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SEGMENTATION OF MOVING OBJECTS BASED ON MINKOWSKI DISTANCE USING K-MEANS CLUSTERING

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Abstract

Segmentation of moving objects is one of the challenging research areas for video surveillance application. The success of object changing position for segmentation is when the moving object completely separate the foreground from its background of frame. It depends on many factors, including the use of suitable clustering method to differentiate the pixels of the foreground and background. This paper propose to use k-means as clustering method for moving object segmentation. The method is evaluated on several distance measures. Several steps are performed to conduct the moving object segmentation, such as frame subtraction, median filtering, and noise removal. These steps are proposed to improve the achievement of moving object segmentation. The performance are evaluated by using Mean of Square Error and Peak Signal to Noise Error. The value of both measurement are 135.02 and 25.52. The experimental result shows that the moving object segmentation performs the best result on Minkowski distance.

Keywords: *K-Means, distance measure, moving object segmentation*

INTRODUCTION

The development of digital technology and the availability of the video-capture-based devices such as digital cameras, mobile phones with camera, lead to rapid increase in storage devices, network and compression techniques in large scale. In video data content with search-based, it is increasing significantly in the study of video data processing in large-scale, particularly in semantic concept fields. Thus, it needs media as facility in browsing and searching the required data for the user. In recent year research in moving object extraction is challenging problem and important to solving for video system as well as semantic of video surveillance, video object annotation, video application based on content retrieval. It is important to have a process of extraction in video having moving objects for advance investigation such as extraction, identification, and categorization of feature.

Image segmentation especially for moving object refers to a procedure of dividing the input in image frame into several regions according to the visual characteristics shared by the pixels. In the past several periods, a lot of segmentation technique have been proposed by many researchers. And these segmentation methods could be divided roughly into the following categories: contour detection or edge [1], thresholding [2] [3], clustering [4] [5] and region extraction [6]. Clustering method is a part of the most popular algorithm in the I mage of sequence segmentation domain. It is an approach of classifying patterns or data into categories, which is on the basis of the samples in the same group have the higher similarity than the ones in different groups. These methods project the input image into their features spaces

The k-means is a clustering algorithm which an iterative technique used to categorize the series of observations points into *K* groups in proportion to the likeness in the middle of them. K-means clustering algorithm was developed by J. Macqueen [7] an unsupervised acquirements algorithms to find the explanation the most simple and widely known grouping. After then, many researchers in the image processing domain applied it on image segmentation to improve the performances.

Based on many of the literature that discusses some of the major problems, especially in the approach to the motion segmentation of moving objects, categorized into four approaches. The main existing approaches including image differencing [8], temporal analysis [9], motion analysis [10] and normal flow [11].

K-means clustering as a computational procedure in [12] is widely accustomed in the utilization of practical applications, the ability to perform k-means clustering is very capable of producing a result. But in the application of k-means clustering has high computational complexity, especially on large datasets. The success of k-means algorithm also determined the preference of primary cluster the midpoints of any data.

Wei Chen et.al in [13] proposed method for new quantization technique in HSV color image segmentation using K-means. The authors proposed a method that aims to produce a color that represent the frequency of value and a histogram of the image that has dimensions of gray to K-Means clustering, which operate differently in color area especially the HSV color, impact through the approach can determine for estimated of midpoint and the numeral of group automatically.

Nasser et.al in [14] proposed an approach for K-means clustering more efficacious and proficient in order the resulting in lower complexity and better group. This method combines the technique of finding the center point of the early and efficient way to determine the measurements points in the group, without reducing the level of accuracy of the method of k-means clustering.

Madhukumar in [15] has made a comparison between the FCM and K-means to evaluate the ability to image segmentation of medical images. The outcome indicate that the method of k-means is able to bring forward more appropriate characterization process than the FCM method, k-means able to characterize 6 class and FCM only yielding 3 edema material characterization class.

In conducting an analysis of the video segmentation process, many researchers apply the methods of image difference [16]. This approach to reducing the current image to the previous image, where the process is beneficial to gain the foreground from the background to the moving object in the image sequence on video in real time.

