Image Segmentation and Image Matting for Foreground Extraction using Active Contour Based Method

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ABSTRACT:

Image segmentation plays essential role in society for identification of objects, persons, and so on. The representation of the image is changed by the image segmentation method. It can change the boundaries and edges easily. It is used in the crime scene analysis for the identification of crime. An efficient method for image segmentation is proposed in this study. Active contour image segmentation method is used for segmentation in this study. The results are used in the code book algorithm. Experimental results show the performance of proposed method.

Keywords: Image segmentation, active contour method, image matting, Gaussian filter

1. INTRODUCTION

A. IMAGE SEGMENTATION

The undertaking of picture division is the initial phase in numerous PC vision based strategies. Principle objective of picture division is to isolate a picture into parts that have a solid relationship with items or zones of this present reality contained in the Image. In picture handling valuable pixels in the picture are isolated from the rest. The aftereffect of picture division is an arrangement of fragments that all things considered cover the whole picture, or an arrangement of shapes separated from the picture.

Picture division could be utilized for question acknowledgment, impediment limit estimation, picture pressure, picture altering, and so on. Numerous division issues can be unraveled effectively utilizing lower-level handling as it were. Complex scene as face location is handled then participation with higher preparing levels which utilize particular learning of the issue space is vital. There are numerous issues that can happen amid picture division related with uncertainty of picture information (many-sided quality of articles, non-uniform shading and power, shadows, reflections).

Until as of late, consideration has been centered around division of dim level pictures since these have been the main sort of visual data that securing gadgets could take and PC assets to deal with. These days shading symbolism has certainly supplanted monochromatic data and calculation control is not any more a restriction in handling extensive volumes of information. This has been utilized as a part of late years for division of shading pictures which are obtained from the foundation of dim level scale division.

2. LITERATURE SURVEY

A. IMAGE SEGMENTATION

The reason for picture division is that items and the Background is isolated into non-covering sets.

In Histogram based Thresholding system, division handle depends on the dim level histogram of the picture. All things considered, the point is to locate a basic esteem or edge. Through this limit, connected to the entire picture, pixels whose dark levels surpass this basic esteem are alloted to one set and the rest to the next. For an all around characterized picture, its histogram has a profound valley between two pinnacles. Around these pinnacles, the protest and foundation dark levels are concentrated.

Along these lines, to portion the picture utilizing some histogram Thresholding strategy, the ideal limit esteem must be situated in the valley locale. By and large, all histogram thresholding strategies work exceptionally well when the picture dark level histogram is bimodal or about bimodal. Then again, a lot of pictures are typically not well characterized prompting a multimodal histogram where, in these cases, the normal histogram thresholding strategies perform ineffectively or even flop as in [1-5].

Zhu et al., [6] proposed a most extreme entropy hypothesis for taking in probabilistic surface models from an arrangement of observational conveyance of channel reactions.

Gimel'farb utilized the distinction co-event insights to show surface [8] and later, Xiuwen Liu et al., [7] proposed a nearby otherworldly histogram, characterized as the negligible disseminations of include insights for surface grouping. In pixel-based plans, for example, standard Markov irregular fields, consider picture division as a naming issue at the pixel level though the district based plans utilize dynamic forms as deformable models as in [9, 10, 11, 12].

We additionally utilize two methods; the first is watershed strategy with new combining strategies in light of mean force an incentive to fragment the picture locales and to distinguish their limits. The second is edge quality procedure to get exact edge maps of our pictures without utilizing watershed technique. In [13-16] versatile bunching calculation and K-implies grouping calculation are summing up to incorporate spatial requirements and to represent nearby power varieties in the picture.

Chart based picture division procedures by and large speak to the issue regarding a diagram G containing V hubs and E vertices in [17, 18], where every hub V relates to a pixel in the picture and the edges in E interface certain sets of neighboring pixels. A weight is related with each edge in view of some property of the pixels that it associates, for example, their picture forces. Contingent upon the technique, there could possibly be an edge associating each combine of vertices. The work of Zahn [18] presents a division strategy in light of the Minimum Spanning Tree (MST) of the diagram.

