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A SMOOTHED DPMVL FOR INTERACTIVE IMAGE SEGMENTATION AND ENHANCED ADAPTIVE MRF FOR SEGMENTATION REFINEMENT

KEY WORDS: Image Segmentation, Simulated Annealing, Adaptive Shape Prior, Adaptive Markov Random Field.

G.S. Gowri	Department of Computer Science, Government Arts College, Coimbatore-641046, Tamilnadu, India.
Dr. P. Ponmuthuramalingam	Department of Computer Science, Government Arts College, Coimbatore-641046, Tamilnadu, India.

ABSTRACT

Image segmentation is a fundamental step in many areas of computer vision including object recognition, video surveillance, face recognition, fingerprint recognition etc. It provides additional information about the contents of an image by identifying edges and regions of similar color and texture. Although a first step in high level computer vision tasks, there are many challenges to ideal image segmentation. Interactive image segmentation is a way to extract foreground objects in complex scenes using simple user interaction. The key to success in interactive image segmentation is to preserve characteristics of the user's interactive information and maintain global data effectively. In Smoothed Dirichlet Process Multiple view learning (sDPMVL) with improved adaptive Markov Random Field (MRF) Model utilized to more accurate and efficient segmentation than traditional MRF model. However the parameter selection is the critical issues in this approach. To overcome this issue the sDPMVL-adaptive MRF with Modified Graph cut utilized to achieve the efficient segmentation and smoothness in the segment label. However, the shape information of objects was not considered in these approaches which this leads to decrease the smoothness of the segment labels. To further increase the smoothness of this approach the sDPMVL- adaptive MRF with Modified Graph cut and Adaptive shape prior utilizes to achieve efficient smoothness. In these approaches the HMC (Hamiltonian Monte Carlo) algorithm utilized to learning new parameter and inference. However, convergence rate of Markov chain and the decorrelation time between independent samples can be problematic. This causes to degrade the accuracy of smoothening and segmentation in the segment label. In order to overcome this issue in this paper the Simulated Annealing (SA) based Smoothed DPMVL (sDPMVL) Adaptive MRF with Modified Graph cut and Adaptive shape prior proposed to improve the new parameter learning and inference. The Performance of the proposed approach is analyzed through accuracy, precision and recall.

1. INTRODUCTION

Interactive foreground/background segmentation [1] is a practical and important problem in image processing. It aims at partitioning an image [2] into constituent regions of interest. The most popular method in recently years is graph cuts which is used to globally optimized energy function with graph cut in gray scale image segmentation [3]. There are many methods used to segment images, from simple ones like edge detection and thresholding to complex ones like active shape models, active contour models, clustering, and graph-based segmentation. Graph cuts addresses segmentation [4] in a global optimization framework and guarantee a globally optimal solution for a wide class of energy functions. Graph cut algorithms have been successfully applied to a wide range of problems in image processing. Besides used in image segmentation, graph cut is also used in image restoration, stereo and motion, image synthesis, region merging, multi camera scene reconstruction, 2D optical flow, interactive object delineation, etc.

In early work the HMC (Hamiltonian Monte Carlo) based Smoothed DPMVL (sDPMVL) [5] Adaptive MRF with Modified Graph cut and Adaptive shape prior utilized the learning parameter and inference to improve the smoothening. However, convergence rate of Markov chain and the decorrelation time between independent samples during the clustering process of image pixels can be problematic. It may be less frequent to transit from an isolated high probability region to another high probability region. In order to overcome this issue in this paper the Simulated Annealing (SA) based Smoothed DPMVL (sDPMVL) Adaptive MRF with Modified Graph cut and Adaptive shape prior proposed for new parameter learning and inference to efficiently improving the accuracy of smoothening and segmentation.

2. LITERATURE SURVEY

Zheng, Q., presented Interactive image segmentation [6] for segmenting single object from images with the complex foreground and background. The result shows the present segmentation algorithm effectively solves the common over segmentation and less segmentation in graph cut additionally recovers the issue in small regions error segmented in the grab cut algorithm. However, the grab cut algorithm does not perform well in the high dimensional images.