In a clustering technique in addition to determine the midpoint of the group, one of the determinants of success to obtain optimal results is the selection of the most appropriate distance metric. In some existing metric Euclidean distance is a metric that is most widely used. The Euclidean distance metric widely used because of its simplicity, but noise cause a sensitivity upon [4] it and suboptimal in the exponential weighting function. Thus, we aim for having evaluation to Minkowski distance measures, and performance compare with another distance as Manhattan, Euclidean, Chebyshev, Bray Curtis, Canberra and Jensen Shannon

Amorim et.al in [17] has proposed weighting of K-means through- Minkowski distance to be a feature that determines the feature weight rescaling factor in the K-means criteria. Besides, the proposed method also for the K-means initialization of the anomalous cluster.

Liu et al. in [18] proposed Fuzzy c-means and using Mahalanobis distance for image extraction. Shao et al. [19] intended to have a technique for determine a limit of scale assessment in segmenting image sequence. The technique is well performed. Thus, it is good to have the method for determining a moving background circumstances, nevertheless it has no user interaction. Moreover, it performs well in preventing the possibility of error which may occurs in propagations basis on a assorted appliance of subtraction process of pixel environments.

Additionally, for a statistical graph corresponding with color close to diffusion distance, Shao in [19] intended also a method in the process. It is able to perform robust tracking for an object motion having no rigorously strict attribute, though it has a very low illumination changes. Moreover, it is the fittest method in the performance of parallel and hardware accomplishment.

The object segmentation improvement has main purpose which is processing segmented object, in order to have better clarity in viewing and assessing the visual information within. The information resulted from object extraction in the image becomes the major state for segmentation process of moving objects.

Advantages of subtraction on background in our previous work [20] bring this study into a conclusion for concerning the difference toward sequential frame in the process of segmenting for moving object.

K-means may be used often for segmenting the object, but the lower pixels intensity may be the problem K-means performance. In this study, the K-means performance needs the distance for differentiating foreground pixels to the background.

RELATED WORKS

Omnia et.al [21] proposed methods E-km based on grouping patterns for clustering moving objects, the proposed algorithm aims to address the weaknesses in the k-means that liable to the choice of inceptive midpoints group and the addiction to the number of group. The proposed approach can produce high accuracy, the accuracy of the results calculated using the coefficient approach silhouette.

In [22], algorithm for segmenting foreground, which was robust, have applied. This approach have applied morphological for refining color information. This method for categorized the foreground and background by applying a multiple threshold..

Into the bargain, the dependable prominence extraction technique had presented in [23]. The combination of investigation for temporal image frame and background of mold image was performed in order to solve the problem arises in scenes of outdoor daylight which triggering intensity transform to the mention image from background in segmentation of object motion.

Meier and Ngan in [24] intended to apply model, which was a binary image, performing segmentation and tracking that was automatic towards objects of moving. This approach applied the technique of detecting the edge from a frame on image so as would produce the binary pattern.

Basuki et al. in [25] proposed fuzzy c-means for improvement quality in moving objects extraction. The author have used DCT-2D approach for filtering the extracted object to smoothing the edge of the object that have any problem in quality.

Arch and Kaup in [26] intended to have an approach of statistic of method for segmenting object in the video frame. The technique was exhausted on consecutive video frames for gaining Gaussian dispersion of pixel distinguishing quality in video frame distinction of background. The outcome be visible denoted exchangeability to the threshold constructing the diversity detection termination. The outcome of segmented process be determined by quality of being intense of difference frames in the method intended miserable the segmentation outcome in deliberate or having a time-consuming.

METHODOLOGY

This section gave the details for the segmenting forward of movement the moving object by using unsupervised techniques. There were steps in segmenting of moving object in each frame. This section will explain in the succeeding subsections. Fig 1., shows the design of our proposed moving object segmentation.

Object Detection

Firstly, we had frame difference technique for detecting of moving objects by employing background subtraction. It was used over two succeeding frames of frame between