The greatest preferred standpoint of the diagram cut calculation is that it tends to division in a worldwide streamlining system and ensures an all inclusive ideal answer for wide class of vitality capacities [19]. Another preferred standpoint is that both the local and the limit properties can be utilized. Furthermore, the UI is straightforward and advantageous - the client denotes some question and foundation "seeds". The seeds can be approximately situated inside the protest and foundation locales, which are simpler contrasted with setting seeds precisely on the limit, as in livewire [20].

Shading picture division utilizing bunching calculations is finished by mapping of a pixel into a point in a n-dimensional element space, characterized by the vector of its component esteems. The issue is then lessened to parceling the component space into discrete bunches [21], which is a general example acknowledgment issue. Delicate figuring contrasts from traditional hard registering in that, not at all like the later, it is tolerant of imprecision, vulnerability, incomplete truth, and estimation.

B. IMAGE MATTING

Image matting alludes to the issue of doling out to every pixel in a picture, a probabilistic measure of whether it has a place with a coveted question or not. This issue finds various applications in picture altering, where the client is intrigued just in the pixels relating to a specific question, as opposed to in the entire picture. In such cases, one lean towards relegating delicate esteems to the pixels instead of a hard order. This is on account of there can be questionable zones where one can't clarify cut choices about the pixels' participation.

Tangling and compositing were initially created for film and video generation [22], where they have demonstrated priceless. All things considered, "pulling a matte" is still fairly a dark workmanship, particularly for certain famously troublesome cases, for example, thin races of hide or hair.

Other than exact extraction of question from foundation and persuading smooth, the ideal matte is free of shading seeping from foundation. To execute these objectives, many methodologies [23, 24, 25, and 26] were proposed. Bayesian-based and PDE (Partial Differential Equation)- based are two classes of tangling approaches.

Tangling on the premise of Bayesian technique [25, 26] is inclined to cause the shading seeping in hazy foundation, while tangling on Poisson PDE is refined with numerous additional neighborhood operations. The difference based Poisson condition is ineffectively fit for catching points of interest, which is utilized as a part of Poisson PDE.

C. CLASSIFICATION OF IMAGE MATTING METHODS

Picture Matting systems extensively fall into two classifications. They are Bayesian Matting and Poisson Matting. In Bayesian system, we will accept that our information picture has just been portioned into three locales: "foundation," "frontal area," and "obscure," with the foundation and closer view districts having been depicted moderately. The objective of our calculation, at that point, is to explain for the frontal area shading F, foundation shading B, and mistiness α given the watched shading C for every pixel inside the obscure district of the picture.

Since F, B, and C have three shading channels every, we have an issue with three conditions and seven questions. Like Ruzon and Tomasi [27], we will take care of the issue to some degree by building frontal area and foundation likelihood appropriations from a given neighborhood. Our strategy, be that as it may, utilizes a constantly sliding window for neighborhood definitions, walks internal from the closer view and foundation districts, and uses adjacent figured F, B, and α esteems in developing focused Gaussian circulations. Further, our approach plans the issue of figuring matte parameters in a very much characterized Bayesian system and settles it utilizing the Maximum a Posteriori (MAP) method.

The Poisson Matting, proposed by Sun et al [24], utilizes PDE which is uniqueness based and can deliver conceivable matte with numerous additional neighborhood operations. It in some sense restricts its expansion to video, and the fine matte created by Poisson strategy needs the client's able mediation.

3. MOTIVATION OF WORK

There are numerous division procedures accessible and they must be picked in view of the application we crave. In this venture, we will remove the frontal area from an edge and composite it on another foundation and send it to the beneficiary. After an extremely weakened Literature Survey and with regards to 3G video call foundation swapping, area based Segmentation positions well over the various strategies and can proficiently play out the assignment of isolating the forefront from a picture. Dynamic Contour based Segmentation demonstrate has been picked as the district based division system as it is observed to be extremely proficient in removing objects from any given picture.

