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A Comparative Study of Hybrid Video Segmentation Techniques using Fuzzy Clustering Algorithms

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Abstract

Video segmentation is an important process in digital media. Here the video is segmented into foreground and background in spatio-temporal environment. In this paper author compared three hybrid video segmentation techniques using fuzzy clustering techniques namely FKM, FCM and Anisotropic Diffusion. Initially the author developed frame intersection method (FIM) which is compared with the existing frame difference method (FDM) that gives better results than frame difference method. In the first phase of the research work, author developed hybrid video segmentation technique using FKM technique. Then author used FCM technique for hybrid video segmentation which gives better results than the earlier hybrid technique using FKM. Even though hybrid video segmentation using FCM produces better results, the segmentation still contains noise disturbances. Hence author finally proposed hybrid video segmentation technique using anisotropic diffusion, which greatly reduces noise and produces accurate and better results than the earlier hybrid video segmentation methods using FKM, FCM.

The average accuracy of AD based hybrid segmentation process is 96%, whereas the average accuracy of hybrid segmentation using FKM and FCM are 86% and 94% respectively. The performance of hybrid segmentation algorithm is also measured using MCC and the result shows increased performance than the FKM and FCM based methods. The KC measure also shows increased performance than FKM and FCM based hybrid segmentation methods.

Index Terms— Anisotrophic Diffusion (AD), Background Subtraction, Frame Difference Method (FDM), Frame Intersection Method (FIM), Fuzzy K-Means (FKM), Fuzzy C-Means (FCM), Spatio-Temporal Video Segmentation.

I. INTRODUCTION

Video segmentation is an attractive and important research topic in computer vision applications. The extraction of objects from video is termed as video segmentation. Image segmentation is the prior process to video segmentation in digital video technology. Video segmentation requires location of moving objects in video sequence. The usage of fixed camera in video segmentation needed the background subtraction. The quantitative analysis of background subtraction algorithms showed the performance in real, synthetic and semi-synthetic video sequence challenges. The segmentation results are improved by combining the preprocessing technique with background subtraction. The extraction of foreground image from the background is performed by using graph-cut based framework. Then, video frames are smoothened by using anisotropic diffusion[3]. The diffusion process is based on the various parameters such as conductance function, gradient threshold and stopping time. Hence, the analysis option considers each parameter. The blurring between the edges of image is removed by using anisotropic diffusion.

The extraction of low level visual and audio visual features in video segmentation is performed by using the scene transition graph. Foveation points represent the integration of information on subsequent fixations in view process of the scene in the real world. Based on the foveated representation of video, the shots are obtained. The motion vectors from shot representation are linked with the segments by using the video retrieval database. The video retrieval analysis requires the determination of the motion features of scene objects and storage requirements. The local key point feature detects the abrupt and gradual transitions between the shots. The detection of moving human object in video and associated key segments are used to construct better video access monitoring systems.

The segmentation process is classified into three types. They are spatial, temporal and spatio-temporal. The video is breaked into arbitrarily shaped regions in spatial domain. Then the regions are breaked into screens or shots in temporal domain. In spatio-temporal mode, video segmentation generates the temporal sequences for arbitrarily shaped region. Many applications are based on the key point in spatio-temporal model. The spatio-temporal algorithms, wavelet based indexing, video retrieval engine and spatio temporal tubes are used for extraction of visual bags. The noise present in the spatio-temporal video segmentation are removed by using self organizing approach and novel video segmentation approaches. The main objectives of spatio-temporal video segmentation are extraction foreground objects[4]and maximization of accuracy. The comparative study of hybrid video segmentation using fuzzy based clustering algorithms FKM, FCM and anisotropic diffusion for maximum accuracy is carried out in this paper.

