ISSN 2278-3091
Volume 9, No.5, September - October 2020
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse170952020.pdf
https://doi.org/10.30534/ijatcse/2020/170952020

Motion Aware Camouflage Modeling (MACM) for Foreground and Background Segmentation using Low-Rank Spatial and Temporal Feature Extraction

Rita Kamble[1], Dr. Pothuraju. Raja Rajeswari[2]
[1]Research Scholar, Department of Computer Science & Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India & Assistant Professor RSCOE, Pune, India,reeta.kamble12@gmail.com
[2]Professor, Department of Computer Science &Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India, rajilikhitha@gmail.com

ABSTRACT

In real-world scenario, demand of security applications and surveillance systems has increased dramatically. In this field of surveillance systems, computer vision based application has attracted researcher community due to their substantial impact on the security applications. Computer vision based surveillance systems has been considered an interesting research area, hence different methods have been introduced during last decade but identification of moving object in complex background scenarios is still considered as a challenging task. Moreover, various fields such as military, face the issue of movable objects in the camouflaged background. To identify the camouflage moving object is a tedious task. Here, we consider, moving camouflage object detection for dynamic and static background and introduced a novel approach called as Motion-Aware Camouflage Modeling (MACM). According to this approach, moving camouflage object detection problem is represented in low-rank representation. In this process, first of all we apply pre-processing phase where motion related information are extracted such as motion field, motion flow and optical flow. Later, the entire frames are decomposed into low-rank representation where we apply Langragian approach to obtain the ideal representation of the given problem. In the next phase, superpixel segmentation, spatial feature and temporal feature extraction methods are applied which are further used for geodesic distance computation. Based on the obtained distance matrices, we identify the background and foreground objects and foreground extraction is performed. Proposed approach is implemented using MATLAB simulation tool where we have conducted experiments for CAMO UOW dataset and CDNet2014 dataset. Performance of proposed approach is compared with the state-of-art techniques. The experimental study work shows that proposed approach achieves better performance in terms of precision, recall and F-measure.

Key words: Camouflage Modeling, Computer Vision, Langragian, Object Detection, Video Analysis

1. INTRODUCTION

Real time survelliance has gained huge attraction among the research community, industrial applications and in academia.Computer-vision based visual surveillance systems are widely adopted in this field for monitoring the activities in the defined region. Development of automated visual surveillance system is substantial task in various other computer vision based applications such as traffic monitoring, vehicle navation and crowd behaviour monitoring etc. [1-2]. The computer vision based video analysis systems perform three basic operations such as object detection, object tracking and behavior recognition where according to the first stage, the interest objects are detection and segmented for further processing throughout the complete video analysis system. In the next case, detected objects are tracked and finally, behaviour recognition is applied to accomplish the ttracking in the video analysis systems. The performance of these methods depends on the object detection accuracy i.e. if the accurate objects are detected then video analysis and monitoring can be more accurate and can be adopted in various real-time application [3].

Moving object detection is considered as a hectic task which has aimportant impact on the various aspects of video analysis systems such as object tracking [5], behaviour recognition [6] and scene classificationcan disturb the system performance [4]. The supervised scheme requires prior knowledge of the current frame which includes background [7-8] and foreground models [9]. In several video sequences, background and foreground may arise complexity issues due to appearance variation and illumination conditions. Hence, supervised schemes suffer from the accuracy issues. Supervised schemes [50] require an initial modeling of background and foreground using labeled datawhereas unsupervised schemes do not need any previous information. Unsupervised schemes utilize the motion information for segmenting the background and foreground models. Several techniques have been introduced for motion segmentation which are based on the frame difference computations [11], background subtraction [10, 13] and optical flow [12] computation for segmentation of background and foreground. Moving object detection is an attractive research field which is broadly adopted in various real-time computer vision based applications. However, it still faces various challenges such as illumination variations, dynamic background, bootstrapping, illumination variations, shadows and camouflage etc. Recently, developed techniques have focused on these aspects and presented some promising techniques such as 3dSOBS+ [17], Zhang et al. presented tracking approach which is robust to the illumination variations [18]. As of the current state of object tracking, camouflage object detection [56] and tracking is studied less and it arises several challenges. Hence, in this work, we focus on the camouflage object tracking.

1.1 Camouflage object detection

In this work, our main aim is to focus on camouflage problem and develop a robust approach for the moving object segmentation in these visual scenes. Camouflage problem is defined as segmentation of moving object which are having similar color back ground. Generally, camouflage image data is categorized into two main categories as: natural camouflage and artificial camouflage. Natural camouflages are identified in the animals, humans etc. to disguise or hide their identity whereas artificial camouflage are induced by using some specific patterns which can be used in military applications for hiding the soldiers and other applications.

Figure 1 shows a sample example of camouflage moving object detection technique. First row of the figure shows original frames, second row shows identified objects using GMM technique and third row shows outcome of DFM (Discriminative feature based modeling). The background pixels and foreground pixels are called as camouflage foreground and camouflage background pixels. Moreover, these pixels are always occluded hence it becomes a challenging task to identify the moving objects.

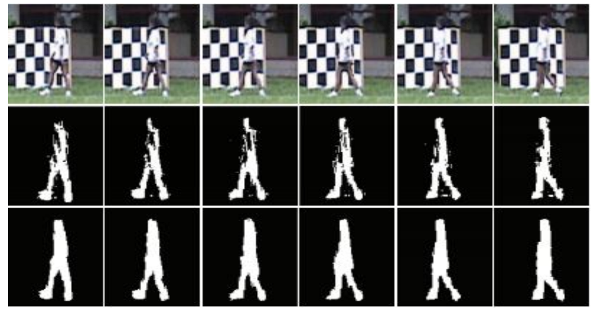

Figure 1 Camouflage detection "Gait Sequence":original frames, GMM [19], DFM [20]

Detection of these moving foreground objects is a tedious task due to difficult structure, occlusion and background similarity. This can be obtained by background subtraction method by applying Gaussian Mixture Model (GMM) [21] and improved Gaussian Mixture Model [19]. In other studies, feature extraction based techniques are also used for foreground object detection. Wavelet based feature extraction computation model is also applied [23]. These techniques provide an improved performance for moving object detection in camouflage scenes. However, these schemes fails where more occlusion, noise and illumination variations are present in the original data.

1.2 Contribution of the work

Based on previous discussion, it can be identified that moving object detection plays important role in the computer vision based visual surveillance systems. However, several techniques have been discussed to deal with this issue but identification of moving object in camouflage type of scene is an interesting field of research which is still need to be resolved to improve the detection performance. In this work, we focus on the development of a novel scheme where we consider, moving camouflage object detection for dynamic and static.