4. PROPOSED METHOD

A. ACTIVE CONTOUR BASED IMAGE SEGMENTATION

It is a novel locale based division calculation that is executed with an exceptional handling named Selective Binary and Gaussian Filtering Regularized Level Set (SBGFRLS) technique, which first specifically punishes the level set capacity to be double, and after that uses a Gaussian smoothing portion to regularize it. Another area based marked weight drive (SPF) work is proposed, which can effectively stop the shapes at feeble or obscured edges.

The outside and inside limits can be consequently identified with the underlying shape being anyplace in the picture.

Locale based ACMs have many focal points over edge-based ones. A standout amongst the most prominent area based models is the C–V demonstrate [41], which depends on Mumford–Shah division methods [42] and has been effectively connected to paired stage division. As pointed in [41], the C–V model can consequently distinguish the greater part of the shapes, regardless of where the underlying form begins in the picture. So we can state that the C–V demonstrate has the worldwide division property to portion all items in a picture. The measurable data inside and outside the form to build a district based marked weight compel (SPF) work [43], which can control the bearing of development, to substitute the ESF.

The proposed SPF work has inverse signs around the protest limit, so the shape can recoil when it is outside the question or extend when inside the protest.

For a given picture I in space Ω, the C–V display is detailed by limiting the accompanying vitality utilitarian and in this manner characterizing c1 and c2 as two constants which are the normal powers inside and outside the shape, separately. With the level set technique, we accept

$$\begin{cases} C = \{x \in \Omega : \phi(x) = 0\}, \\ \text{inside}(C) = \{x \in \Omega : \phi(x) > 0\}, \end{cases} \tag{1}$$

$$\text{outside}(C) = \{x \in \Omega : \phi(x) < 0\}.$$

By minimizing the energy constraints, we can get the solutions for c1 and c2 as given below,

$$c_1(\phi) = \frac{\int_\Omega I(x)H(\phi)dx}{\int_\Omega H(\phi)dx} \tag{2}$$

$$c_2(\phi) = \frac{\int_\Omega I(x)(1-H(\phi))dx}{\int_\Omega (1-H(\phi))dx} \tag{3}$$

Where H(φ) is the Heaviside Function defined by

$$H(\phi) = \frac{1}{2}\left(1 + \frac{2}{\Pi}\arctan\left(\frac{z}{\varepsilon}\right)\right) \tag{4}$$

The Stopping Point Function (SPF) defined in [43] has values in the range [-1, 1]. It modulates the signs of the pressure forces inside and outside the region of interest so that the contour shrinks when outside the object, or expands when inside the object. Based on the analysis, we construct the SPF function as follows:

$$spf(I(x)) = \frac{I(x) - \left(\frac{c_1 + c_2}{2}\right)}{\max\left(|I(x) - \left(\frac{c_1 + c_2}{2}\right)|\right)} \tag{5}$$

where c_1 and c_2 are defined in equations (2) and (3). The variation of the Heaviside function for various values of z and ε are shown in Figure 3.1 below

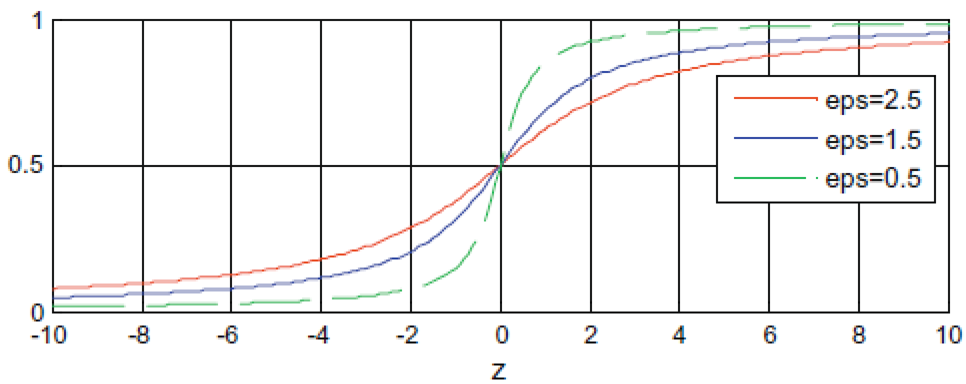


Figure 1 The Heaviside function w.r.t to different ε values

To take care of these issues, we propose a novel level set technique, which uses a Gaussian channel to regularize the particular twofold level set capacity after every cycle.

