depends on the centre of mass, adjacency pixels and boundary box. The proposed method also defines the statistical features of the blobs such as rectangular enclosure size, location of centre gravity, membership functions and the pixel count of a blob. The blob detection is widely used to track the objects in the videos due to the interest points in significant Baseline Stereo Matching (BSM). The KFCM algorithm applied on blob detected portions is described in the following section.

It is difficult to determine the best centroids clusters among other clusters using KFCM for segmenting object. The GWO helps in finding the best centroids clusters by matching with KFCM. The obtained best centroids clusters are segmented using LS algorithm. As LS algorithm faces over segmentation problem, GWO is used to overcome the over segmentation problem. All the three techniques are dependent on one another and thus, in the proposed method hybrid of these 3 techniques KFCM-GWO-LS is used for segmentation process.

1.2 KFCM based Segmentation process

The FCM is used to classify the similarity between the data points [17-18]. The FCM algorithm gives best segmentation results for the images without any noise, but it neglects the classification of the noisy information because of the inconsistencies of the element information. The inconsistencies of the element information are the fundamental reason behind inappropriate segmentation that happens while processing the Noisy image by the FCM [19]. In this study, the object segmentation is done by the KFCM algorithm and it uses nonlinear mapping capacity to change an input over the information in the plane of images into advanced dimensional

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element space. Eq. (1) expresses non-linear map function.

$$\phi : x \rightarrow \phi(x) \epsilon F \quad (1)$$

Here, the whole data point is denoted as X that consists of $\{x_1, x_2, \dots, x_n\}$ that classified into $V = \{v_1, v_2, \dots, v_c\}$ homogenous cluster groups. The transformed feature space with higher infinite dimensions is denoted as F. The objective function minimized in the KFCM is expressed in Eq. (2).

$$J_m(U.V) \equiv \sum_{I-1}^{C} \cdot \sum_{k-1}^{n} u_{ik}^m \|\phi(x_i) - \phi(v_i)\|^2 \quad (2)$$

Where, $\|\phi(x_i) - \phi(v_i)\|$ is used for calculation of kernel function in the input space is calculated by using Eq. (3).

$$\|\phi(x_i) - \phi(v_i)\|^2 = K(x_k, x_k) + K(v_i, v_i) - 2K(x_k, v_i) \quad (3)$$

Where,

$$K(x, y) = \langle \phi(x), \phi(y) \rangle = \phi(x)^T . \phi(y) \quad (4)$$

The function is represented as u; $\phi(x_i)$ and $\phi(v_i)$ are the kernel spaces of x_i and v_i respectively; x_i and v_i are the d^{th} dimensional i^{th} measured data and center of cluster in d^{th}dimensional respectively; number of clusters is C and intuitionistic fuzzy complement is n.

$K(x, y) = \phi(x)^T \phi(y)$specifies the inner product of kernel function. The $K(x, x) = 1$, when the Gaussian function is adopted as a kernel function which is given by Eq. (5).

$$K(x, y) = exp(-\|x - y\|^2 / 2\sigma^2) \quad (5)$$

Where $K(x, y)$ is an inner product kernel function and the Gaussian function is adopted as a kernel function as shown in Eq. (5). Then the following Eq. (6) is rewritten based on Eq. (2) and (3). Substituting Eq. (3) in (2) becomes Eq. (6).

$$J_m(U.V) \equiv \sum_{I-1}^{C} \cdot \sum_{k-1}^{n} u_{ik}^m \left(1 - K(x_k, v_i)\right) \quad (6)$$

Reducing Eq. (6) under the constraints of $u_{ik}, m > 1$. Where J_m is used for minimizing the objective function in KFCM. The first order for J_m with respect to u_{ik} =0 and v_i=0. For local extrema the equation becomes as shown in Eq. (7) and Eq. (8).

$$u_{ik} = \frac{\left(1/\left(1-K(x_k,v_i)\right)\right)^{1/(m-1)}}{\sum_{j=1}^{c}\left(1/\left(1-K(x_k,v_i)\right)\right)^{1/(m-1)}} \quad (7)$$