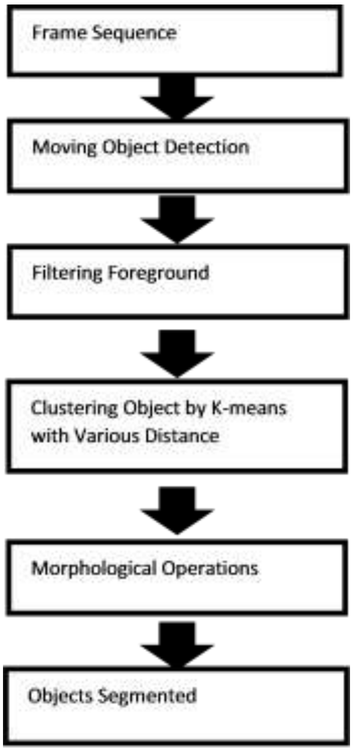
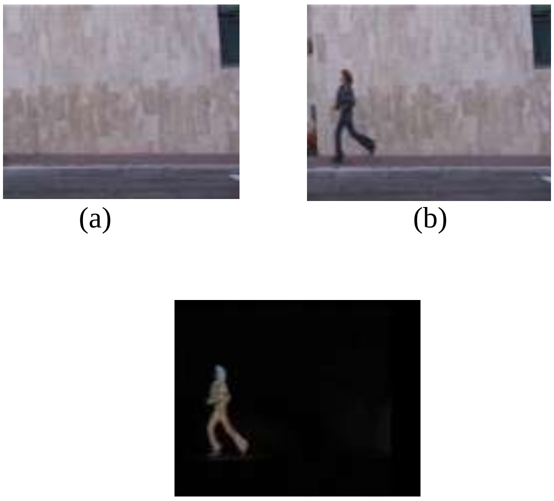


Figure 1. Proposed Method



(a) (b)

(c)

Figure 2. The outcome of background modeling : (a) Background model, (b) Frame original (c) Background subtraction model

$$D_f(a,b) = \left| f_c(a,b) - f_b(a,b) \right| \tag{1}$$

Where it was intended in detecting object that was moving and finding the different in current and background image [13].

$$fb_{i+1} = \left| fb_{i+1} - fb_i \right| \tag{2}$$

Filtering Foreground

In an image processing filtering is a technique used to modify or improve the quality of the image. As a non-linear filtering technique the median filter which serves to smooth and reduce clatter or interference in the image frame [27]. Median is a nonlinear filter because the way the filters are not included into the category of convolution operation. Nonlinear operations are calculated by sorting the group of pixel intensity values, and then replace the pixel values are processed with the specified value.

At a median filter filters that contain an odd number of pixels per point is shifted points over the entire image area. Values that are at the filters are sorted in ascending and then

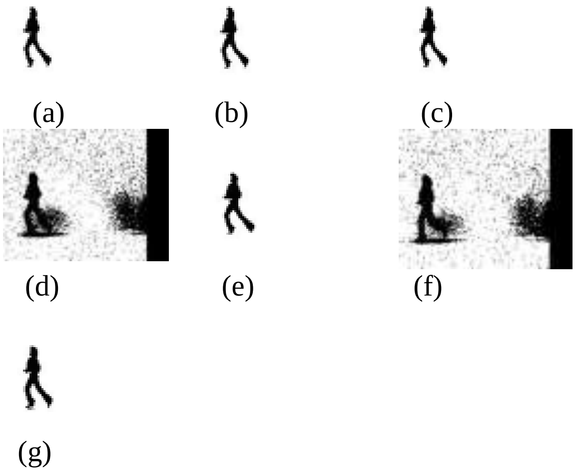


Figure 3. Proses Filtering : (a) SAD, (b) Euclidean, (c) Minkowski, (d) Canberra, (e) Chebyshev, (f) Jansen Shannon, (g) Bray Curtis

calculated the median value. The value will replace the values that are at the center of the field of windows. When a filter is placed on a plane image, the pixel values in the central areas of the window can be calculated by finding the median of a group of pixel intensity values that have been sequenced.

Clustering Moving Object using K-means with Various Distance

The k-means is a prevalent unsupervised hard clustering technique [21]. These is engaging in usual procedure, by reason of its straightforward and the most case good in accelerated. It segregation the operated on by any process dataset into k group. Each group is correspond to an adjusted diversify midpoint, come into existence by several an existing values as well-known seed-points.

The k-means calculates between input data points as the squared distances and midpoints, and nominate inputs to the located a short distance to centroid. The process towards come a cluster for N input an identifiable element in a data set $x_1, x_2, ..x_n$ inside k to elaborate a part of large group G_i wherein the value of $i = 1, 2..., k$ each have substance n_i an identifiable elements in data set, wherein $0 < n_i < N$, reduce to the smallest possible amount with the succeeding mean-square-error function:

$$SSE = \sum_{i=1}^{k} \sum_{x_t \in g_i} (x_t - g_i)^2 \tag{3}$$

Therefore X_t is a quantity having direction as well as magnitude equate with the t^{th} an identifiable element in a data set in the group G_i and, G_i is the center of mass of geometric object of uniform density G_i. Eventually, this technique purpose at reducing the goal function, in these circumstance a squared of error function, wherever $(x_t - g_i)^2$ is a selected distance mensuration among an identifiable element in a data set x_t and the group center g_i.