Panchhi, P., proposed Interactive grab cut algorithm [7] for segmentation of color images. The proposed Interactive grab cut algorithm performs the segmentation in HSV (Hue, Saturation, Value) image rather than RGB (Red, Green, and Blue) image. This method was initially taken the input image in RGB model then converts the RGB image in to HSV image. After that, Apply grab cut algorithm on the HSV image till they require segmented images. Finally, convert the output of the HSV image into RGB image. The result shows the proposed method performance efficiently improved compare to traditional method. However, the interactive grab cut algorithm was does not provided the optimal solutions.

Björkman, M., presented Markov Random Field inference methods [8] for segmentation. The proposed segmentation allows for multi object detection, modelling and tracking. Then, consider all image pixels for classification, not just consider only the around object of interest. The proposed method was needed the minimal requirements on user input for initialization. The performances were evaluated in terms of segmentation and computational costs.

Lea, C. S., & Corso, J. J. proposed Two Hierarchical Markov Random field models [9] for segmenting objects in video. The proposed Hierarchical Markov Random field models efficiently differentiate the connected objects using tiered, binary (foreground/background) label sets. The aim of this research was detected and classified the features using a camera at the intelligent ground vehicle competition. The proposed Hierarchical Markov Random field models were initially eliminated shot noise and de-noising larger mislabeled segments.

Göring, C., presented Semantic segmentation [10] by Grabcut algorithm. The aim of this research was segmented object in images through completely automatic manner and labels them as one of the learned objects categories. In this research, present two different approaches like C-Grabcut and L-Grabcut that extend Grabcut by using training images. The C-Grabcut derives the multiple class specific segmentation and classifies them by using shape and color information. The L-Grabcut utilized in the initial step an object localization algorithm, which was classified the bounding box as a hypothesis of an object in the image. After that, this hypothesis utilized as an initialization for the Grabcut algorithm. However the Semantic segmentation is only based on local features.

Hernández-Vela, A., presented Grabcut based Human segmentation [11] in the video sequences. The Grabcut was initially performed by HOG (Histogram of oriented Gradients) - based subject detection, detection of face, and the skin color model. The spatial information was included by the mean shift clustering whereas temporal coherence was considered by the historical of the Gaussian mixture models. Additionally, the full face and pose recovery was found by combining the human segmentation with active appearance models and traditional random fields.

Lee, H. S., presented Learning based interactive segmentation [12] with supervised classification of super pixels. In this approach, specifically user labelled pixels is interpreted as labelled data which are to be used as the training data for classification of task. After completing training the classifier with these seed data, the unlabeled pixels are labeled by classifying these unlabeled data as test data. The proposed method consists of two steps such as supervised classification of super pixels as initial segmentation and pixel wise classification as label refinement. However, the Learning based interactive segmentation has some limitations such as take more time for initialization.

Ghosh, A., presented Multi Layer compound Markov Random Field [13] with Distributed Differential Evaluation (DDE) optimization technique to detect the moving objects from the given video sequence. The proposed MRF model preserves the boundary information of the segmented regions. In the proposed DDE, mutate the each target vector instead of considering the whole population. Then, consider the small window corner as the target vector for reducing the computation time which was better compared to traditional DDE algorithm.

Wang, T., presented Fast image and video segmentation using single touch interaction [14] for segmenting image and video sequence with minimal user interaction. The proposed algorithm requires only a single finger to identify the object of interest in the image or first frame of the video. However image and video object segmentation algorithm with minimal user intervention does not perform well in tablet and touch screen devices.

Zhang, G., presented Integrating trajectories from points and regions [15] for video object segmentation. The proposed approach was taken the both advantages of point trajectories and region trajectories. The point trajectories is delivered the basic clustering cues then further employ region trajectories generated from hierarchical over segmentation. In the textured areas, the labeling information of region trajectories was obtained from the point trajectories. In the texture less areas, the labeling information can be propagated from the labeled region trajectories by using the GMM (Gaussian Mixture Models) model. Then, finally utilized the region trajectories consider as the high order constraints in the conditional random field to get the segmentation results.

3. PROPOSED METHODOLOGY

In this paper, the Simulated Annealing based Smoothed DPMVL (sDPMVL) Adaptive MRF with Modified Graph cut and Adaptive shape prior proposed in new parameter learning and inference to improve the accuracy of smoothening and segmentation of the segmentation label.