The paper is organized as follows. Section II describes the related works carried out in spatio-temporal video segmentation. Section III presents the proposed work Section IV presents the segmentation of foreground objects using Fuzzy K Means (FKM) algorithm. Section V describes the extraction of objects in spatio-temporal video using the Fuzzy C-Means (FCM) algorithm. Section VI presents the anisotropic diffusion technique to increase the efficiency of the hybrid video segmentation process. The performance analysis of FKM, FCM and anisotropic diffusion process on the performance parameters of sensitivity and specificity are given in section VII and the paper concludes in section VIII.

II. RELATED WORK

This section deals with the work related to video segmentation techniques based on clustering methods and the associated sub modules i. e. the background subtraction, audio-visual feature extraction and noise removal techniques. The traditional approaches were used to solve the problems related to change detection and localization of moving object. The important task in the image sequence analysis is video segmentation. The results of segmentation described the motion features and also used to minimize the storage requirements[5]. Various algorithms had its own features and applications [6]. The video segmentation is carried out using three approaches namely edge information, clustering and change detection [7]. The research proposed in this paper is based on clustering based approach. A process, which classifies objects or patterns on similar samples to one another is termed as clustering. Hard clustering and fuzzy clustering are used and they had own characteristics for implementation [8]. The segmentation results from the hard clustering was that pixel of image belongs to one class. Hence, the fuzzy based approach was used to improve the quality of segmentation results. *Ali et al.,* applied the Fuzzy-C Means (FCM) algorithms to the image segmentation. A new frame work based on FCM was carried out to incorporate the specific information of object such as pixel location, intensity and shape. The image segmentation extended to medical applications for time utilization [9]. *Oke. et. al.* utilized the Fuzzy K-C-Means algorithm for Magnetic Resonance Image (MRI) in medical image segmentation. They focused the time, accuracy and iterations involved in medical image segmentation. The extraction of object from background and preservation of edges required to improve the quality of image[10]. The threshold technique [11] improved the video segmentation with change detection, background registration. Five phases were used in baseline mode of threshold techniques such as frame difference, Background registration, background difference, object detection and post processing. Initially, the frame difference between current and previous frames is estimated then, the information about background was extracted. The change detection mask was generated by using the background difference mask (BDM). Both FDM and BDM were input to object detection to produce the Initial Object Mask (IOM). The noise in the IOM was removed in the pre-processing stage.