An input in identifiable element in a dataset using k-means algorithm assigns to x_t inside the i^{th} group in case the fact being a member of a group function $I(x_t, i)$ is 1

$$I(x\_t, i) = \begin{cases} 1 & if\ i = argmin(x_t - g_j)^2 \quad j = 1 \cdots k \\ 0 & otherwise \end{cases} \tag{4}$$

There are $g_1, g_2, \cdots, g_k$ are named group centers which are acquiring by the subsequent phases:

1. Select objects to be k initial centroid randomly
2. Calculate the distance of each centroid to the each object using distance or similarity metric; assign each object to the cluster with the located a short distance centroid point.
3. Compute the new centroid point.
4. Return to the step 2 if the current centroid are different to the previous.

Distance Analysis

Cluster analysis had basic idea that was amount of space between two point evaluation or affinity. Distance was the extension gauge between two objects point; the data dimension was the standard of measurement; the closeness was quantified by calculating the adjacency size in the qualitative appropriateness data.

The determination of similarity of two objects was performed by applying distance metrics [28]. The crucial role was in distance of clustering the data target. The distance between two data target $x_i$and x_j was denoted by $d(x_i, x_j)$. It was called metric distance when distance measured contained following properties:

Euclidean Distance

Euclidean distance was in detail exhausted in any discipline machine learning and computer vision field, which also in observe and direct the execution, and not done under supervision the acquisition of knowledge algorithm machine. It was roughly calculate the value by Eq. (5).

$$dist\left(x_i, z_j\right) = \sqrt{\sum_{k=1}^{d} \left| x_{i,k} - z_{j,k} \right|^2} \qquad (5)$$

City Block Distance

This distance was so well-known Manhattan distance. The robustness of outlier was within metric of city block distance. It was calculated by the sum of exact dissimilarity data object is surrounded by attribute of variable quantity from image frame and approximate judgement by Eq. (6).

$$dist\left(x_i, z_j\right) = \sum_{k=1}^{d} \left| x_{i,k} - z_{j,k} \right| \qquad (6)$$

Canberra Distance

Canberra distance function is used to find the distance of two objects with features of the first object and features of the second object and the number of features each object. The process is finding the difference of the first feature first object and a second object is then divided by the number of first features on the first and second object. And so do the sum with a second feature to all. This applied in distance numeral computation between a distinctive attribute vectors and query, it calculated roughly by Eq. (7).

$$dist\left(x_{i,}, z_j\right) = \sum_{k=1}^{n} \frac{|x_{ik} - z_{ik}|}{|x_{ik}| + |z_{ik}|} \qquad (7)$$

Chebyshev Distance

Chebyshev distance is a method that measures the distance primary on the absolute value of distinction the middle of the coordinates from a point pair. If there are 2 pieces of different vector values, then the distance measured by the infallible value of the distinction vector basis that should be the same amount of data automatically. The results obtained when the infallible value of the distinction in vector form with the highest value or maximum. The formula generally is as follows by Eq. (8).

$$dist\left(x_i, z_j\right) = \max_{i=1,2,..n} \left| x_{i,k} - z_{j,k} \right| \qquad (8)$$

Minkowski Distance

The comprehensive pattern of amount space between two objects was defined as:

$$dist\left(x_i, z_j\right) = \sqrt[p]{\sum_{k=1}^{d} \left| x_{i,k} - z_{j,k} \right|^p} \qquad (9)$$

In which p is a positive numeral, it offered other distance as a method of measuring for constructive equivalent of p, as a illustration of p =1 presented the Manhattan, and p = 2 for the Euclidean. As comparison the value of p = 3 as acquired metric distance to the Minkowski.