We can utilize a Gaussian separating procedure to additionally regularize the level set capacity. The standard deviation of the Gaussian channel can control the regularization quality. Since we use a Gaussian channel to smooth the level set capacity to keep the interface consistent and our model uses the factual data of locales, which has a bigger catch range and limit of antiedge spillage, the level set plan of the proposed model can be composed as takes after:

$$\frac{\partial \phi}{\partial t} = spf(I(x)).\alpha \,|\, \nabla \phi \,|, \; x \in \Omega \qquad (6)$$

ALGORITHM 1:

The main procedures of the proposed algorithm are summarized as follows:

1. Initialize the level set function φ as,

$$\phi(x, t = 0) = \begin{cases} -\rho & x \in \Omega_0 - \partial\Omega_0 \\ 0 & x \in \partial\Omega_0 \\ \rho & x \in \Omega - \Omega_0 \end{cases} \qquad (7)$$

   Where $\rho > 0$ is a constant, Ω_0 is the subset in the image domain and $\partial\Omega_0$ is the boundary of Ω_0.

2. Compute $c_1(\varphi)$ and $c_2(\varphi)$ using Equations (2) and (3), respectively.
3. Evolve the level set function according to Equation (6).
4. Let $\varphi = 1$ if $\varphi > 0$; otherwise, $\varphi = -1$. This step has the local segmentation property. If we want to selectively segment the desired objects, this step is necessary; otherwise, it is unnecessary.
5. Regularize the level set function with a Gaussian filter, i.e., $\varphi = \varphi * G_\sigma$.
6. Check whether the evolution of the level set function has converged. If not, return to Step2.

V. RESULTS AND PERFORMANCE EVALUATION

A. EVALUATION MODELS

The ACM algorithm is implemented in MATLAB R2008a (Version 7.6) and the simulation results for various images will follow later in this chapter.

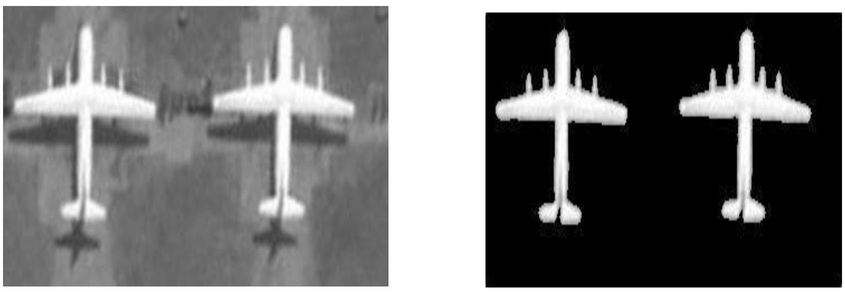
Table 1 Simulation Parameters

SNO	Parameter	Values	Significance
1	σ	0.8 to 1.5	Standard Deviation of Gaussian filter for Smoothening the contour edges.
2	ρ	1	Level Set Values.
3	K	<6	Gaussian Kernel size.
4	ϵ	1.5	Heaviside function parameter.

The values of the parameters tabulated above are considered for simulation. The results of simulation are available later in this chapter.