Where $i = 1,2, \dots, c, k = 1,2, \dots, n$

$$v_i = \frac{\sum_{j=1}^{n} u_{ik} K(x_k,v_i) x_k}{\sum_{k=1}^{n} u_{ik}^m K(x_k,v_i)} \quad (8)$$

Where $i = 1,2, .., c$

Here, the Gaussian kernel function is used for the straightforwardness. Eqs. (7) and (8) are modified, if the segmentation process uses additional kernel functions. The Eq. (3) is analyzed as a kernel which induces new metrics in data space and it is expressed in the following Eq. (9).

$$d(x, y) \triangleq \|\phi(x) - \phi(y)\| = \sqrt{2\left(1 - K(x, y)\right)} \quad (9)$$

where, $d(x, y)$ is the metric in the original space in the case of $K(x, y)$; the $K(x, y)$ defines the Gaussian kernel function. The data-point x_k has the capability of an additional weight $K(x_i, v_i)$ in Eq. (8). The weight $K(x_i, v_i)$ computes the similarity among x_k and v_i when the x_k is an outlier. The higher distance from the x_k and other data points creates lesser weight value. Therefore, the weighted sum of Data Points (DP) is stronger.

KFCM Algorithm

Step 1: Selection of initial class prototype
Step 2: Update all membership u_{ik} with Eq. (7)
Step 3: Obtain the prototype of clusters in forms of weighted average with Eq. (8)
Step 4: Repeat step 2 to 3 till termination.

The GWO algorithm is applied on the KFCM information to select the initialized centroids of the required clusters. The principle of GWO is clearly explained as follows.

1.3 Grey wolf optimizer (GWO) algorithm

The GWO is developed as an intelligent optimization algorithm and is inspired by the hunting behavior and leadership hierarchy of grey wolves. In GWO, the grey wolves are classified into four different types such as alpha (α), beta (β), delta (δ) and omega (ω) which are used to simulate the leadership hierarchy [20]. The proposed KFCM segmentation hierarchy helps GWO to achieve the better solutions during object segmentation. The decision for hunting, resting and forwarding are created by the leader wolf α. The β wolf helps to produce decision and reinforce α's commands. Next, the δ wolf takes the decision and manages ω wolves, which are the lowest level of grey wolves hierarchy. Before processing the hunting process, the grey wolves initially encircle the prey. Eq. (10) shows the distance between the prey and wolf. Then the updated position of wolf is expressed in the Eq. (11).

$$d = \left|c.h_p(t) - h(t)\right| \tag{10}$$

$$h(t+1) = h_p(t) - ad \tag{11}$$

Where, the present iteration is represented as t; the position vector of prey is represented as h_p; the two coefficient vectors are a and c; the grey wolf's position vector is denoted as h. Two coefficient functions are expressed in Eqs. (12) and (13).

$$a = 2v\gamma_2 = v \tag{12}$$

$$c = 2\gamma_1 \tag{13}$$

Here, γ_1 and γ_2 are random vector between zero and one, v is vector, it reduces from two to one linearly in iteration course. The hunting process is controlled by β and δ wolves after encircling the targeted prey. The locations of β and δ wolves are used to obtain the location of all wolves in the search space. Next, the position of wolf is obtained by using Eqs. (14) and (15).

$$d_\alpha = |c_1 h_\alpha(t) - h(t)| d_\beta = \left|c_2 h_\beta(t) - h(t)\right|,$$
$$d_\delta = |c_3 h_\alpha(t) - h(t)|, \tag{14}$$

$$h_1 = h_\alpha - a_1 d_\alpha, h_2 = h_\beta - a_2 d_\beta$$
$$h_3 = h_\delta - a_3 d_\delta$$
$$h_p(t+1) = \frac{h_1 + h_2 + h_3}{3} \tag{15}$$

Once the position of wolf is obtained by using Eq. (14) and (15), best optimal value selection is important by using fitness value. The Best fitness value will be obtained only if the minimum distance of the clusters is also less. The distance value is calculated by using the Eq. (16).

$$d(x,y) \triangleq \|\phi(x) - \phi(y)\| = \sqrt{2\left(1 - K(x,y)\right)} \tag{16}$$

GWO Algorithm
Input: MaxIter number of interations for optimization, n number of grey wolves in pack.
Step1: Initialize a population of an n grey wolves' positions randomly.
Step2: While stopping criteria not met do
Step 3: Compute fitness value based on alpha, beta and gamma position.
Step 4: Update Alpha, gamma and delta.
Step 5: Update A and C
Step 6: Update position of research agents contains omegas
Step 7: end
Output: Optimal gray wolf position. Best fitness value.