Bray Curtis Distance

The distance of Bray Curtis is a distance possess similarity into Manhattan distance. The formulation is assigned point out to Eq. (10).

$$dist\left(x_{i,}, z_j\right) = \frac{\sum_{i=1}^{n} |x_{ik} - z_{ik}|}{\sum_{i=1}^{n} (|x_{ik}| + |z_{ik}|)} \qquad (10)$$

Jensen Shanon Divergence

Jensen Shannon Divergence (JSD) is prevalent particular form of procedure to quantify the likeness among two possibility distributions. This distance measure is construct on Kullback–Leibler discrepancy. JSD is stipulated as

$$JSD(x,y) = \frac{1}{2}\left(\sum_{i}^{N} x_i ln x_i + \sum_{i}^{N} y_i ln y_i\right) - \frac{x_i + y_i}{2} ln\left(\frac{x_i + y_i}{2}\right) \quad (11)$$

Wherein x and y is the object of x and y.

Morphological Operation

As the time when operation of background subtraction was processed frame by frame of video frame, object in motion as foreground, were clearly undetectable out of the background frame. Morphology in the concept of the image, two model of basic condition of functioning are dilation and erosion was stated in [29]. In the process of morphological, it engaged in the part of a view that is nearest to the observer performance from clamorous.

In this section, a morphology process was engaged in order to the modification purpose for attribution in video frame grounded in the outside formation or presence feature. The opening point was for removing unwanted pixel. Thus, it could refine and simplify images by computing or trapping derived objects.

The opening process [30] was applied for the objects smoothing contour course. We denoted it with opening of operation of set *F* by structuring element of *G* as seen Equation (12).

$$F \circ G = (F \ominus G) \oplus F \quad (12)$$

The influence of opening operation was to eliminate slightly and remote objects from the inside of the image frame foreground and placed them on background of the image sequence. Along with the opening process of performing the foreground, a closing was hold to the morphological process of dilation followed by erosion of the equal structuring

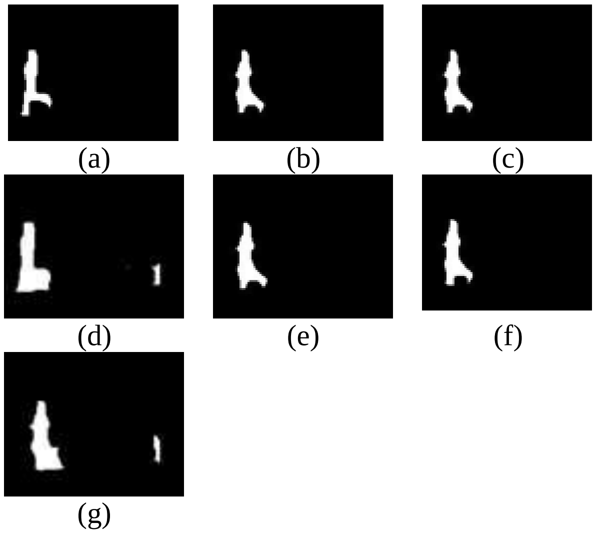


Figure 4. Morphology Operation Result **:** (a). SAD (b). Euclidean (c). Minkowski (d). Camberra (e). Chebychev (f). Jansen Shanon (g). Bray Curtis

element. We denoted the closing of set *F* by element composition *G*, as

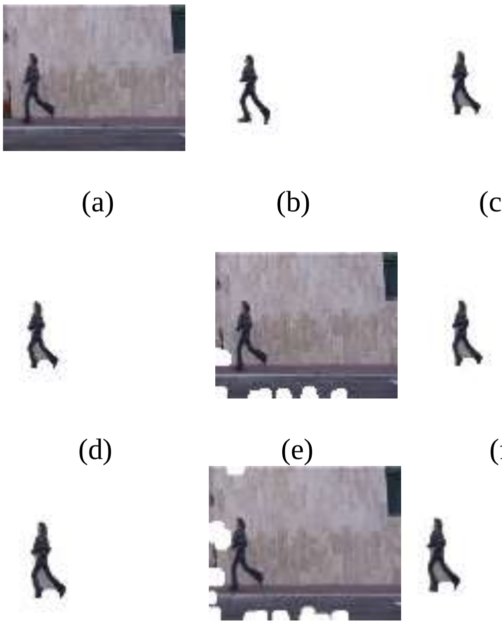
$$F \bullet G = (F \oplus G) \ominus F \quad (13)$$

At the same time part of object view that is nearest to the observer was successfully detected, it seemed that only view of objects foreground segmented was well connected, i.e. holes in object foreground. In order to solve the problem occurred, the morphology process of dilation and erosion was involved iteration, therefore that the foreground of the objects was totally segmented from image background.