3.1 Simulated Annealing based Smoothed DPMVL (sDPMVL)with Adaptive MRF

The Dirichlet mixture models (DPMMs) allows the automatic computation of the number of components. In this model the data points are pointed with respective polya um methods

$x_i|\theta_i \sim f(\theta_i)$, $\theta_i|G \sim G$, $G \sim D(G_0, \gamma)$ (3.1)

x_i - be the data point, θ_i - be the model parameter associated with $x_{i,}$ f be the parametric density function, G - be the distribution over parameters, which is drawn from a Dirichlet process D with G_0 and γ , $G_0 -$ be the Base distribution γ -be the scale parameter. The DPMVL model consider both the image features and segment labels at the seeding pixels as inputs, and the result of a segment label for each unlabeled pixel. In the DPMVL model X^1 and X^2 represents the features of two complementary data denote as the same image. In this model are shade vector and diffusion signature. The color vectors contain the RGB mean values of the constituent pixels. The major parameter of images is show by allocating the boundary probability for the image pixels.

Naturally the images with background to semantic objects have lower strength than external that outline objects. The spatial location of the pixels based on the boundaries and provides the cues for computing the segment label. These cues are used to combine the similar features to the pixel inside the same semantic objects and combine various features to the pixel in different objects.

To show the overall boundary constraints the diffusion signature are established as the feature vector for each vertex. These are derived and utilized the diffusion process in the graph. To deliver the numerical form of descriptions, then place the labeling sources on the two sides of the B_i (Boundary Fragment). Here the S = $\{S_j\}$, representing the set of vertices depends on the labeling sources.

The U represents the set of unlabeled vertices and Λ represents the mean value of boundary probabilities at pixels insideB_i. In two sides of boundary fragment, + Λ and - Λ are allocate. The vector form is

$f_s^i = [f(s_1, B_i), f(s_2, B_i), \ldots\ldots. f(s_{|s|}, B_i)]^T$ (3.2)

By utilizing the equation (3.2) the stationary solutions to find out the whole unlabelled locations determine as the

$f_U^i = -\Delta_{U,U}^{-1} \ \Delta_{U,S} \ f_s^i$ (3.3)

$\Delta -$ denotes the sub laplacian matrix of graph G_b

After generate of f(v, B_i), the system characterize the diffusion signature vector at v as

$[f(v, B_1), f(v, B_2),, \ldots f(v, B_{|B|})]^T$ (3.4)

The signature of the diffusion process is on the subspace learned by principle component analysis (PCA). Then the compact representation with dimensions of the small variances results from the boundaries with small strength filtered out. After that it can be seen in the pixels splitted by main boundaries, it's used to represents the segment indicators. It has the significant distance with their diffusion signature representations. Y is the output which represents the segment label.

Especially all the components in the mixture modes has the parameter $\varphi = (\mu, \Sigma , \alpha, B)$. The two perspectives cooperate to decides the possibility of the apply for sampling the same time as the data allocate to additives. In the parameter the re-estimation is combined with each view inside the components are separately updated, and the weight parameters are decides the interaction between the two views to approximately trade them off.

Then we define g= [p(y=1|x^1), [p(y=1|x^2)] ^{T}.

$$P(y=j|x^1, x^2, \alpha, \beta, \tau, v) = \frac{\exp(T_j + g^T v_j}{\sum_{K=1}^{J} \exp(T_k + g^T v_{k})}. \quad (3.5)$$

$\{\tau_i, v_i\}$ -Denotes the set of regression parameters.

The constituent probabilities p(y=j| x^i) in the vector g and the probability densities $p^i(x^i)$in each view are calculated. The DPMVL models are efficiently solve the interaction among the two complementary views. Additionally this version mechanically alter the stability between the conditional distributions found out from the two complementary perspectives, such that the view that consists of more information for segmentation will be favoured using this extra layer of regression.

3.1.1 The New Parameter Learning and Inference Phaseby using Simulated Annealing

In order to improves the parameter learning the Simulated Annealing (SA) algorithm used for posterior sampling. To apply the SA to specific model, the SA specify the following parameters: The state space, Energy (goal) function E (), Candidate Generator procedure neighbour (), Acceptance probability function P (), Annealing schedule temperature () and initial temperature <init temp>.