1.3 Organization

The complete article is organized as follows: section II presents brief study about the recent techniques and methodology present in the moving object detection field for better surveillance. Section III presents a complete proposed solution for camouflage moving object detection, section IV gives an elaborative discussion on experimental setup & results obtained using proposed solution. Finally, section V gives concluding remarks about this work.

2. LITERATURE REVIEW

This section describes the methodology and their outcome of recent techniques. As discussed before, the complete process of camouflage moving object detection is classified into two main categories which are: (a) supervised techniques and (b) unsupervised techniques. Significant amount of works has been carried out using these techniques. Here we discuss some recent techniques of moving object detection using aforementioned schemes.

(a) Supervised/semi-supervisedtechniques of moving object detection

According to supervised technique, a background and foreground structure need to be modeled for processing the video sequence. These algorithms also can be used for tracking the moving object. Based on this assumption, Grabner et al. [24] discussed about the binary classification schemes for object tracking and identified that these techniques suffer from the drifting issue which leads toward the tracking failure due to appearance variations in the moving objects. In order to resolve this issue, authors presented an online boosting approach which helps to reduce the error in tracking. However, in this method first frame is used for labeling the data and the remaining frames are left unlabeled during training phase. Motivated by this, Babenko et al. [25] presented a novel classification approach for object detection and tracking using Multiple Instance Learning (MIL) methodology where trained classifier is used for discriminate the fore ground and back ground of the given frame. In another work, Nam et al. [26] presented CNN (Convolution Neural Network) based learning scheme for visual tracking in video sequences. In this technique, a huge sequence is trained using network pattern learning process. This trained model consists of domain-specific shared layers which corresponds to the individual training sequence. Based on CNN learning approach, Wang et al. [27] presented video tracking scheme using two-layer feature learning scheme. Temporal hierarchical features are learned by embedding the features into a stacked architecture which makes it more robust.

These techniques further can be considered as background subtraction based technique for moving object detection. Farcas et al. [28] a supervised approach for visual object detection using subspace learning scheme known as Incremental Maximum Margin Criterion (IMMC). In this process, the data samples are learned in the subspace manner and eigenvectors are updated incrementally. This technique shows faster computation because of IMMC which doesn't require matrix reconstruction for upcoming data samples. Azim et al. [29] introduced supervised classification scheme for moving object detection for 3D data by considering four different classes as bus, car, bike and pedestrian. According to this model, 3D feature layers are segmented into multiple 2D layers for feature extraction which are later trained using AdaBoost classifier and object classes are identified. In this field of object detection, CNN [51,

55based schemes such as R-CNN and Fast R-CNN have improved the performance of computer vision based object detection. According to a recent study, Kang et al. [30] reported that these techniques are efficient for object detection from still images but results in poor performance for videos where objects are moving. To address this issue, authors presented CNN based approach where contextual and temporal features of tubelets [52] are considered for processing which improves the performance of system.

(b) Unsupervised techniques of moving object detection

In this section we present a brief discussion about recent unsupervised methods for moving object detection. Xiao et al. [31] iterative process moving object detection. This work reports that the conventional methods require a clustered region to train the data which results in poor performance. To mitigate this issue, easy-to-group samples are identified and grouped together to update the appearance model in the temporal adjacent frames. These Spatio-temporal tubes are used for identifying the foreground objects. Elafi et al. [32] introduced a new approach to address the issue of moving object detection. This method uses particle filtering based methodology for background subtraction for detection and tracking of multiple moving objects with considering any prior knowledge and information. discussed about video object segmentation using video saliency based schemes. In order to perform these tasks, a pixel labeling scheme is introduced which uses geodesic distance measurement scheme and performs the temporal saliency measurement. Moreover, pixel-wise segmentation [53, 54] and energy minimization problem is formulated to obtain the object segmentation from the video sequence. Hence, this process can be implemented for object detection video sequences but illumination and other conditions may affect the performance. Koh et al. introduced a concept of primary object discovery in video sequences. According to this approach, color and motion based object are modeled initially using random walk scheme. This process is called as proposal formulation which gives the info about the video frames. Later, foreground confidence is computed and unreliable proposals are removed, this suppression helps to create a robust data model. In this work evolutionary primary object modeling technique is introduced to find the primary objects in the sequence.

(c) Camouflage object detection

Previous sub-sections describe the object detection techniques from moving and static background images. As discussed before, camouflage moving object detection is considered as a challenging task in the field of computer vision applications. Recently, Zhang et al. discussed about the camouflage issue in moving object detection where image background and moving objects contains the visually similar background. However, moving object detection schemes are based on the Discriminative modeling (DM) but camouflage problems cannot be solved using DM hence authors presented camouflage modeling approach which helps to identify the camouflaged foreground pixels. The main complexity in this case it that pixels of both foreground and background are involved in camouflage hence discrimination of these blocks becomes complex. In order to deal with this issue, a combined global model is developed which considers pixels of both regions and identifies the true camouflaged region. Zhang et al. [20] also studied about the camouflage issue in the video analysis and presented camouflage modeling for moving object detection using discriminative feature based modeling (DFM). This modeling suggests that camouflage region information is very much dependent on the foreground and nearby to the background region. Hence, background model and camouflage foreground modeling is presented where later DF and CM are combined and fused to identify the moving objects.

In general, if video frames or images are light camouflaged, in that case, these methods can provide the better performance incomplex camouflaged regions these techniques fail to achieve the desired performance. Based on these assumptions, Li et al. [23]presented a new scheme for camouflage foreground object detection. This scheme uses wavelet domain based strategy for formulating the fusion framework. Initially, wavelet decomposition is applied which provides the basic difference between image domains which is highlighted using wavelet bands. In the next phase, likelihood parameters are computed based on the foreground models and background models which are constructed using wavelet bands. The performance of these approaches also depends on the image quality and image pre-processing phases. According to Bao et al. , based on the image quality, the camouflage can be classified into two main categories as: light and dark camouflage. Existing techniques of camouflage detection are able to recognize the camouflaged foreground object for the test sequences which are having good illumination and lighting conditions but when dark or poor lighting conditions are present then these techniques obtains poor performance. In order to deal with these issue, authors introduced hill-climbing histogram equalization based approach for pre-processing in camouflage moving object detection[49,50]. The complete process is categorized into three main regions as segmentation, enhancement and integration. With the help of this approach, moving camouflaged foreground is identified and later these segmented regions are processed further process of image enhancement using hill-climbing method.

In this section, we have discussed several techniques of moving object detection and camouflage foreground detection. These techniques are based on the motion segmentation, background extraction and foreground extraction using various techniques[51,52]. This study displays that several promising techniques have been introduced for moving object detection but camouflaged foreground detection is still considered as a challenging task.