This operation is phase-object points *F* worth one becomes part of the background which is worth 1 based on the value of *G*. Erosion is used to take into narrow the desired area with a certain pattern defined as seen Equation (14):

$$F \otimes G \quad (14)$$

Dilatation set *F* by *G* is denoted as in the Equation (15).
Wherein each point x in image *F* are translated or shifted and then combining all results.



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Figure 5. MO segmentation application on 43th frame by using K-MEANS and varied distance. (a) Genuine Frame (b) GT Frame (c) Euclidean (d) Manhattan (e) Canberra (f) Chebyshev (g) Minkowski (h) Bray Curtis (i) JSD

This operation is the jointing stage is worth 0 points become part of the object F is worth 1 basis on the value of G is used, stipulated as seen in Equation (15).

$$D(F,G) = F \oplus G \quad (15)$$

RESULT AND DISCUSSION

At this stage it will be discussed about the evaluation results of the experiments that have been done. Already mentioned, the results obtained from experiments evaluated by MSE and PSNR. In this experiment we employed a concatenation video frame of Weizmann dataset in [31] involve 50 frames of sequence with resolution (180x144) at 25 fps of constancy.

Through the experiment data with the dataset used to be obtained by the MSE and, PSNR of a moving object detection using frame difference. Furthermore, the same dataset K-means algorithm with calculation application distance variations that exist in the K-means proposed and applied in the process detection of moving objects with the same dataset. From the results of both experiments are compared to determine the presence and absence changes that occur.

In this study, the expected difference in frame the K-means algorithm proposed work well.We performed the evaluations by performing MSE in the method intended on the process of segmenting for clustering moving objects [32]. MSE was the average squared error among the original image frame with the image frame processing result which mathematically can be formulated as follows:

$$MSE\left(GT,FR\right) = \frac{1}{QY}\sum_{i=1}^{Q}\sum_{d=1}^{Y}\left[GT(i,d) - FR(i,d)\right] \quad (16)$$

Accordingly, the cultivated result the image frame of segmented moving object of image whish were less high MSE value is denoting preferable achievement of approach. In which case GT is the image frame for the ground truth, afterwards FR is the result segmented of image frame which measurement $Q \times Y$ and maximum amount viable pixel value of the image frame.

Peak Signal to Noise Ratio (PSNR) are employed to quantify the achievement in segmentation proposed of our moving object. The less high value of MSE become as more appropriate image frame segmentation. Alternatively, the supreme value of PSNR the preferable of image frame segmentation [4]. Both of MSE and PSNR could be evaluated by (16) and (17), in succession:

$$PSNR\left(GT,FR\right) = 10.\log_{10}\left(\frac{\max^2}{MSE\left(GT,FR\right)}\right) \quad (17)$$

Table 1. Table Performance (Iyova Dataset)

Distance	**Accuracy**	
	MSE	**PSNR**
1.SAD	135.67	25.50
2.Euclidean	135.62	25.51
3.Chebyshev	137.13	25.14
4.Minkowski	135.02	25.52
5.Canberra	10.251	8.50
6.Bray C	10.361	8.55
7. J.S.D	1.109	17.75

In our experimentation, we employed two variant image sequence to assesment our suggested for moving object of segmentation. At Fig 6., and Fig 7. reveal the MSE, and PSNR from k-means of Daria walk moving segmentation, respectively. Table 1. represents the perform of k-means in moving object segmentation from other dataset in various distance measures.

CONCLUSION

This paper proposes to use k-means as clustering technique on moving object segmentation. The model is evaluated on several distance measures. From the comparison of distance, Minkowski was confirmed to have the best segmentation result.