Simulated annealing may be modelled as a random walk on a search graph, whose vertices are all possible states, and whose edges are the candidate moves. An essential requirement for the neighbour () function is that it must provide a sufficiently short path on this graph from the initial state to any state which may be the global optimum – the diameter of the search graph must be small.
The SA is an adaptation of the Metropolis–Hastings algorithm, a Monte Carlo method to sampling the new parameter components. In the SA the distribution is modified with temperature parameter T.

$$p(x) = \frac{1}{Z(T)} exp\left(\frac{-E(x)}{T}\right) \quad (3.6)$$

The original distributions corresponds T=1. The new sampled parameters from this modified distributions. In the simulated annealing, the T value is initialized T>1 and then iteratively reduces to 1. This analysis deemphasizes transition between high probability region and low dimensional region. So the SA is increases the chances of transition from the high probability region to another. Moreover the SA is to decompose the energy function E(x)

$$p(x) = \frac{1}{Z(T)} exp\left(-E_0(x) + \frac{E_1(x)}{T}\right) \quad (3.7)$$

$E_0(x)$ – The property of separable and convex

$E_1(x)$ - Represents the difference between $E_0(x)$ and Energy Function E(x).

The new values are k which is dimensionality of the T. Then the supplementary variables are drawn randomly via Gaussian distribution independently of the new values of the variables. The P is representing as the new parameter. The current state is represent as the (p, q). The p(x_i) *and* p(y_i=j|x_i) =j|x_i) of the unlabelled training consider the computed similarity is the labelled examples.

As a replacement for of p(y_i|x_i^1, x_i^2) , the DPMVL used E{p(y_i|x_i^1, x_i^2)} for an unlabeled training example. We resolve

$$E\{p(y_i|x_i^1, x_i^2)\} = \sum_{j=1}^{J} p(y_i = j| x_i^1, x_i^2)\, p(y_i = j) \quad (3.8)$$

p(y_i=j) is determined from the labelled data. In this technique the unlabelled data are exploited to learn the multiple-view feature distributions instead of being discarded. Once find the $\theta_i^t = (\mu_i^{j,t}, \sum_i^{j,t}, \propto_i^{j,t}, \beta_i^{j,t}, \tau_i^t, v_i^t)$, for t=$T_0$+1,..... T_0+ T,i=1,....n and j=1,2 , then use it to compute the predictive distribution of class label $y_*$for new test data (x_1^*, x_2^*) according to P(y_*= j|x_*^1, x_*^2)= P(y_*= j, x_*^1, x_*^2)/ p(x_*^1, x_*^2).

$$P(y_* = j, x_*^1, x_*^2) = \frac{1}{T} \sum_{t=T_0+1}^{T_0+T} \int p(y_* = j, x_*^1, x_*^2 | \theta_*^t) p(\theta_*^t | \theta^t, G_o) d\theta_*^t \quad (3.9)$$

$$P(x_*^1, x_*^2) = \frac{1}{T} \sum_{t=T_0+1}^{T_0+T} \int p(x_*^1, x_*^2\ \theta_*^t) p(\theta_*^t | \theta^t, G_o) d\theta_*^t \quad (3.10)$$

Assume the above equations the test components parameter are samples from the distribution which is drawn from the Dirichlet process D=(G_0, , γ)

$$\theta_*^T \sim \frac{1}{n+\gamma} \sum_{i=1}^{n} \delta(\theta_i^T) + \frac{\gamma}{n+\gamma} G_0 . \quad (3.11)$$

The DPMVL method removes the hard decisions on the allocating input vectors to components. It provides the flexibility in modelling the color and boundary information. Finally each test example is allocated to a segment class with the highest predictive probability for image segmentation.

3.2 Simulated Annealing (SA) based sDPMVL-adaptive MRF with Modified Graph cut

The adaptive shape prior with modified graph cut algorithm is utilized to efficiently increasing the smoothness of the each segmentation label.

3.2.1 Adaptive shapes prior

The adaptive shape prior proposed new energy function in the classical graph cut energy function which is denoted as the following way

$$E = E_i + \alpha E_s \quad (3.12)$$

E_i- be the original image energy

E_s- be the Energy term depends upon the shape prior and the constant balance between E_i and E_s

The adaptive shape prior improve the segmentation process to modify the energy function of the modified graph cut segmentation with the shape prior by the following way

$$E(F) = \mu \sum_{p \in P} D_p(f_p) + \sum_{(p,q)\in N: f_p \neq f_q} V_{pq}(f_p, f_q) + \sum_{(p,q)\in N: f_p \neq f_q} \frac{1}{e^{(\alpha_p - \alpha_q)^2}} E_{pq}(f_p, f_q) \quad (3.13)$$

3.2.2 Shape probability map

In shape possibility map α can be representing in several approaches which is used to realize the shape prior for each pixel of a picture. The term α can be used to refer the shape prior probability map. The probability map can be producing from the available image level

data. On this approach α may be predicts from the supervised getting to know and the training is a totally simple technique. So the modified energy function (3.15) used in the pixel pair p and q with the neigh boring pixels.