Prediction of motion vector from input video sequence is an attractive research in spatial video segmentation. *Chung et al* developed a predictive watershed-based video segmentation algorithm which, used motion vector information about the input video sequence [12]. The algorithm incorporated Sum of Absolute Difference (SAD) criterion to create new frames from the motion vectors. Hence, the segmentation results were improved. The availability of digital video data made the indexing, annotating and the retrieval process were crucial. *Mendi et. al.* developed the automated system for medical video segmentation and retrieval [13]. They provided online tool for indexing, browsing and retrieving the neurosurgical video tapes, which allowed the people to retrieve the specific information. Content based copy applications required an algorithm for detection of cuts and gradual transitions. *Kucuktunc et. al.* presented a color histogram based shot-boundary detection algorithm. They detected shot boundaries and reduced false alarms compared to other boundary detection algorithm [14]. *Chasanis et al* obtained the semantic correlated units from movie segmentation [15]. They failed to detect the scenes of dynamic content since there is no information about the correlated units in low level features. The information in text processing preserved and smoothed histogram obtained by using Low bow framework. The image segmentation analysis required the spatial information. *Jaffar et al* improved the quality of video content by using Fuzzy C-Means (FCM) with spatial information [16]. The utilization of noise spatial information reduced the weighting of noisy cluster for noisy pixel. The misclassified pixels were corrected by FCM approach. *Ishikawa et al* utilized estimated background brightness to extract the object from scenes[17]. *Moscheni et. al* defined the spatial information as a brightness information and temporal information as a motion information [18]. The spatio-temporal similarity between the regions measured and they represented as s graph. The clusters of similar regions also detected by using the graph based hierarchical clustering algorithm. The traditional methods were carried out without consideration of spatial information sensitive to noise. *Su et al* embedded the motion vectors into the MPEG bit streams to generate the motion flows. The video retrieval process is enhanced by linking local motion vectors on consecutive video frames. The objective function includes the spatial homogeneity to validate the effectiveness of method [19]. The extraction of low and high level features required in temporal video segmentation approaches. *Sidiropoulos. et. al* utilized Scene Transition Graph (STG) to jointly exploit the low and high level features to increase the computational efficiency and efficient extraction of visual model vectors from the HSV model[20, 21]. The detection of abrupt and gradual transition between shots was an important task in HSV model. *Huang et al* proposed local key point matching of video frames to detect the abrupt and gradual transitions between shots [22]. The authors presented three modes to implement algorithm. They were baseline mode, shadow cancellation mode and adaptive threshold mode. The implementation of algorithm is performed with change detection, background registration and real time adaptive threshold techniques. The traditional methods were carried out without consideration of spatial information sensitive to noise. *Despotovic et. al* presented the extension of FCM to overcome the problem of noise by incorporating the spatial information. The performance of the system was validated on synthetic and real images. The capture of long range temporal interactions was required to construct the new clustering cost function in the video segmentation [23]. *Lezama et. al* incorporated the long range motion cues from the past and future frames and developed the clustering cost function to capture the long range temporal interactions. The design of video database requires compressed visual information [24]. *Murumu et. al* presented the Wavelet transform for efficient compression of visual content. The transition detecting metrics was implemented by using shot transition detection algorithm[25]. *Maddalena et. al* proposed an approach which handles the scenes containing moving backgrounds and gradual illumination variation in the image. The detection accuracy in terms of processing speed measured and compared with traditional techniques. The critical issue in preservation of edge is noise in frames [26]. *Padmakala et. al* presented the novel video segmentation approach for noisy color video sequences to construct the effective video retrieval. The background also estimated by using the expectation maximization algorithm for segmentation of video objects [27]. *Parks et. al.* explained the way of post processing that affects the performance of the system. The foreground segmentation mask process was improved by enhanced background subtraction method. The development of multimedia data types and the bandwidth evolved the text based retrieval system to the Content Based Video Retrieval (CBVR) [28]. *Patel et al* reviewed the selected features and selected the good features among them. The good feature selection is achieved using the reduction of time and space cost of retrieval process. The effective storage and fat retrieval in video segmentation module needed to reduce the time [29]. *Islam et. al* used three types of clustering such as k-Means clustering, K-medoids clustering and hierarchical clustering to enhance the storage and retrieval process in the video segmentation. The performance comparison of three algorithms also carried out and proved the hierarchical clustering yielded the better result than the other [30]. *Trichet et. al* proposed the temporal video segmentation based on the effective dense trajectory clustering in the articulation of objects. The hierarchical fusion algorithm also used to provide available segmentation information in multiple linked scales. The valuable contextual information in the video was preserved by the creation of histogram of visual words [31]. *Kim et. al* proposed the simple moving human object detection method for video surveillance and access monitoring system. The detection of moving human object carried out by frame difference and threshold method and human object segmentation performed by using the labeling method. The reconstruction of objective function contains the neighborhood information was required to create the cluster center [32]. *Lee et. al* identified the object liked regions by using the fuzzy algorithms. The binary partition for segments was created to discover the hypothesis groups with persistent appearance and motion. Initial number of clusters and initial center were obtained using the fuzzy algorithms [33]. *Ding et. al* proposed the FCM algorithms for creation of clusters and the cluster center. They used spatial information to reconstruct the objective function that contains neighborhood information [34]. Smoothing of preserved edge is required to describe the level of noise removal. *Tsiotsios et. al* presented the automatic stopping criterion of anisotropic diffusion method to achieve smoothing [35]. The difficulties faced by the traditional algorithms were extraction of foreground object and accuracy. Hence, anisotropic diffusion proposed with the FCM and FKM to provide the maximum accuracy.