Table 1 Notations used in this article

Definition	Notation	Definition	Notation
Frames	p	Background	$\mathcal{Z}$
Vector column matrix	$\mathcal{V}$	Smooth factor	γ
Sequence vector	$\mathbb{S}$	Dynamic frame	$\mathcal{D}$
Background	$\mathcal{B}$	Sequence	$\mathcal{S}$
Remaining region	$\mathcal{M}$	Motion mask	$\mathbb{M}$
Sparse matrix control coefficients	β	Position	e
Foreground	$\mathcal{F}$	Optical flow	$\mathcal{Q}$

3. PROPOSED MODEL

This section presents proposed solution for camouflaged moving object detection. The complete process of camouflaged moving object detection is carried out using following stages where first of all we present a problem formulation for camouflage moving object detection and later the proposed method is implemented using following stages:

(a) Motion mask, motion information and optical flow computation.
(b) Low-rank representation of the obtained motion matrix.
(c) Spatial, temporal feature extraction and superpixel segmentation.
(d) Geodesic distance computation model.
(e) Object identification and foreground extraction.

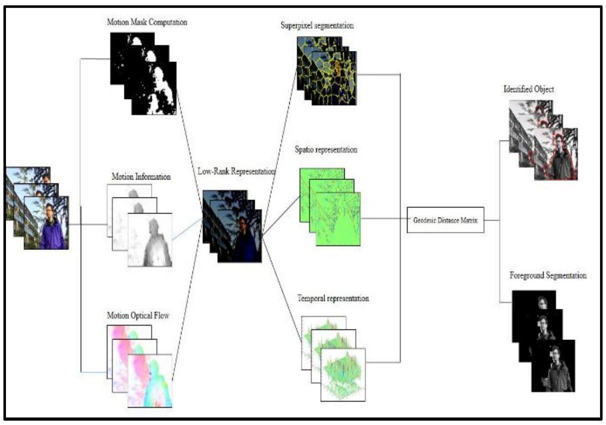

Figure 2 Overall system architecture of proposed approach

(a) Problem formulation

In order to deal with the camouflage foreground moving object detection we consider a frame sequence where total p_t frames are present. To consider the all frame sequence, we construct a column matrix as $\mathcal{V} \in \mathbb{S}^{p_t \times p_h p_v}$ where p_v denotes the width of frame and p_h denotes the height of frames and $\mathbb{S}$ denotes the vectorized sequence. In general cases, video sequence video frame contains a static background hence background region can be expressed as $\mathcal{B} \in \mathbb{S}^{p_t \times p_h p_v}$ and the remaining data as$\mathcal{M} \in \mathbb{S}^{p_t \times p_h p_v}$. With the help of this, $\mathcal{V}$ can be rewritten as $\mathcal{V} = \mathcal{B} + \mathcal{M}$ which is denoted as observation matrix. In this phase, $\mathcal{M}$is considered as sparse matrix. Here, $\mathcal{B}$ and $\mathcal{M}$ are having higher degree of correlation which leads towards the decomposition of background as low-rank and the object detection can be performed by constructing a low-rank representation optimization problem which is expressed as:

$$\min_{\mathcal{B},\mathcal{M}} rank(\mathcal{B}) + \beta \|\mathcal{M}\|_0 \quad subject\ to\ \mathcal{V} = \mathcal{B} + \mathcal{M} \tag{1}$$

Where β denotes the weight controlling parameter of sparse matrix$\mathcal{M}$.

However, the above mentioned low-rank representation for moving object detection is applicable for the scenarios where the background is static but it fails to model the problems where background is dynamic and the sudden illumination variation conditions because the background data cannot be as low-rank model. According to the moving object scenario, the $\mathcal{M}$ contains foreground and moving background data hence it can be decomposed further as foreground($\mathcal{F}$)and dynamic background($\mathcal{Z}$) as $\mathcal{F} \in \mathbb{S}^{p_t \times p_h p_v}$ and $\mathcal{Z} \in \mathbb{S}^{p_t \times p_h p_v}$ respectively. With the help of these assumptions, the optimization problem can be restructured as:

$$\min_{\mathcal{B},\mathcal{M},\mathcal{F},\mathcal{Z}} rank(\mathcal{B}) + \beta_1 \|\mathcal{M}\|_0 + \beta_2 \|\mathcal{Z}\|_0 + \beta_3 \gamma(\mathcal{F}) \quad subject\ to\ \mathcal{V} = \mathcal{B} + \mathcal{M} \text{ where } \mathcal{M} = F + \mathcal{Z} \tag{2}$$

Whereβ_1,β_2 and β_3 denote the weight controlling factor, γ denotes the function for spatial coherent and temporal smooth background which is performed by using total variation norm[4] as:

$$\min_{\mathcal{B},\mathcal{M},\mathcal{F},\mathcal{Z}} rank(\mathcal{B}) + \beta_1 \|\mathcal{M}\|_0 + \beta_2 \|\mathcal{Z}\|_0 + \beta_3 \|\mathcal{F}\|_{TV} \quad subject\ to\ \mathcal{V} = \mathcal{B} + \mathcal{M} \text{ where } \mathcal{M} = F + \mathcal{Z} \tag{3}$$

Where $\|\mathcal{F}\|_{TV}$ denotes the total variation function. With the help of this optimization problem, we represent the background model as low-rank. However, due to dynamic background, some error may occur during the reconstruction of low-rank matrix hence the optimization of this problem can help to minimize the error and identifying the accurate background for segmentation.

(b) Background motion approximation

In order to minimize the error for accurate segmentation of background, we apply the motion approximation process which helps to identify the motion mask and motion field which helps to discriminate the foreground and background pixels. This motion information is obtained by applying the optical flow computation for the given sequential frames. In this work, given video sequence is denoted by $\mathcal{S}$ and dynamic frames are given as$\mathcal{D}$. With the help of optical flow model, we estimate he motion mask and motion field model for the considered consecutive frame. Let us consider that two consecutive video frames are given as s_i and s_{i-1} at time t and $t-1$, respectively whose horizontal (x direction)and vertical (y direction) motion vector components are denoted as $v_{i,e}^{x}$ and $v_{i,e}^{y}$ respectively. Let $\mathbb{M}$ denote the motion mask which is in the form as $\mathbb{M} \in \{0,1\}$ which can be computed as:

$$\mathbb{M}_{i,k} = f(x) = \begin{cases} 1, & if \sqrt{\left(v_{i,e}^{x}\right)^2 + \left(v_{i,e}^{y}\right)^2} < \tau \\ 0, & otherwise \end{cases} \quad (4)$$

Where τ denotes the motion magnitude threshold value. This can be computed by taking the average pixel value in the obtained motion field. If the value of thee computed motion is larger than the threshold, then it is assigned as foreground pixel otherwise it is considered as background pixel.