3.2.3 sDPMVLAdaptive MRF with Modified Graph cut

The modified graph cut algorithm used to overcome the limitation of the graph cut method. The algorithm efficiently used in image segmentation without the usage of the regularizing parameter. This technique consider only the boundary region. The region information contains in the classical graph cut furthermore the regularizing parameter is removed. This technique used to reduce the energy function by using the following equation.

$$E_{P(L)} = \sum_{\{p,q\}\in N} B(p,q)\, \delta(L_p \neq L_q) F_c(p,q) \quad (3.14)$$

$F_c(p,q)$- Denotes the penalty for allocate both the p and q in the same label which is defined as

$$F_c(pq) = pr\left(\frac{IA_p}{A_p} = 0\right) pr\left(\frac{IA_q}{A_q} = 0\right) + pr\left(\frac{IA_p}{IA_p} = -1\right) pr\left(\frac{IA_q}{IA_q} = 1\right) \quad (3.15)$$

The probability of the pixel p rhymes along with the intensity histogram of the object background is provided by the following ways

$$pr\left(\frac{IA_p}{IA_p} = 1\right) \text{ and } pr\left(\frac{IA_q}{IA_q} = 0\right) \quad (3.16)$$

The modified graph cut algorithm efficiently reduces the memory size by the absence of the regional information. The mixture model for the color images also used to handle color images the intensity of the mixture model is provided by $IA_p = \pi^T A_t(C_p)$, the π denotes the color transformation factor to transform color images (RGB) to gray scale.

3.2.4 Simulated Annealing based sDPMVLAdaptive MRF with Modified Graph cut and Adaptive shape prior

The adaptive shape prior technique takes plenty of reminiscence space while implementation performed inside the graph cut segmentation. So as to conquer this problem the proposed technique used the less energy function. By way of using the modified graph cut algorithm the energy function written as following methods.

$$E=E_m + E_A \quad (3.17)$$

E_M -Denotes the modified graph cut energy function, the size of this energy function is small compare to classical graph cut energy function

E_A- the adaptive shape prior energy function

E_A- the adaptive shape prior energy function

$$E_m=\sum_{\{p,q\}\in N} B(p,q)\, \delta\left(L_p \neq L_q\right) F_c(p,q) \quad (3.18)$$

The parameters are explained in the equation 2.1.

$$E_A = \sum(p,q) \in N: f_p \neq f_q \frac{1}{e(\alpha p-\alpha q)^2} E_{pq}(f_p, f_q) \quad (3.19)$$

ap,aq - Denotes the probability values which is originate from the probability map *a* at pixels p, q, $E_{pq}(f_p, f_q)$ denotes the pair wise shape constraint term preset at the p and q pixels. The proposed algorithm used for generate the shape prior for the energy function is basically comes from the kernel method algorithms such as the principal component analysis, functional analysis and the filtering algorithms.

The energy function for the proposed method is given as the following ways

$$E(G) = \sum_{\{p,q\}\in N} B(p,q)\, \delta\left(L_p \neq L_q\right) F_c(p,q) + \sum(p,q) \in N: F_p \neq F_q * \frac{1}{e(\alpha p-\alpha q)^2} E_{pq}(F_p, F_q) \quad (3.20)$$

Using Equation 3.20 the shape of the image taken by the adaptive shape prior using modified graph cut algorithm. The proposed technique used to increase the smoothness in the segmentation labels.