III. HVS TECHNIQUES

Here the Hybrid Video Segmentation (HVS) use fuzzy based clustering algorithms to extract the object. Then background subtraction method alongwith frame difference method is used to segment the static and dynamic objects. The track frames are collected in every frame by using anisotropic diffusion method to characterize the object boundaries by removing noises. The Fuzzy K-Means (FKM) segments foreground objects without considering the global constraints. The objects are identified by FKM clustering process. The object extraction is performed by using Fuzzy C-Means (FCM) algorithm and concentrates on more objects by combination of FCM with the background subtraction method. Finally, the efficiency of video segmentation process is increased by anisotropic diffusion. Initially, the objects in every frame are identified for segmentation. The objects in the frames are identified by using the fuzzy k-means clustering process. The 3 D color histogram is calculated for every frame to find the number of objects in a frame which is given as the value of K. The frames which are in RGB format is converted into LAB color space format. The LAB format represents the lightness of the color (L), color balance between the Green and Magenta (A) and color balance between Blue and Yellow (B). The 3 D histogram is constructed by splitting the range of data into equal sized bins termed as classes. Then, for each bin, the number of points from the data set is counted.

The FKM receives the inputs of gray scale converted frames of the shot and produces the clusters as output. Initially, checks whether the gray scale frame is equal to shot value are not. The guesses for individual mean are initialized. The mean value is updated from i=1 to K values and stored it in the clusters until there is no changes in the mean. The accuracy of the segmented objects is less in FKM algorithm. Hence, Fuzzy C-Means algorithm is used to improve the accuracy of segmented objects. In Fuzzy C-Means (FCM) clustering, the assigning of pixels to the fuzzy clusters are carried out without using the labels. The piece of data belongs to two or more clusters is allowed in FCM. Thus, the points in the center of cluster is more degree than the points on the edge of a cluster. The FCM approach segments both the dynamic and static foreground objects without considering the global motion constraints. The partitioning of video sequence by detecting the scene changes is essential for characterization and categorization of video. The segmentation of static and dynamic objects in an environment of abrupt and gradual scene changes, the object detection and extraction is a crucial process. The elimination of hue and saturation information is performed and the frames in RGB format is converted to grey scale format to retain the luminance. Hence, the points in the center of cluster is more degree than the points on the edge of a cluster leads to better accuracy than the FKM.

IV. HYBRIDIZATION ALGORITHM

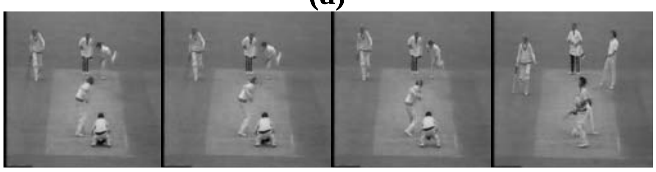
The hybrid video segmentation fuzzy proposed to improve the accuracy and Kappa's coefficient by hybridization algorithm as follows:

Hybridization Algorithm

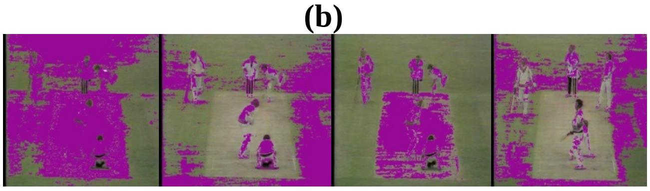
Input: Frames in each shot
Output: Dynamic Foreground and Static foreground objects in a frame
Procedure:
Select the frames A &B and convert it into binary forms
Let frame C = converted frame B & frame D = converted frame B
For j=3 to N
Convert j^{th} frame to binary form.
Perform the OR operation on frame C and binarized j^{th} frame
Store the result in frame C
Perform the AND operation on frame D and converted j^{th} frame
Store the result in frame D
Perform frame difference procedure with 1^{st} frame and j^{th} frame
Result = foreground
Perform the AND operation on foreground and frame C
G = result frame
Remove uneven background using disk filter
Pixel values of G = 1 represents non-moving objects
Pixel values of frame D=1 represents moving objects
Resultant frame = moving objects + non-moving objects
End

The overall resultant frame is obtained from representation of moving and non-moving objects.