From the Eq. (16), based on the distance of cluster, centroids of the clusters are determined and these centroids will be processed for LS algorithm. If the distance value of the cluster is less, then the fitness value will be less. If less fitness value is present, a best optimal solution is obtained and these optimal values will be processed for LS algorithm.

The process of hunting prey goes to the successive iteration to generate the three different optimal solutions. This iteration repeats until the stopping criterion is satisfied.

The GWO algorithm used to initialize the centroids of required clusters in KFCM and the LSA is used to detect the segmented regions from the video sequences.

1.4 Level Set Algorithm

In past decades, the LSA is generally used as a numerical approach to track interference and shape of object, so it has been increasingly applied to image segmentation. In this research, the LSA is used to extract the properly segmented region of object. This LSA mainly depends on the improved contour C as the zero level set of graph in high dimensional function $\emptyset\,(x,k,y)$ which is mathematically expressed in Eq. (17).

$$C_k = \{(x,y)|\emptyset(x,y,k) = 0\} \tag{17}$$

where, the artificial time marching parameter is represented as k. The topology is changed and singularities are improved by using the level set. Based on the conditions of Eq. (17), the evaluation of the curve is expressed in Eq. (18).

$$\frac{\partial c}{\partial k} = VN \tag{18}$$

where, curve evaluation speed is represented as V and normal vector of inward unit is represented as N. Eq. (19) is expressed from the $\emptyset(C_k, k)$.

$$\left(\frac{\partial \emptyset}{\partial k}\right) + \nabla\emptyset \cdot \left(\frac{\partial c}{\partial k}\right) = 0 \qquad (19)$$

Eq. (20) shows the related curve evaluation of LSA.

$$\frac{\partial \emptyset}{\partial k} = V\|\nabla\emptyset\| \qquad (20)$$

The initial curve is used to generate the initial LS function. Therefore, the GWO and LSA is effectively detects the objects from the video sequences. An advantage of the proposed GSO-KFCM-LS is that, KFCM is used for choosing centroids and the Level set algorithm during segmentation degrades the edges thereby results over segmentation problem. This over segmentation problem is overcome by using GWO algorithm. By integrating all these 3 techniques, the proposed method is free from over segmentation problems and in turn the complexity of the system is also reduced.

3. Result and discussion

The KFCM-GWO-LS method is implemented in the MATLAB stimulator software version 2018b. The entire implementation work is executed using i3 processor operating system with 4 GB Random Access Memory (RAM) and the performance of the KFCM-GWO-LS method has validated in SBM-RGBD dataset. The SBM-RGBD dataset delivers a large set of synchronized color, and depth sequence of video obtained by Microsoft Kinect. This dataset has 33-videos which are taken from indoor environment to cover a wide range of background modelling challenges for moving object detection. In SBM-RGBD dataset, the collected videos have 640×480 spatial resolution and their length varies from 70 to 1400 frames and the depth images are recorded in the range of 16 bits or 8 bits. The dataset taken for this study has two types of videos: top view video and multi-view video and the proposed method has been validated in multi-view video. The performance of the KFCM-GWO-LS method is analysed by means of recall, specificity, precision and false measure (F-measure).

1.5 Performance metrics

The performance of the proposed KFCM-GWO-LS method is evaluated by means recall, specificity, precision and f-measure. Definition of each performance metrics are briefly explained as follows.