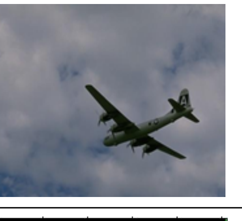
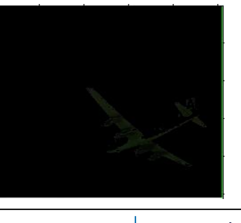
4. RESULT AND DISCUSSION

4.1 Dataset description

In the Berkeley segmentation dataset**,** 12000 hand-labelled segmentations of 1000 Corel dataset images from 30 individual salient data are collected. By presenting the data with the color image and gray scale image, half of the segmentations and remaining half of the segmentations are obtained. The public scale based on this data consists of all gray scale and color segmentations for 300 images. The total images are separated into a training set of 200 images, and a test set of 100 images.

Input images are taken from the Berkeley segmentation dataset and the output of the given image is shown in Figure 4.1 which shows the comparison results of segmentation images.

These segmentation processes separate an object of interest from the remaining image. The experimental results are conducted to evaluate the performance of the improved adaptive MRF model, modified graph cut technique and modified graph cut technique with shape prior in terms of accuracy, precision and recall.

Original Image	
HMC- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior	

SA- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior	

Figure 4.1 Comparison Results of Segmentation Images

4.2. Accuracy

The Accuracy of the system is calculated via the values of the True Negative, True Positive, False Positive, False negative actual class and predicted class outcome it is defined as follows,

$$Accuracy = \frac{(True\ positive + True\ negative)}{(True\ positive + True\ negative + False\ positive + False\ negative)}$$

The corresponding results of the HMC- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior, SA- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior compared in terms of accuracy.

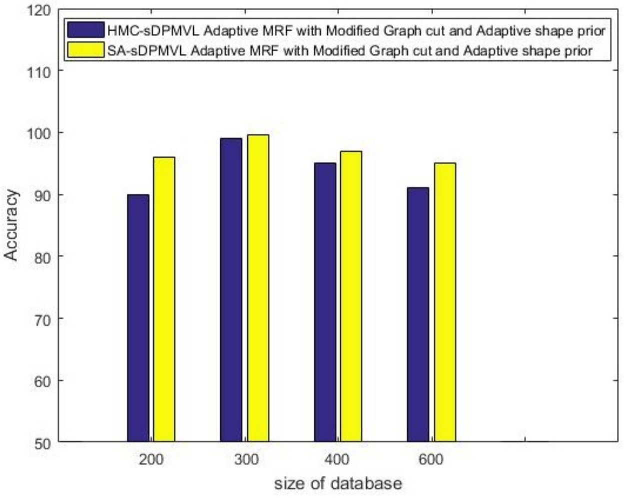


Figure 4.2 Comparison of Accuracy

In figure 4.2, the size of the dataset is plotted on the x axis and the accuracy values are plotted on the y axis. The accuracy value of proposed sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior achieves high accuracy values for all sizes of dataset compared to existing HMC-sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior model.

Table1 4.1 Comparison of Accuracy

Size of dataset	Accuracy value in %	
	HMC- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior	**SA- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior**
200	90	96
300	99	99.7
400	95	97
600	91	95

The table 4.1 represents the accuracy value of the HMC- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior and SA- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior. The experimental result shows that the SA-sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior provides better accuracy value.

4.3. Precision

Precision is defined as the fraction of accurate predicted results from the input.

$$Precision = \frac{True\ Positive}{(True\ Positive + False\ Positive)}$$

The corresponding results of the HMC-sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior and SA-sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior compared in terms of Precision.