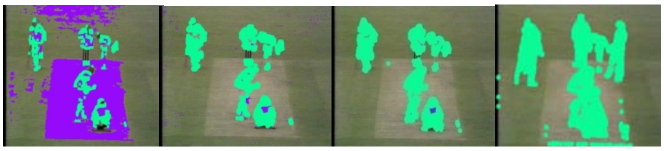
(a)



(b)



(c)



(d)

Fig. 1 (a) Sample frames, (b) Grey Scale Images, (c) Extracted Objects, (d) Segmented Objects

Fig. 1 (a), (b), (c), (d) represents the sample frame-3, grey scale images and the extracted objects and segmented objects from the frames respectively by using the FCM algorithm. The addition of anisotropic diffusion method for extraction of objects in the video shots proves the effective segmentation process. The accuracy of the method is more than the traditional FKM and FCM clustering algorithm.

V. COMPARATIVE ANALYSIS

The performance of the clustering algorithms and the noise removal techniques analyzed by the statistical measures of sensitivity and specificity. The statistical measures are based upon the setting parameters as follows:

- True Positive (TP): Valid objects are correctly segmented
- False Positive (FP): Invalid objects are incorrectly segmented
- True Negative (TN): Invalid objects are correctly non-segmented
- False Negative (FN): Valid objects are incorrectly non-segmented.

The inter-rate agreement for qualitative items provides more robust measure than the simple percentage calculation is termed as Kappa's Coefficient (KC). The Kappa's coefficient is defined by,

$$Kappa = \frac{Observed\ Agreement - Expected\ Agreement}{1 - Expected\ Agreement}$$

The statistical measures of comparison of frame difference, frame intersection and FKM approach frames 3, 4, 5, 44 are listed in table-I and for frames 330, 331, 332 and 333 listed in table II. The table-III and table IV shows the comparison between the fuzzy based clustering methods with the proposed AD method. From the tables I and II, it is observed that the accuracy of FKM based method is 94 %, whereas the average accuracy of FDM and FIM are 92. 5 and 89 % respectively. The result shows that the performance of FDM and FIM enhanced by using proposed hybrid segmentation algorithm. The measure of KC provided the maximum performance compared to FDM and FIM.

From the tables III and IV, it is observed that the accuracy of proposed AD based method is 98. 97 %, whereas the average accuracy of FKM and FCM are 95. 25 and 97. 77 % respectively. The result shows that the performance of FKM and FCM enhanced by using proposed hybrid segmentation algorithm. The measure of KC provided the maximum performance compared to FKM and FCM.

TABLE I STATISTICAL MEASURES

Measures	Frame 3			Frame 4			Frame 5			Frame 44		
	FDM	FIM	FKM	FDM	FIM	FKM	FDM	FIM	FKM	FDM	FIM	FKM
TP	4446	3986	5270	4136	3687	5814	4180	3701	8914	4563	3986	6731
TN	92966	42876	92966	93355	91022	93355	90323	40012	90323	93650	91210	93650
FP	3964	3574	3140	3885	3245	2207	6873	4145	2139	3163	3754	995
FN	4360	3956	1756	3437	3137	2841	3023	3037	8285	3729	3256	5219
Accuracy	92. 13	86. 15	95. 25	93. 01	93. 68	95. 16	90. 52	85. 88	90. 49	93. 44	93. 13	94. 17
KC	0. 94652	0. 91343	0. 94149	0. 94654	0. 94748	0. 95751	0. 92352	0. 89284	0. 96362	0. 95369	0. 96121	0. 98070