3.1.1 Recall:

The recall is sum of True Positive (TPs) divided by the sum of TPs and False Negatives (FNs). The performance of recall is important to analyse the ability of a classification model to identify all related instances. The recall is expressed by using Eq. (21).

$$Recall = \frac{TP}{TP+FN} \times 100 \qquad (21)$$

3.1.2 Specificity

The specificity is the sum of True Negatives (TNs) is divided by the total number of TNs and the False Positives (FPs). The performance of specificity computes the proportion of the properly identified actual negatives. The specificity is computed using the following Eq. (22).

$$Specificity = \frac{TN}{TN+FP} \times 100 \qquad (22)$$

3.1.3 Precision

The precision is defined as the sum of TPs is divided by the sum of TPs and FPs. The performance of the precision is computed for segmented object and it is capable of a returning only related instances to the classification model. The precision is expressed in Eq. (23).

$$Precision = \frac{TP}{TP+FP} \times 100 \qquad (23)$$

3.1.4 F-measure

F-measure is defined as the weighted harmonic mean of the precision and the recall is mathematically expressed in Eq. (24).

$$F - measure = 2 \times \frac{Precision \times Recall}{Precision+Recall} \times 100 \qquad (24)$$

1.6 Performance analysis of object segmented image

Table 1 shows the average result of the objects segmented frame by KFCM-GWO-LS method. In this study, the different number of frames are validated by means of recall, specificity, precision, and F-measure by using KFCM-GWO-LS method and all these performance metrics are frequently utilized to evaluate object segmentation in videos. The overall accuracy of the proposed KFCM-GWO-

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Table 1. Average results of the object segmented frame by KFCM-GWO-LS method

Name of Video	Frame Number	Recall (%)	Specificity (%)	Precision (%)	F-measure (%)
Type1:Multipeople Video	Frame -30	99.25	99.72	96.14	97.62
	Frame -150	99.26	99.80	96.18	97.65
	Frame -280	99.27	99.82	96.25	97.61
Type2:Multipeople Video	Frame -58	99.28	99.78	96.29	97.63
	Frame -162	99.30	99.88	96.30	97.68
	Frame -270	99.31	99.85	96.31	97.69

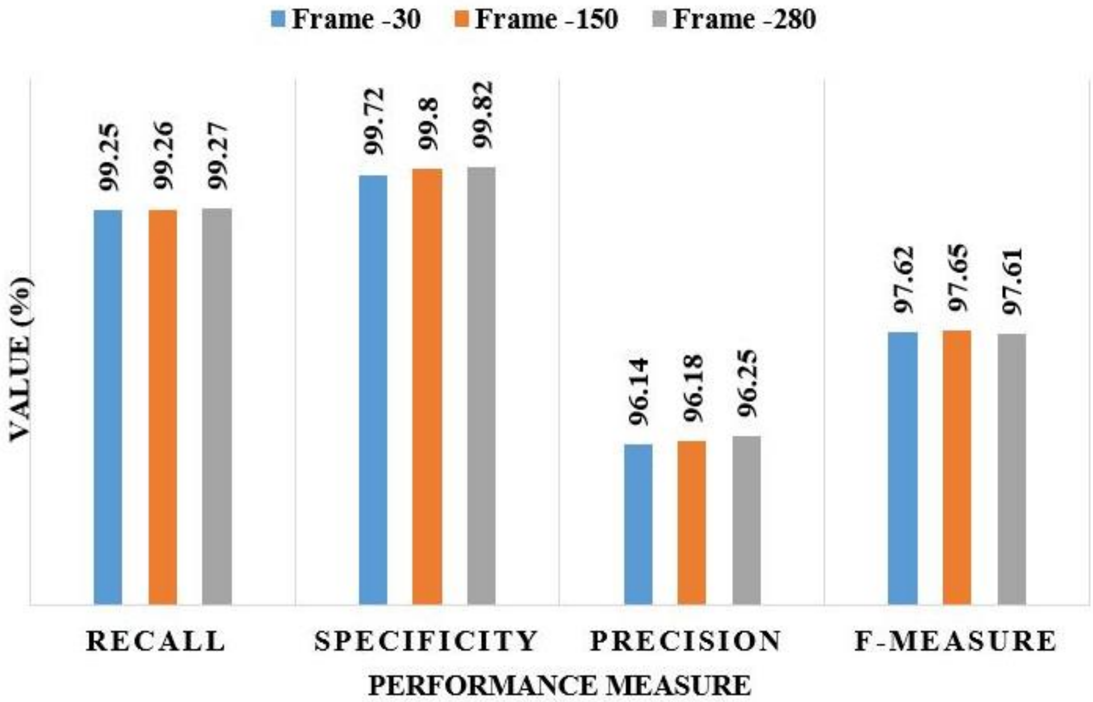


Figure. 2 Comparison graph of the object segmentation for Type1: Multi people Video