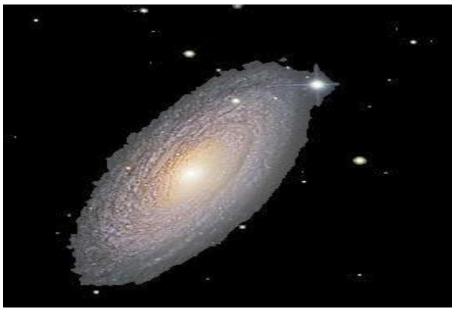
1. Simulation Results of Images with simpler background and perfectly Extracted Foreground

The simulation results are shown in Figure 2 and 3 respectively. In Figure 2, image of aero planes is considered for foreground extraction. In Fig 3, image of a galaxy is considered for foreground extraction. Upon running the algorithm for a specified number of iterations (100) the foreground extraction results are shown below. The foreground is extracted and put on a black background temporarily and it can be changed based on the application and needs.



a b

Fig. 2 a. Original Image (319*127 bmp) , b. Foreground extracted Result



a b

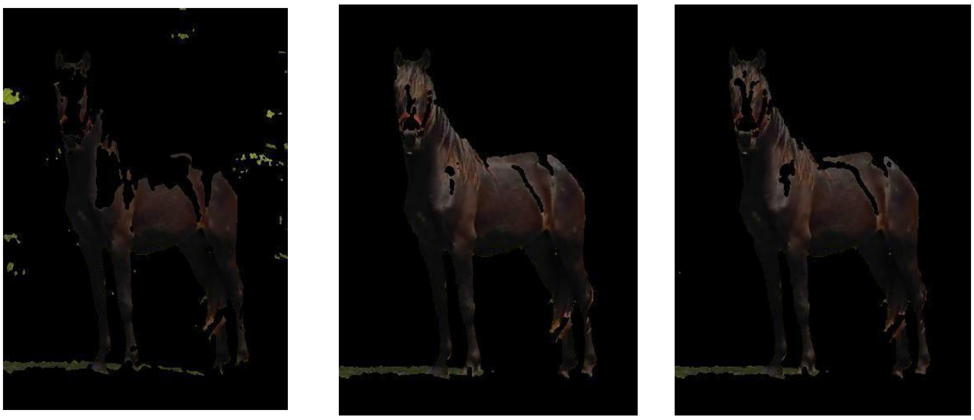
Fig. 3 a. Original Image (272 * 297 jpeg), b. Foreground extracted Result

The background of Image in Fig 3.a and b. may look similar but upon seeing it with closer look we may find that the image in Fig 3.a has a textured black background while that of b. has a pure black background which is due to the segmentation result.

2. **Simulation Results of Images with more intensity fluctuations in the background and extracted Foreground**

Two different types of images are considered for having more intensity fluctuations in the background. They are shown in Figure 4 and Figure 5. The image chosen in Figure 4 produced different segmentation results when segmented in different image planes (Gray scale, R, G, B). The image chosen in Figure 5 is also shown below and the foreground from it is extracted perfectly.

a b



c d e

Fig. 4 a. Original Image(350 * 446 jpeg), b. Foreground extracted Result in gray scale plane, c. R- Plane Foreground extraction d. G-Plane Foreground extraction , e. B-Plane Foreground extraction

a b

Fig 5 a. Original Image (508*356 jpeg), b. Foreground extracted Result

3. Simulation Results of Images with plain/textured background and the extracted Foreground

Three images are considered having plain/textured background. The foreground extraction results are shown in Figures 4.5, 4.6 and 4.7

a b

Fig.6 a. Original Image (640 * 480, jpeg, textured) b . Foreground extracted Result

a b

Fig. 7 a. Original Image (640 * 480 jpeg, plain) b. Foreground extracted Result

a b

Fig. 8 a. Original Image (183 * 275 jpeg, textured) b. Foreground extracted Result

4. Simulation Results of Images with low quality Segmentation

For images that have a complicated background, ACM does not extract the foreground perfectly in spite of segmentation in different planes. Figure 4.8 illustrates it.