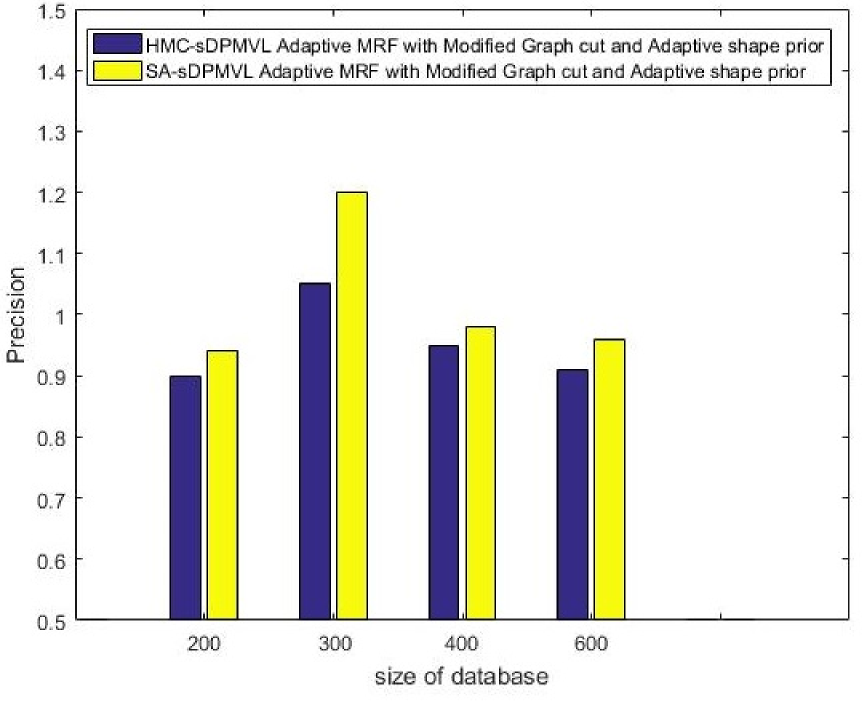


Figure 4.3 Comparison of Precision

In figure 4.3, the size of the dataset is plotted on the x axis and the Precision values are plotted on the y axis. The Precision value of proposed sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior achieves high accuracy values for all sizes of dataset compared existing HMC- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior model.

Table 4.2 Comparison of Precision

Size of dataset	Precision value	
	HMC- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior	**SA- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior**
200	0.90	0.94
300	1.05	1.2
400	0.95	0.98
600	0.91	0.96

The table 4.2 represents the Precision value of the HMC- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior and SA- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior. The experimental result shows that the SA-sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior provides better Precision value.

4.4. Recall

The recall or true positive rate (TP) is defined as the percentage of positive cases that were accurately identified, as calculated using the equation:

$$Recall = \frac{True\ Positive}{(True\ positive + False\ negative)}$$

The corresponding results of the HMC- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior and SA- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior are compared in terms of Recall.

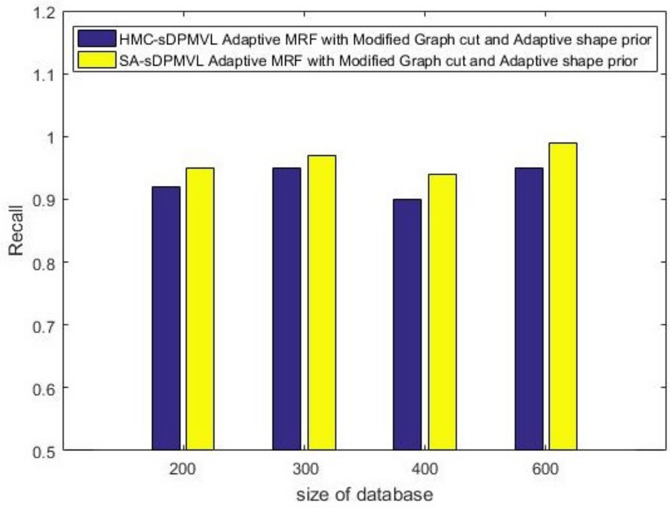


Figure 4.4 Comparison of Recall

In figure 4.4, the size of the dataset is plotted on the x axis and the Recall values are plotted on the y axis. The recall value of proposed sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior achieves high accuracy values for all sizes of dataset compared to existing HMC- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior model.

Table 4.3 Comparison of Recall

Size of dataset	Recall value	
	HMC- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior	SA- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior
200	0.92	0.95
300	0.95	0.97
400	0.9	0.94
600	0.95	0.99

The table 4.3 represents the recall value of the HMC- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior and SA-sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior. The experimental result shows that the SA-sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior provides better recall value.

5. CONCLUSION

The proposed Simulated Annealing (SA) based Smoothed DPMVL (sDPMVL) Adaptive MRF with Modified Graph cut and Adaptive shape prior is efficiently used in new parameter learning and inference to improve the accuracy of smoothening and segmentation. This simulated algorithm overcomes the limitation of the HMC algorithm for learning the new parameter and inference. Moreover, the proposed SA algorithm can deal with highly non linear models and many constraints in the process of learning and achieves optimal solutions. The experimental result shows, the proposed SA- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior approach outperforms than existing HMC- sDPMVL Adaptive MRF with Modified Graph cut and Adaptive shape prior approach in term of accuracy, precision and recall.

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