(c) Proposed motion-aware camouflage modeling

In this section, we present thefunction for the optimization problem given in (1) using low-rank representation. The motion analysis method is called ass Motion-aware camouflage Modeling (**MACM**). Given sequence is $\mathcal{D} \in \mathbb{S}^{p\times c}$ where c denotes the total number of dynamic frames. Here, our aim is to compute the $\mathcal{B}$ in the low-dimensional subspace. In this stage, we define a motion matrix as $M \in \mathbb{S}^{p\times c}$ which is obtained by eq. (2) as$[\mathbb{M}_1, \mathbb{M}_2, \dots, \mathbb{M}_c]$. We consider the $\mathcal{D}$ matrix for evaluation and identify the pixels with 0 as pixel value and denote this as missing data in M. Main aim to optimize the error for improved performance for background pixel identification, as given in (3), it can be simplified as:

$$\min_{\mathcal{B},\mathcal{F}} \|\mathcal{B}\|_* + \beta_1 \|\mathcal{F}\|_1 \text{ such that } M \circ \mathcal{D} = \left((\mathcal{B} + \mathcal{F}) \circ M\right) \quad (5)$$

The obtained observation matrix $(M \circ \mathcal{D})$ still carries some outliers which can affect the performance of background subtraction process. In order to deal with this issue, we apply Spatio temporal data modeling which helps to identify the frame data. In order to obtain the Spatio temporal representation of input frame, we apply spatial edge map computation, superpixel segmentation and motion boundary detection. Later, Geodesic distance computation is applied to identify the relevance of the superpixel i.e. background and foreground pixel identification. Based on the computation of Spatio-temporal and Geodesic distance based models we refine the optimization problem as:

$$\min_{\mathcal{B},\mathcal{F}} \|\mathcal{B}\|_* + \Psi_c(\mathcal{B},\mathcal{F}) + \Psi_g(\mathcal{B},\mathcal{F}) + \beta_1 \|\mathcal{F}\|_1 \text{ such that } M \circ \mathcal{D} = \left((\mathcal{B} + \mathcal{F}) \circ M\right) \quad (6)$$

Ψ_c and Ψ_g denotes Spatio temporal coefficient and geodesic distance coefficients. This function is related to the $\mathcal{D}$ and $\mathcal{B}$ and be related with the $\mathcal{B}$ and $\mathcal{F}$ as:$\Psi_c(\mathcal{B},\mathcal{D}) = \Psi_c(\mathcal{F}+\mathcal{B},\mathcal{B}) = \Psi_c(\mathcal{B},\mathcal{F})$. Hence, geodesic distance and Spatio-temporal correlation coefficients can be expressed as:

$$\begin{aligned} \Psi_c(\mathcal{B},\mathcal{F}) &= \frac{\rho_1}{2} Tr(\mathcal{B}^\intercal \mathcal{B} \mathcal{L}_s^c) + \frac{\rho_2}{2} Tr(\mathcal{B}^\intercal \mathcal{B} \mathcal{L}_t^c) \\ \Psi_g(\mathcal{B},\mathcal{F}) &= \frac{\rho_3}{2} Tr\left(\mathcal{B}^\intercal \mathcal{B} \mathcal{L}_s^g\right) + \frac{\rho_4}{2} Tr\left(\mathcal{B}^\intercal \mathcal{B} \mathcal{L}_t^g\right) \end{aligned} \quad (7)$$

Here we minimize the values of $tr(\mathcal{B}^\intercal \mathcal{B} \mathcal{L}_s^c), tr(\mathcal{B}^\intercal \mathcal{B} \mathcal{L}_t^c), tr\left(\mathcal{B}^\intercal \mathcal{B} \mathcal{L}_s^g\right)$ and $tr\left(\mathcal{B}^\intercal \mathcal{B} \mathcal{L}_t^g\right)$with the help of Spatio-temporal regularization.

(d) Spatio-temporal regularization, geodesic distance and super pixel modeling

In this sub-section, we present Spatio-temporal regularization, geodesic based graph construction and superpixel segmentation model. Let us consider $\mathcal{S} = [s_1, s_2, \dots, s_t]$ sequence whose probability map is computed as $\mathcal{P}_c^t(x_i^t)$ which corresponds to the k^{th} frame s_k at pixel x_i^k. As discussed before, we compute the optical flow for the consecutive frames which is denoted as $\mathcal{Q}$, let $\mathcal{Q}^t$ be the optical flow of frame s_k, hence the gradient magnitude of this can be given as $\mathcal{E}_o^t = \|\nabla \mathcal{Q}^t\|$. Further, we apply superpixel segmentation and denote it as $\mathcal{W}_k = \{w_1^t, w_2^t, \dots w_k^t\}$. With the help of pixel edge map $\mathcal{E}_c^k$, edge probability of each super pixel $\mathcal{W}_n^k$ can be computed by taking the ten largest edge probability values. This helps to generate the superpixel edge map $\hat{\mathcal{E}}_c^k$. In next phase, superpixel optical flow map is computed ass $\hat{\mathcal{E}}_o^k$. With the help of these measurements, the spatiotemporal edge probability can be given as:

$$\mathcal{E}_k = \hat{\mathcal{E}}_c^k . \hat{\mathcal{E}}_o^k \quad (8)$$

At this stage, we consider geodesic distance measurement to discriminate the visual regions from the background and compute the likelihoods for foreground. In order to perform this task, we construct a undirected graph as $G_k = \{\mathbb{V}_k, \mathbb{E}_k\}$ with superpixel data as $\mathcal{W}_k$. The weights of superpixel which can be given as:

$$e_{mn}^k = \|\mathcal{E}_k(\mathcal{W}_m^k) - \mathcal{E}_k(\mathcal{W}_n^k)\| \quad (9)$$

$\mathcal{E}_k(\mathcal{W}_m^k)$ and $\mathcal{E}_k(\mathcal{W}_n^k)$ denotes the Spatio-temporal boundary values of corresponding superpixel. Based on thi obtained graph structure $|\mathbb{V}_k| \times |\mathbb{V}_k|$, we compute the weight matrix as $\mathbb{W}_k$. The (m, n) elements of this matrix are given as $\mathbb{W}_k(m, n) = e_{mn}^k$. At this stage, for each superpixel data the probability of foreground is computed based on the shortest geodesic distance to the image boundaries which can be expressed as:

$$P_n^k = \min_{\mathcal{J} \in \mathcal{J}^k} d_{geo}\,(W_n^k, \mathcal{J}, G_k) \quad (10)$$

Where $\mathcal{J}^k$ denotes the superpixel in the obtained image boundary, geodesic distance is computed between tow superpixel $v_1, v_2 \in |\mathbb{V}_k|$ and can be expressed as $d_{geo}(v_1, v_2, G_k)$. This distance can be computed as:

$$d_{geo}(v_1, v_2, G_k) = \min_{C_{v_1,v_2}} \sum_{\wp=0,1} \mathbb{W}_k \,.\, C_{v_1,v_2}(\wp) \quad (11$$

where$C_{v_1,v_2}(\wp)$ denotes the node connectivity where $\wp$ denotes the connecting status for v_1, v_2. If the obtained superpixel is outside from the desired object, the foreground probability is small because image boundaries are not passing the spatiotemporal region whereas of the superpixel is inside the desired object then it has higher probability of edges which leads towards the increased distance from image boundaries.