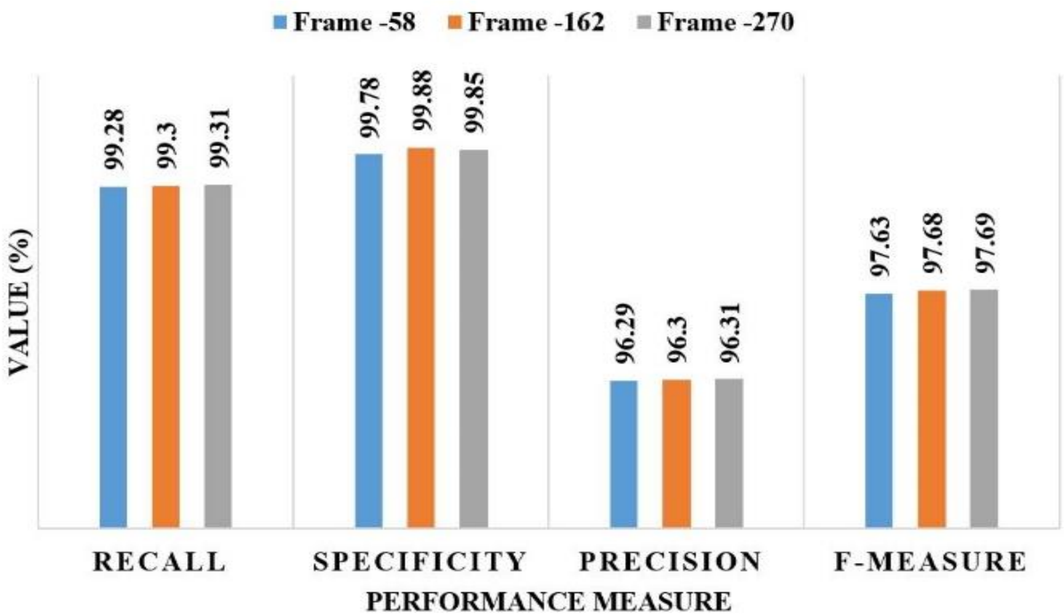


Figure. 3 Comparison graph of the object segmentation for Type 2: Multi people Video

LS method is compared to existing methods Multi-Sensor Scheduler Algorithm and Statistical Inference Theory model.

In Table 1, the KFCM-GWO-LS method is evaluated in light of recall, specificity precision, and f-measure. The average recall and specificity of the KFCM-GWO-LS method is 99.27% and 99.83% respectively. Similarly, the average precision and f-measure of the KFCM-GWO-LS method are 96.24% and 97.64% respectively. Table 1 shows that the proposed KFCM-GWO-LS method performs efficiently on SBM-RGBD dataset. Fig. 2 and 3 shows the graphical representation of the quantitative analysis of the KFCM-GWO-LS method using SBM-RGBD dataset.

In the Table 1, as the multi people videos are present, two or more than two people or objects are overlapping. It was difficult to separate multi people during segmentation process. This degradation in segmentation gave rise to lower values of precision.

The performance evaluation of KFCM-GWO-LS method is carried out by using SBM-RGBD dataset is presented in this section. The segmentation of moving objects in SBM-RGBD dataset is represented in the Table. 2.

1.7 Comparison analysis

The comparative analysis of proposed and existing works is detailed in Table 3. Table3 clearly shows the performance of object detection segmentation that is improved by KFCM-GWO-LS method compared to the existing methods.