a

b

c

d

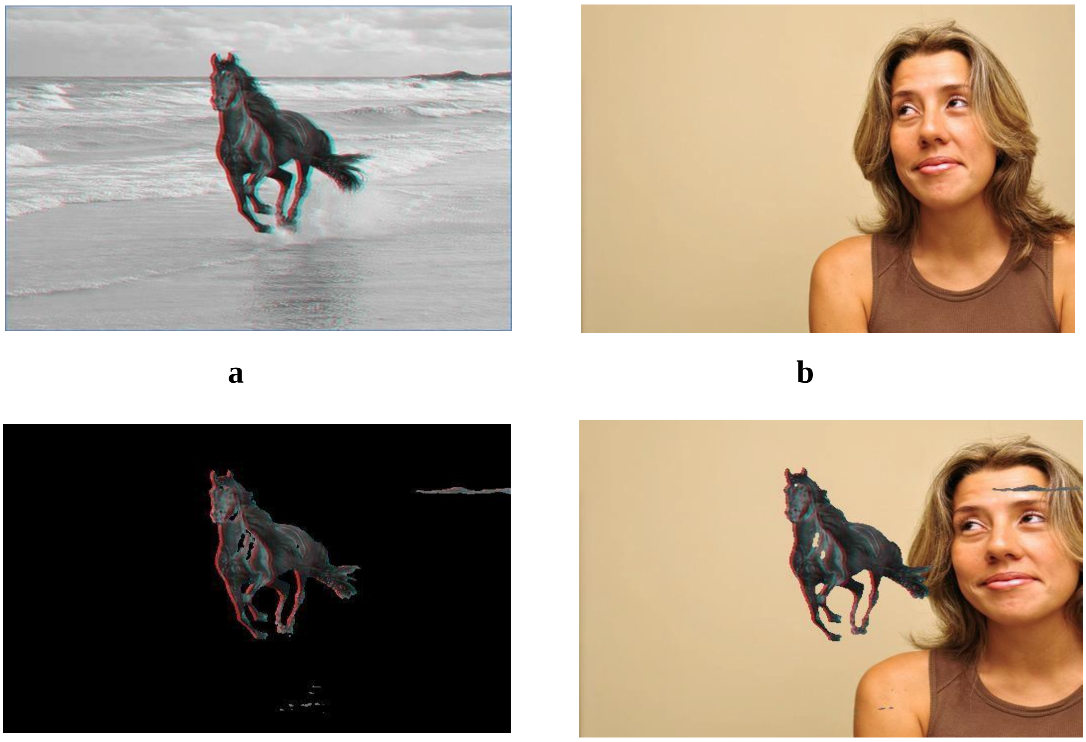
e

Fig. 9 a. Original Image (300 * 428, jpeg), Foreground extracted Result (Gray plane segmentation), c. R- Plane Foreground extraction, d. G-Plane Foreground extraction, e. B-Plane Foreground extraction

5. Simulation Results of Background swapped still Images

In the process of foreground extraction for background extraction, first the images are subjected to ACM and then processing is done after that. Once the foreground is extracted from the image, we need to logically perform pixel wise multiplication to composite the foreground on a new background.

The new background may be a plain/textured/homogenous/heterogeneous background depending on the user choice. Figure 4.9 illustrates the process of background swapping for still images onto a different background. The composition process is so delicate that care should be taken to nullify any evidence of merging the extracted foreground with the new background.



a b

Fig. 10 a. Original Image (for which Foreground is to be extracted), b. New background on which extracted foreground will be merged c. Extracted foreground for the a. image d. Extracted foreground composited on the new background

VI. PERFORMANCE EVALUATION

Now let us evaluate the performance of the algorithm based on AEM, runtime statistics and the color intensity variation graphs.

A. Algorithm runtime Statistics

The run time statistics of the algorithm are tabulated below:

Table 2 – Runtime Statistics

Total Time	**Parameters**	**Conditions**
2.65 seconds	Iterations = 50	Full Program including image displays
4 seconds	Iterations = 100	
2 seconds	Iterations = 50	Only the algorithm Excluding all Image displays
3.35 seconds	Iterations = 100	

From the above tabular column, we infer that as the number of iterations increase, the total time taken also increases thereby making the algorithm computationally inefficient. As we are simulating the results in MATLAB, many unwanted display, plot and other lines can be commented out to give a minimum execution time of 2 secs for 50 iterations and 3.35 secs for 100 iterations. The computational complexity also depends on the type of the image, how complex it is and the clarity of foreground/background borders where the contours have to identify and extract the region of interest.