(e) Optimization stage

As of now, we have obtained the background and foreground region pixels based on the aforementioned computations. Here we present a further optimization process using augmented Lagrangian formulation which is expressed as:

$$\begin{aligned}\mathcal{L}(\mathcal{B}, \mathcal{F}, \mathbb{L}, \omega) = \min_{\mathcal{B},\mathcal{F}} \|\mathcal{B}\|_* + \Psi_g(\mathcal{B}, \mathcal{F}) \\ + \Psi_c(\mathcal{B}, \mathcal{F}) \\ +\beta_1 \|\mathcal{F}\|_1 + tr\big(Y(M \circ (\mathcal{D} - \mathcal{B} - \mathcal{F})\big) \\ + \frac{\omega}{2} \|M \circ (\mathcal{D} - \mathcal{B} - \mathcal{F})\|_{\mathcal{F}}^2\end{aligned} \quad (12)$$

Where $\mathbb{L} \in \mathbb{S}^{c \times p}$ denotes a Lagrangian multiplier matrix and $\omega > 0$ denotes the penalty factor for violating the optimization constraints. Here, we present an optimal solution where first we update parameter of $\mathcal{B}$ by keeping other parametersas constant and later we present the update process of $\mathcal{F}$ by keeping other parameters as constant. First of all, we present the updating process of $\mathcal{B}$ when other parameters are fixed. This can be denoted as:

$$\mathcal{B}^{k+1} = \operatorname{argmin} \mathcal{L}_\omega(\mathcal{B}^k, \mathcal{F}^k, M^k, \mathbb{L}) \quad (13$$

The updated solution can be written by computing the SVD for the given set as:

$$\begin{aligned}(\mathcal{U}.\Omega, \mathbb{V}) = SVD(O - M^k + \frac{1}{\omega^k} X^k) \\ \mathcal{B}^{k+1} = \mathcal{U}\mathcal{N}_{\frac{1}{\omega^k}}(\Omega)\mathbb{V}^T\end{aligned} \quad (14)$$

$\mathcal{U}\Omega\mathbb{V}^T$ denotes a monotonically increasing sequence which is singular value decomposition of $(O - M^k + \frac{1}{\omega^k} X^k)$ and $\mathcal{N}$ denotes the shrinkage scalar operator which is given as $\mathcal{N}_{\varepsilon>0}(.) = sgn(x)\max(|x| - \varepsilon, 0)$. Similarly, we update the parameter of $\mathcal{F}$ by fixing. Hence the problem can be rewritten as:

$$\begin{aligned}\mathcal{F}_{k+1} = \operatorname*{argmin}_{\mathcal{F}} \mathcal{L}\,(\mathcal{B}_{k+1}, \mathcal{F}, \mathbb{L}_k, \omega_k) \\ = \operatorname*{argmin}_{\mathcal{F}} \beta \,\|\mathcal{F}\|_1 \\ + Tr\Big(\mathbb{L}\big(M \\ \circ (\mathcal{D} - \mathcal{B}_{k+1} - \mathcal{F})\big)\Big) \\ + \frac{\omega_k}{2} \big\|\big(M \\ \circ (\mathcal{D} - \mathcal{B}_{k+1} - \mathcal{F})\big)\big\|_{\mathcal{F}}^2\end{aligned} \quad (15$$

The closed form solution for this problem can be written as:

$$\mathcal{F}_{k+1} = \frac{\mathcal{N}_\beta}{\omega_k}(M \circ (\mathcal{D} - \mathcal{B}_{k+1}) + \frac{\mathbb{L}_k}{\omega_k} \quad (16)$$

With the help of this closed form solution the updated foreground can be obtained for each current frame and this process is repeated until the entire frames are analyzed. This approach helps to extract the foreground object from the camouflage frame.

4. Results and discussion

In this section, we present an extensive experimental study for camouflage moving object detection, tracking and segmentation using proposed Motion-Aware Camouflage Modeling (MACM). The proposed approach is implemented on different type of datasets using MATLAB simulation tool and performance of proposed approach is compared with the existing techniques of camouflage moving object detection methods.

Experiment 1: CAMO_UOW dataset [23]

This dataset includes 10 real time captured scenes which includes in-house and out-of-house case. This dataset includes 10 video sequences with multiple resolution and different type of formats (grayscale and RGB). The complete details of this dataset is given in table 2. These sequence are camouflaged sequence because the user wears the similar clothes to the background. Ground truth data is manually labeled for all frames.

Table 2 CAMO_UOW Dataset details

Video Sequence	Total Frames	Resolution	Format
Sequence 1	371	1620 × 1200	Grayscale
Sequence 2	176	1620 × 1200	Grayscale
Sequence 3	371	1620 × 1200	Grayscale
Sequence 4	371	1620 × 1200	Grayscale
Sequence 5	371	1620 × 1200	Grayscale
Sequence 6	373	1620 × 1200	Grayscale
Sequence 7	272	1920 × 1080	RGB
Sequence 8	466	1920 × 1080	RGB
Sequence 9	288	1920 × 1080	RGB
Sequence 10	458	1920 × 1080	RGB

The performance of proposed approach is carried out in terms of F-Measure and compared with the several popular state-of-art techniques such as "MOG2 [19]", Fuzzy integral , Adaptive SOM , MultiLayer [40], SuBSENSE [41], Pixel based adaptive segmentation [42], DECOLOR [43], COROLA [44] and FWFC [23]. The comparative performance in terms of F-measure for camouflage moving object detection is presented in table 3.