TABLE II STATISTICAL MEASURES

Measures	Frame 330			Frame 331			Frame 332			Frame 365		
	FDM	FIM	FKM	FDM	FIM	FKM	FDM	FIM	FKM	FDM	FIM	FKM
TP	5490	4520	6058	6390	5490	6185	6682	6490	6875	7460	6682	10331
TN	67021	63987	67021	67266	67021	67266	67015	66021	67015	66080	53015	66080
FP	4289	4023	3721	3144	4289	3349	3103	3089	2910	3260	3103	389
FN	8277	8934	3000	11087	8277	3688	14737	13277	4739	20724	17737	24455
Accuracy	85. 28	84. 09	87. 74	83. 81	85. 22	91. 26	80. 51	81. 58	90. 62	75. 41	74. 12	75. 46
KC	0. 92735	0. 90349	0. 93695	0. 94531	0. 92735	0. 95623	0. 94813	0. 94852	0. 94982	0. 95117	0. 94813	0. 99413

TABLE III STATISTICAL MEASURES

Measures	Frame 3			Frame 4			Frame 5			Frame 44		
	FKM	FCM	AD	FKM	FCM	AD	FKM	FCM	AD	FKM	FCM	AD
TP	5270	5307	6886	5814	7569	9478	8914	10854	13795	6731	7189	8731
TN	92966	94858	96772	93355	97385	98890	90323	91422	90874	93650	93650	9554
FP	3140	1125	1004	2207	1266	1124	2139	347	217	995	537	995
FN	1756	1158	1027	2841	1266	1109	8285	12660	10789	5219	6304	5219
Accuracy	95. 25	97. 77	98. 07	95. 16	97. 64	97. 98	90. 49	93. 86	94. 58	94. 17	93. 65	94. 37
KC	0. 94149	0. 94699	0. 96773	0. 95751	0. 97571	0. 98196	0. 96362	0. 99384	0. 99385	0. 98070	0. 98948	0. 9899

TABLE IV STATISTICAL MEASURES

Measures	Frame 330			Frame 331			Frame 332			Frame 365		
	FKM	FCM	AD	FKM	FCM	AD	FKM	FCM	AD	FKM	FCM	AD
TP	6058	8659	12672	6185	8524	11800	6875	9256	12875	10331	11275	14275
TN	67021	69485	85283	67266	68562	91261	67015	67015	92456	66080	75252	95252
FP	3721	1125	250	3349	1220	325	2910	1158	290	389	56	31
FN	3000	5625	4822	3688	2305	3900	4739	5891	6900	24455	3569	2369
Accuracy	87. 74	92. 05	95. 07	91. 26	95. 63	96. 06	90. 62	91. 54	93. 61	75. 46	95. 98	97. 85
KC	0. 9170	0. 9617	0. 9813	0. 9262	0. 9648	0. 9734	0. 9348	0. 9725	0. 9826	0. 9942	0. 9992	0. 9998