In [14] foreground segmentation, background detection, target detection and monitoring the tracked tasks are performed. The developed multi-sensor scheduler Algorithm used SBM-RGBD

Table 2. Segmentation of moving objects by using KFCM-GWO-LS method

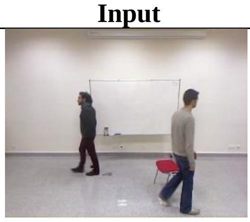
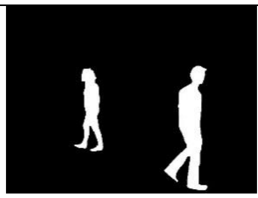
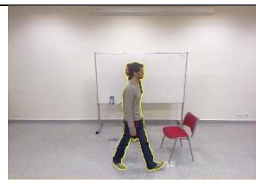
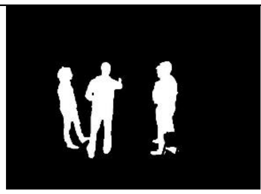
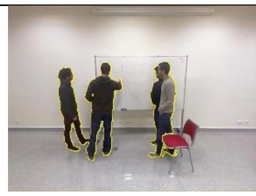
Frame	Input	Ground Truth	KFCM-GWO	Output of LS
Sample 1				
Sample 2				
Sample 3				
Sample 4				

Table 3. Comparison performance of object segmentation for existing and proposed KFCM-GWO-LS method

Method	Dataset	Recall (%)	Specificity (%)	Precision (%)	F-measure (%)
Multi-Sensor Scheduler Algorithm [14]	SBM-RGBD	90.79	99.71	95.36	93.02
Statistical Inference Theory model [15]	SBM-RGBD	85.87	-	68.42	74.18
KFCM-GWO-LS	SBM-RGBD	99.27	99.83	96.24	97.64

dataset for the experimentation that achieved Recall of 90.79 %, Specificity of 99.71%, Precision of 95.36%, F-measure of 93.02 %. In [15], the developed model identified objects with similar motions thereby characterized motion using a statistical inference theory to assess similarities. The developed Statistical Inference Theory model used SBM-RGBD dataset for the experimentation that achieved Recall of 85.87 %, Precision of 68.42 %, F-measure of 74.18%. The approach decreased the power consumption overall in the system and also reduced the computational overheads. The limitation of the existing method was that over segmentation problem that gave rise to system degradation. In the proposed KFCM-GWO-LS, the KFCM-GWO is used for selecting the best centroids. Based on the selected centroids object segmentation is performed by using LS algorithm. However during segmentation, the objects were overlapped in few instances that give rise to over segmentation problem. The over segmentation problem is overcome by using GWO algorithm. Thus, KFCM, GWO and LS algorithms are integrated in the proposed method, in where the results showed that the proposed method improved the system performance from 0.3 % to 14.35 % better. The proposed KFCM-GWO-LS method achieved considerable segmentation rate in all performance metrics namely Recall, specificity, Precision, and F-measure when compared to the all other existing methods Multi-Sensor Scheduler Algorithm and Statistical Inference Theory model.

2. Conclusion

In this study, a KFCM-GWO-LS method is implemented to segment object in the video for improving the object detection performance. The main aim of this research is to cluster the images without being affected by any noises using SBM-RGBD dataset. The blob detection process used to obtain a specific region of interest to perform the object segmentation after the frame isolation. Next to the blob detection, the objects were segmented using KFCM algorithm. The GWO algorithm was applied on the KFCM information to select and initialize the centroids of required clusters. At last, LS algorithm is used to extract the properly segmented regions. The KFCM is used for choosing centroids clusters and the Level set algorithm during segmentation degrades the edges that results with over segmentation problem. The over segmentation problem is overcome by using GWO algorithm. The proposed KFCM-GWO-LS experimental results showed that the proposed method improved the system performance from 0.1 % to 9.68 % better. The proposed KFCM-GWO-LS was compared to other existing methods CWisardH+ and MFCM in object detection and segmentation by means of recall, specificity, precision, and f-measure which shows average 0. 1-9.68 % of the improvement in the object and segmentation processes. In the future, the proposed work can be extended for various approaches to improve the tracking performance of objects present in videos.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, have been done by 1st author. The supervision and project administration, have been done by 2nd author.

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