Table 3 F-score comparison

Sequence	MOG2 [19]	Fuzzy	ASIM	ML [40]	SuBSENSE [41]	Pixel based [42]	DECOLOR [43]	COROLA [44]	FWFC [23]	MACM
S1	0.79	0.88	0.8	0.9	0.89	0.89	0.92	0.80	0.94	0.95
S2	0.82	0.79	0.8	0.82	0.88	0.8	0.83	0.58	0.96	0.96
S3	0.88	0.86	0.85	0.91	0.9	0.8	0.9	0.82	0.94	0.96
S4	0.89	0.9	0.76	0.93	0.78	0.88	0.95	0.87	0.94	0.95
S5	0.84	0.86	0.82	0.83	0.82	0.8	0.82	0.75	0.91	0.94
S6	0.93	0.87	0.77	0.95	0.92	0.95	0.97	0.72	0.94	0.95
S7	0.76	0.83	0.88	0.91	0.87	0.79	0.91	0.83	0.96	0.98
S8	0.83	0.87	0.85	0.87	0.93	0.86	0.86	0.68	0.96	0.94
S9	0.89	0.9	0.87	0.84	0.92	0.87	0.86	0.78	0.88	0.95
S10	0.89	0.86	0.89	0.91	0.90	0.90	0.94	0.85	0.96	0.98
Avg.	0.852	0.862	0.829	0.887	0.881	0.854	0.896	0.768	0.939	0.956

This comparative study shows that the proposed approach achieves significant performance for these type of camouflaged moving objects where background is static.

Proposed approach achieves average F-measure performance as 95.6% which shows a significant improvement in the performance.

Based on the obtained foreground detection, we compute the other performance measurement parameters such as average precision, average recall and average F-measure. Comparative performance of these measurements is depicted in table4.

Table 4 Avg. precision, Avg. Recall and Avg. F-measure performance

Technique Used	Precision	Recall	F-Measure
MOG2 [19]	0.89	0.68	0.74
Fuzzy	0.9	0.64	0.71
ASIM	0.78	0.81	0.78
ML[40]	0.91	0.72	0.79
SuBSENSE [41]	0.89	0.76	0.78
Pixel Based [42]	0.95	0.61	0.71
DECOLOR [43]	0.92	0.75	0.8
COROLA [44]	0.79	0.76	0.76
FWFC [23]	0.85	0.9	0.87
MACM (Proposed)	0.94	0.93	0.95

The above experiment is conducted for camouflage moving objects where background scenes are static.

In this work we present another experimental study which is conducted for the video sequences where background scene are dynamic.

(i) Dynamic background moving object detection

This section presents experimental study for the moving object detection where background scenes are dynamic and foreground objects are moving. In order to perform this experiment, we have considered CDnet 2014 dataset [45] which contains total 11 videos of different categories which are known as bad weather, dynamic background and baseline and so on. To show the performance of our work, we have considered dynamic background sequence which has six different categories named as Boats, Canoe, Fountain01, Fountain02, Overpass and fall. The performance of proposed approach is compared with the existing techniques which are: IGMM technique [21], codebook [22], ViBe technique [46], SOBS technique [17], SuBSENSE [41], LBSP technique [47], PAWCS technique [48] and Spatio-temporal classification [49].

In order to show the performance of proposed approach we randomly selected video frames and performed the background subtraction model. The considered frames are as follows: Boat sequence 1996th frame, 960th frame in canoe, 719th frame in Fountain01, 1268th frame in fountain02 sequence, 2452nd sequence in overpass sequence and 3982nd frame in fall sequence. The results of background subtraction are depicted in figure 3.

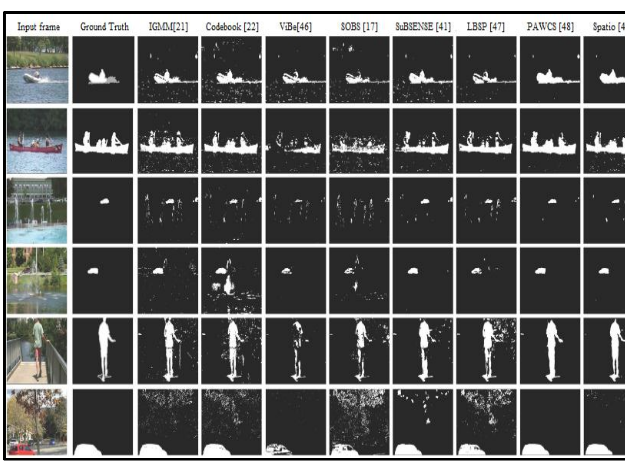

Figure 3 Foreground detection results of IGMM [21], Codebook [22], ViBe [46], SOBS [17], SuBSENSE [41], LBSP [47], PAWCS [48], STC [49] and proposed approach.

Based on the experiments, we have computed the performance measurement matrices as precision and recall and compared the performance with the aforementioned existing techniques. A comparative performance in terms of precision, recall and F-measure is given in table 5.

Table 5 Comparative performance for CDN 2014 Database

Sequence	**Evaluation metrics**	**IGMM [21]**	**Codebook [22]**	**ViBe [46]**	**SOBS [17]**	**SuBSENSE [41]**	**LBSP [47]**	**PAWCS [48]**	**STC [49]**	**Proposed Approach**
Boats	Precision	0.46	0.32	0.39	0.44	0.43	0.66	0.75	0.81	0.89
	Recall	0.85	0.88	0.77	0.74	0.86	0.74	0.92	0.89	0.91
	F-Measure	0.6	0.47	0.52	0.55	0.58	0.69	0.83	0.85	0.90
Canoe	Precision	0.50	0.60	0.73	0.52	0.73	0.80	0.79	0.87	0.92
	Recall	0.50	0.60	0.73	0.52	0.73	0.80	0.79	0.87	0.91
	F-Measure	0.638	0.70	0.61	0.60	0.75	0.80	0.84	0.86	0.95
Fountain01	Precision	0.222	0.29	0.21	0.14	0.58	0.31	0.85	0.36	0.92
	Recall	0.26	0.21	0.14	0.14	0.26	0.24	0.197	0.24	0.62
	F-Measure	0.224	0.24	0.17	0.14	0.36	0.27	0.32	0.292	0.66
Fountain02	Precision	0.222	0.29	0.21	0.14	0.58	0.31	0.85	0.36	0.89
	Recall	0.26	0.21	0.14	0.14	0.26	0.24	0.197	0.24	0.62
	F-Measure	0.718	0.42	0.54	0.58	0.83	0.76	0.83	0.84	0.91
Overpass	Precision	0.68	0.48	0.84	0.59	0.75	0.61	0.87	0.93	0.95
	Recall	0.83	0.86	0.42	0.68	0.78	0.83	0.90	0.87	0.93
	F-Measure	0.74	0.61	0.55	0.63	0.72	0.70	0.89	0.90	0.93
Fall	Precision	0.28	0.25	0.62	0.16	0.59	0.27	0.90	0.91	0.94
	Recall	0.98	0.97	0.52	0.72	0.78	0.81	0.90	0.86	0.93
	F-Measure	0.434	0.39	0.54	0.26	0.70	0.40	0.91	0.91	0.94

The above given table 5 shows a comparative performance analysis using CDN 2014 database. In this table, we have presented various performance measurement parameters such as precision, recall and F-measure. The complete experimental study shows that the proposed approach obtained significant improvement in the foreground segmentation using proposed approach.