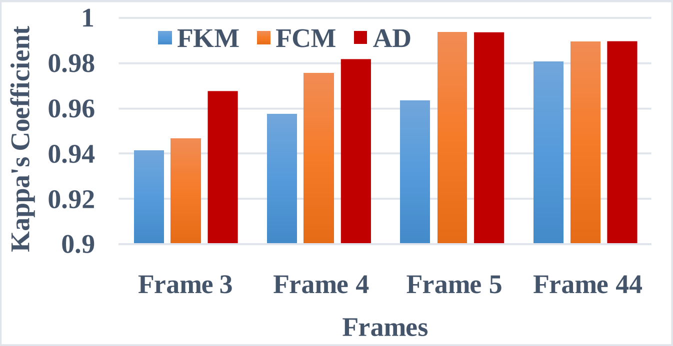


Fig. 4 Frames vs. Kappa's coefficient

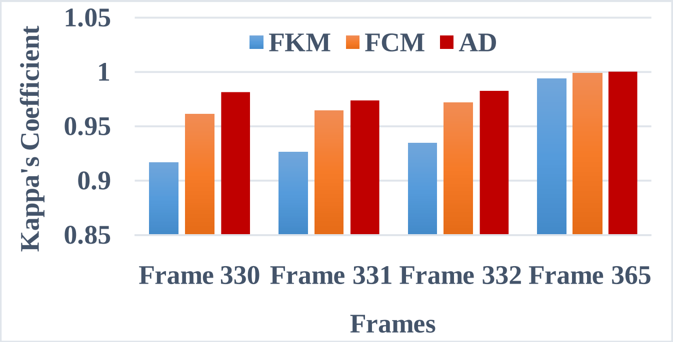


Fig. 5 Frames vs. Kappa's coefficient

Fig. 4 and Fig. 5 depicts the comparison between the number of frames and Kappa's coefficient for FKM, FCM and AD. The proposed AD approach provides better Kappa's coefficient compared to the traditional FKM and FCM methods confirms for effective segmentation.

The degree of closeness of measurement values to the actual value is termed as accuracy. The accuracy of proposed segmentation and FKM and FCM are measured and plotted for different frames shown in fig. 6 and fig. 7.

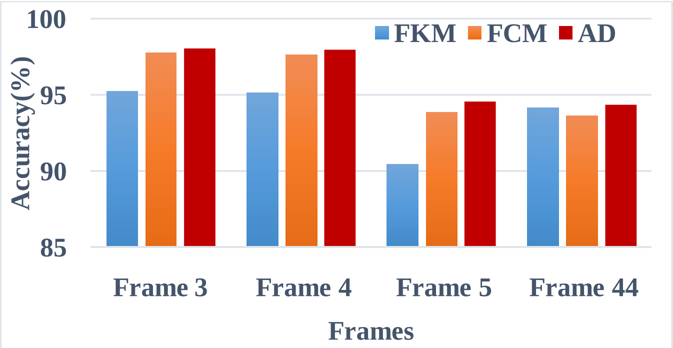


Fig. 6 Frames vs. Accuracy

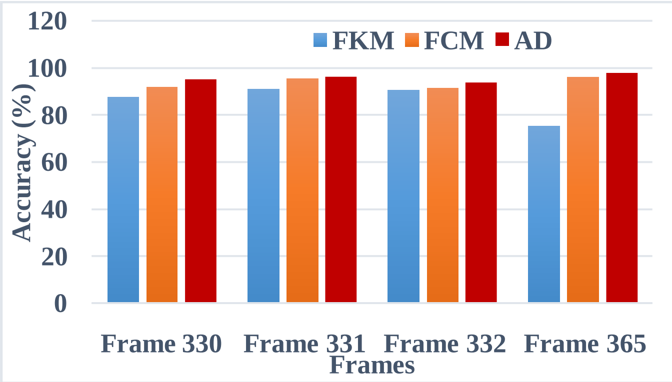


Fig. 7 Frames vs. Accuracy

Fig. 6 and Fig. 7depicts the comparison between the number of frames and accuracy using proposed AD method, FKM and FCM. The proposed AD method provides more accuracy than the traditional FKM and FCM.

VI. CONCLUSION

In this paper, an overview of various clustering based segmentation techniques are presented. The survey shows the comparative analysis of FKM, FCM and anisotrophic Diffusion (AD). FKM and FCM are the very powerful clustering techniques to cluster and extract the objects in the region. The statistical measures of TP, TN, FP and FN are calculated for FKM, FCM and AD. The comparison shows that the proposed AD provided the better statistical measures than the FKM and FCM approaches. The Kappa's Coefficient (KC) computed and compared with the clustering algorithms. The measurement of KClies between 0. 8 and 1. 0 concludes that the segmented objects are perfect compared to the traditional algorithms. The measurement of accuracy for proposed hybrid video segmentation based on fuzzy clustering approaches confirms the effectiveness compared to conventional segmentation algorithms. The performance of clustering is increased by combining with the anisotropic diffusion techniques. The efficient clustering based image segmentation approach can be formulated based on the FKM, FCM and anisotropic diffusion algorithms to attain the best quality in hybrid segmentation.

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