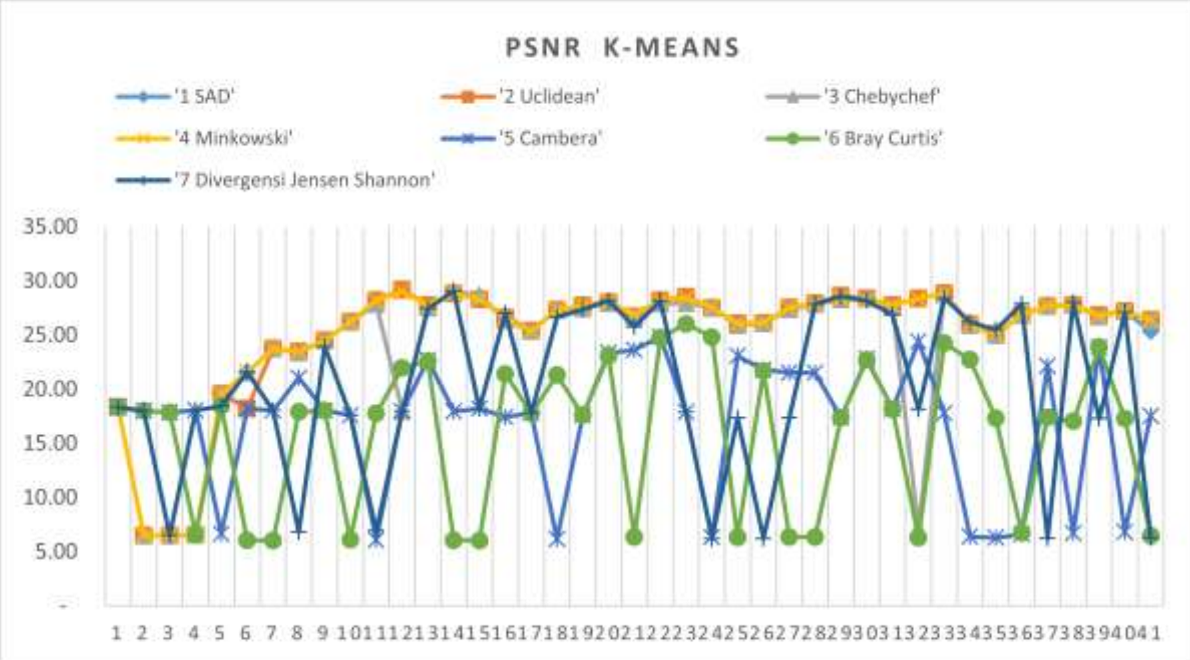


Figure 6. PSNR K-means Moving Object Segmentation

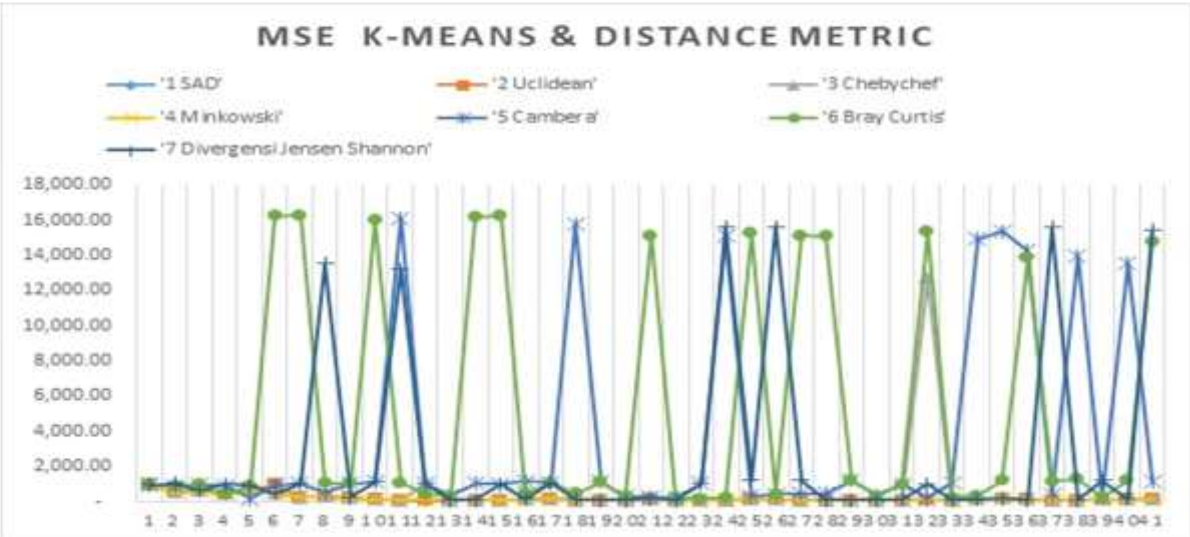


Figure 7. MSE K-Means Moving Object Segmentation

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