5. CONCLUSION

In this article, we have focused on the moving object detection from the static and dynamic video sequences along with this, we have considered a dynamic background scenarios where moving objects are camouflaged. The proposed approach considered both static and dynamic background along with moving camouflaged objects. According to this study, the camouflage object detection and foreground subtraction problem is formulated as low-rank representation problem where first of all we apply pre-processing phase. In this phase, motion related information and optical flow models are computed for the given frames. In next phase, we apply, low-rank representation approach which helps to obtain the optimal solution for the given problem using Lagrangian method. Further, we apply superpixel segmentation, spatial and temporal feature extraction which are used to represent the geodesic distance and later the obtained information are used for identification of the object and segmentation. Experimental study shows a significant improvement in the foreground object detection and segmentation when compared with the existing techniques.

REFERENCES

1. A. Yilmaz, O. Javed, and M. Shah, “Object tracking: A survey,” ACM computing surveys, vol. 38, no. 4, pp. 1–45, 2006.
2. T. Moeslund, A. Hilton, and V. Kruger, “A survey of advances in vision-based human motion capture and analysis,” Comput. Vis. Image Und., vol. 104, no. 2-3, pp. 90–126, 2006.
3. Bouwmans, T., 2014. Traditional and recent approaches in background modeling for foreground detection: An overview. Computer Science Review, 11, pp.31-66.
4. Cao, X., Yang, L. and Guo, X., 2016. Total variation regularized RPCA for irregularly moving object detection under dynamic background. IEEE transactions on cybernetics, 46(4), pp.1014-1027.
5. Yazdi, M. and Bouwmans, T., 2018. New trends on moving object detection in video images captured by a moving camera: A survey. Computer Science Review, 28, pp.157-177.
6. Chen, C., Jafari, R. and Kehtarnavaz, N., 2017. A survey of depth and inertial sensor fusion for human action recognition. Multimedia Tools and Applications, 76(3), pp.4405-4425.
7. Eum, H., Yoon, C., Lee, H. and Park, M., 2015. Continuous human action recognition using depth-MHI-HOG and a spotter model. Sensors, 15(3), pp.5197-5227.
8. Lan, T., Zhu, Y., RoshanZamir, A. and Savarese, S., 2015. Action recognition by hierarchical mid-level action elements. In Proceedings of the IEEE International Conference on Computer Vision (pp. 4552-4560).
9. Chen, C., Liu, K. and Kehtarnavaz, N., 2016. Real-time human action recognition based on depth motion maps. *Journal of real-time image processing*, *12*(1), pp.155-163.
10. Shaikh, S.H., Saeed, K. and Chaki, N., 2014. Moving object detection using background subtraction. In Moving Object Detection Using Background Subtraction (pp. 15-23). Springer, Cham.
11. Han, X., Gao, Y., Lu, Z., Zhang, Z. and Niu, D., 2015, September. Research on moving object detection algorithm based on improved three frame difference method and optical flow. In Instrumentation and Measurement, Computer, Communication and Control (IMCCC), 2015 Fifth International Conference on (pp. 580-584). IEEE.
12. Kajo, I., Malik, A.S. and Kamel, N., 2016, August. An evaluation of optical flow algorithms for crowd analytics in surveillance system. In Intelligent and Advanced Systems (ICIAS), 2016 6th International Conference on (pp. 1-6). IEEE.
13. Wu, Y., He, X. and Nguyen, T.Q., 2017. Moving object detection with a freely moving camera via background motion subtraction. IEEE Transactions on Circuits and Systems for Video Technology, 27(2), pp.236-248.
14. Maddalena, L. and Petrosino, A., 2014. The 3dSOBS+ algorithm for moving object

detection. Computer Vision and Image Understanding, 122, pp.65-73.
15. Zhang, K., Liu, Q., Wu, Y. and Yang, M.H., 2016. Robust visual tracking via convolutional networks without training. IEEE Transactions on Image Processing, 25(4), pp.1779-1792.
16. Z. Zivkovic and F.V.D. Heijden," Efficient adaptive density estimation per image pixel for the task of background subtraction," Pattern Recognition Letters, vol. 27, no. 7, pp. 773-780, Jul. 2006.
17. Zhang, X. and Zhu, C., 2015, July. Camouflage modeling for moving object detection. In Signal and Information Processing (ChinaSIP), 2015 IEEE China Summit and International Conference on (pp. 249-253). IEEE.
18. ZoranZivkovic, "Improved adaptive gaussian mixture model for background subtraction," in Proceedings of the 17th International Conference on Pattern Recognition. IEEE, 2004, vol. 2, pp. 28–31.
19. Kim, K., Chalidabhongse, T.H., Harwood, D., et al.: 'Real-time foreground-background segmentation using codebook model', Real-Time Imaging, 2005, 11, (3), pp. 172–185.
20. Li, S., Florencio, D., Li, W., Zhao, Y. and Cook, C., 2018. A Fusion Framework for Camouflaged Moving Foreground Detection in the Wavelet Domain. IEEE Transactions on Image Processing, 27(8), pp.3918-3930.
21. Grabner, H., Leistner, C. and Bischof, H., 2008, October. Semi-supervised on-line boosting for robust tracking. In European conference on computer vision (pp. 234-247). Springer, Berlin, Heidelberg.
22. Babenko, B., Yang, M.H. and Belongie, S., 2009, June. Visual tracking with online multiple instance learning. In Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on (pp. 983-990). IEEE.
23. Nam, H. and Han, B., 2016. Learning multi-domain convolutional neural networks for visual tracking. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 4293-4302).
24. Wang, L., Liu, T., Wang, G., Chan, K.L. and Yang, Q., 2015. Video tracking using learned hierarchical features. IEEE Transactions on Image Processing, 24(4), pp.1424-1435.
25. D. Farcas, C. Marghes, T. Bouwmans, Background subtraction via incremental maximum margin criterion: A discriminative approach, Mach. Vis. Appl. 23 (6) (2012) 1083–1101.
26. Azim, A. and Aycard, O., 2014, June. Layer-based supervised classification of moving objects in outdoor dynamic environment using 3D laser scanner. In Intelligent Vehicles Symposium Proceedings, 2014 IEEE (pp. 1408-1414). IEEE.
27. Kang, K., Li, H., Yan, J., Zeng, X., Yang, B., Xiao, T., Zhang, C., Wang, Z., Wang, R., Wang, X. and Ouyang, W., 2016. T-CNN: Tubelets with convolutional neural networks for object detection from videos. arXiv preprint arXiv:1604.02532.
28. Xiao, F. and Lee, Y.J., 2016, June. Track and Segment: An Iterative Unsupervised Approach for Video Object Proposals. In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 933-942). IEEE.
29. Elafi, I., Jedra, M. and Zahid, N., 2016. Unsupervised detection and tracking of moving objects for video surveillance applications. Pattern Recognition Letters, 84, pp.70-77.
30. Koh, Y.J. and Kim, C.S., 2017. Unsupervised Primary Object Discovery in Videos Based on Evolutionary Primary Object Modeling With Reliable Object Proposals. IEEE Transactions on Image Processing, 26(11), pp.5203-5216.
31. Zhang, X., Zhu, C., Wang, S., Liu, Y. and Ye, M., 2017. A Bayesian approach to camouflaged moving object detection. IEEE Transactions on Circuits and Systems for Video Technology, 27(9), pp.2001-2013.
32. Bao, L., Panetta, K. and Agaian, S., 2018, May. Hill climbing-based histogram equalization for camouflage object detection. In Mobile Multimedia/Image Processing, Security, and Applications 2018 (Vol. 10668, p. 106680H). International Society for Optics and Photonics.
33. F. El Baf, T. Bouwmans, and B. Vachon, "Fuzzy integral for moving object detection," in IEEE International Conference on Fuzzy Systems, 2008, pp. 1729–1736.
34. L. Maddalena and A. Petrosino, "A self-organizing approach to background