Figure 5.0 gives the variation of AEM with respect to σ. We will observe from the plot that AEM reaches a minimum in the range of 0.6 and 1.0. So we should take

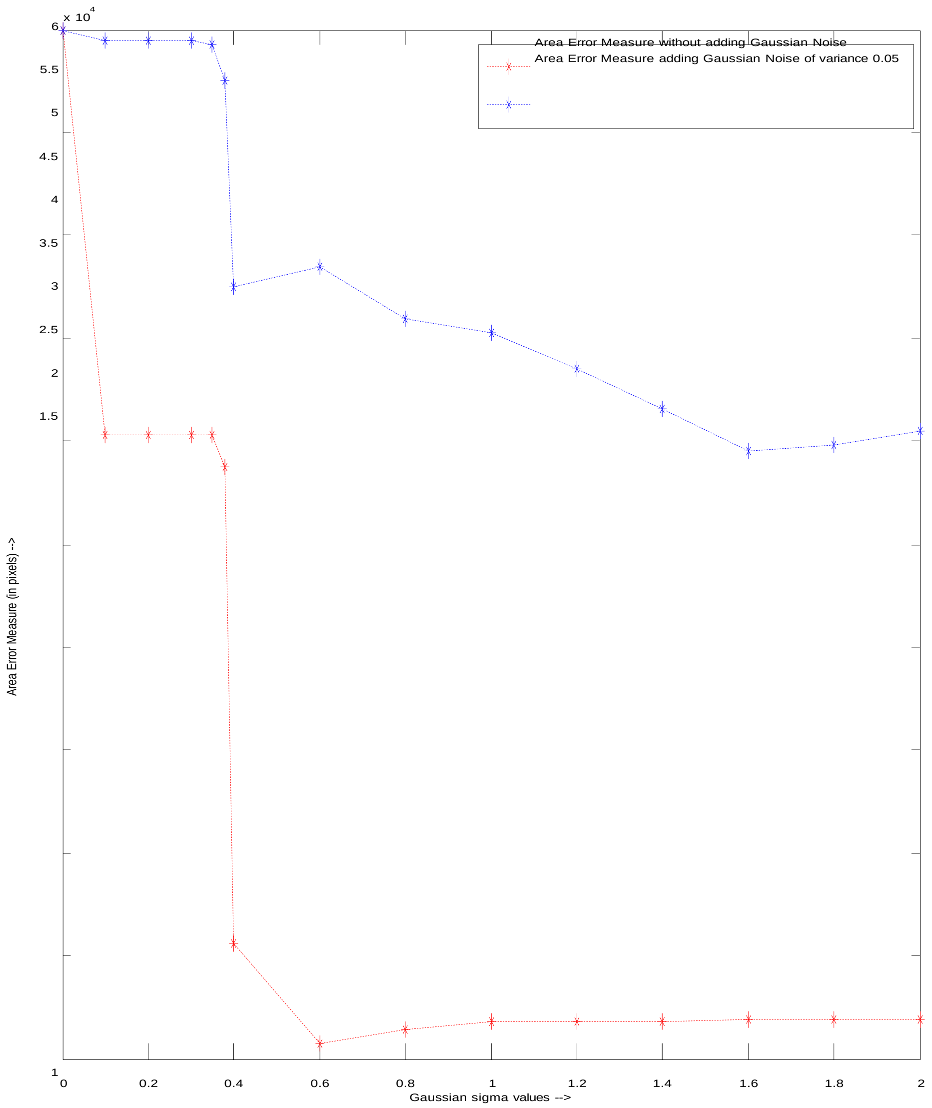


Fig.11. AEM Performance Measure Curve

VII. CONCLUSION

From the successful implementation of ACM for foreground extraction, we find the algorithm has a potential application in the video domain. The background of an entire video stream can be altered using the ACM model. If the background of the video is static, then we can use any normal method like Mean, Median, Mode, Mixture of Gaussians and many other techniques to subtract the background and insert a new background for each frame of the video. It is a relative easy process when compared to videos having dynamically changing background.

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