subtraction for visual surveillance applications," IEEE Transactions on Image Processing, vol. 17, no. 7, pp. 1168–1177, 2008.

35. Wang, Y., Jodoin, P.M., Porikli, F., et al.: 'CDnet 2014: An expanded change detection benchmark dataset'. Computer Vision and Pattern Recognition Workshops, Ohio, USA, 2014, pp. 393–40.
36. Barnich, O., Van, D.M.: 'Vibe: a universal background subtraction algorithm for video sequences', IEEE Trans. Image Process., 2011, 20, (6), p. 1709– 1724.
37. St-Charles, P.L., Bilodeau, G.A.: 'Improving background subtraction using local binary similarity patterns'. Applications of Computer Vision, Colorado, USA, 2014, pp. 509–515.
38. St-Charles, P.L., Bilodeau, G.A., Bergevin, R.: 'Universal background subtraction using word consensus models', IEEE Trans. Image Process., 2016, 25, (10), pp. 4768–4781.
39. Li, X., Li, G. and Jiang, Q., 2018. Dynamic background subtraction method based on spatio-temporal classification. *IET Computer Vision*, *12*(4), pp.492-501.
40. Prediction Of Stock Market Exchange Using LSTM Algorithm K.SaiSravani, Dr.P.rajarajeswari, International Journal Of Scientific &Technology Research Volume 9, Issue 03, March 2020 Issn 2277-8616.
41. A Novel Hybrid Framework for Cuff-Less Blood Pressure Estimation based On Vital Bio Signals processing using Machine Learning Santosh. A. Shinde , Dr. P. Raja Rajeswari, International Journal of Advanced Trends in Computer Science and Engineering, Volume 9 No.2, March -April 2020.
42. A Deep Learning Approach For Brain Tumor Segmentation using Convolution Neural Network AmulyaP[1]*, SaiMeghana S[2], Manisha A[3], Rajarajeswari P International Journal of Scientific and Technology Research, December 2019.

44. Mohammed Ismail B , K. Bhanu Prakash, M. Nagabhushana Rao "Collaborative Filtering-Based Recommendation of Online Social Voting" International journal of Engineering and Technology" (3) 1504-1507 July 2018.
45. The performance of proposed approach is carried out in terms of F-Measure and compared with the several popular state-of-art techniques such as "MOG2 [19]", Fuzzy integral , Adaptive SOM , MultiLayer [40], SuBSENSE [41], Pixel based adaptive segmentation [42], DECOLOR [43], COROLA [44] and FWFC [23]. The comparative performance in terms of F-measure for camouflage moving object detection is presented in table 3.
46. Vidyullathapellakuri, "Performance analysis of machine learning techniques for intrusion detection system", 2019Proceedings – 2019, 5th International Conference on Computing, Communication Control and Automation, ICCUBEA 2019.
44. Sajana T and Narasingarao, "A comparative study on imbalanced malaria disease diagnosis using machine learning techniques. Journal of Advanced Research in Dynamical and Control Systems, 2018, 10,552-56.
45. Detection of Community within Social Networks with Diverse Features of Network Analysis PranavatiJadhav and Dr.BurraVijayaBabuJournal of Advanced Research in Dynamical and Control Systems ISSN: 1943-023X Volume 11 | 12-Special Issue Pages: 366-371.2019.

46. YanishPradhananga, PothurajuRajarajeswari, Tiarrah Computing: The Next Generation of Computing, International journal of Electrical and Computer Engineering 81(2),pp. 1247-1255. 2018.
47. Dr.P.RajaRajeswari, Supriyamenon.M, A contemporary way for enhanced modeling of context aware privacy system in PPDM. Journal of Advanced Research in Dynamic and Control systems,Vol.10,01-issue,July 2018.
48. Angel Prathyusha K, Mahitha.Y, RajaRajeswari.P, A survey on prediction of Suitable crop selection for Agriculture Development using Data Mining Classification Techniques,International Journal of Engineering and Technology, Article ID:14498, DOI: 10.14419/ijet.v7i3.3.14498 ,vol 7, No.3.3 (2018).
49. M.Supriyamenon , Dr. P.Rajarajeswari A Review on Association Rule Mining Techniques with respect to their Privacy Preserving Capabilities (KLEF), International Journal of Applied Engineering Research July 2017 ,ISSN 0973-4562 Volume 12, Number 24 (2017) pp. 15484-15488.

50. Rita R Kamble and Dr.P. Raja Rajeswari, "A review of various camouflage moving object detection techniques", Journal of Engineering and Applied Sciences 2017.
51. "Improved Prediction of Diabetes based on Glucose Levels in blood using Data Science Algorithms" Sowjanya V, Divyambica CH, Gopinath P, Vamsidhar M, B.VijayaBabu, International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249-8958, Volume-8 Issue-4, April 2019.
52. Sajana T and Narasingarao, "A comparative study on imbalanced malaria disease diagnosis using machine learning techniques. Journal of Advanced Research in Dynamical and Control Systems, 2018, 10,552-56.
53. kumar S.A, Vidyullatha P, "A comparative analysis of parallel and distributed FSM approaches on large-scale graph data", International Journal of Recent Technology and Engineering, Volume 7, Issue 6, April 2019, Pages 103-109.
54. Vidyullathapellakuri, "Performance analysis of machine learning techniques for intrusion detection system", 2019Proceedings - 2019 5th International Conference on Computing, Communication Control and Automation, ICCUBEA 2019.