OBJECT TRACKING BASED ON BAYESIAN MONTE CARLO EMPLOYING PARTICLE GAUSSIAN INFORMATION FILTER

K.Saravanan[1] and P. Hima Bindu[2]

[1]Professor/ Department of Computer Engineering, Shadan Women's College of Engineering and Technology, Khairtabad, Hyderabad
[2]Vice principal and Professor, Shadan Women's College of Engineering and Technology, Khairtabad, Hyderabad

ABSTRACT

VISUAL tracking is one of the rapidly developing fields of computer vision. In visual field, Object tracking is a significant task in various computer vision applications like surveillance, augmented reality, human-computer interfaces and medical imaging. Moving object detection and tracking is an essential image processing analysis in several applications for crowd monitoring. Moving object detection is utilized to enhance the image processing analysis. The object detection method is employed to detect the moving object areas with different size of objects and video progression. Then, Object tracking is vital condition for every logical video surveillance system. The existing work presented a Cognitive Control Inspired Approach (CCIA) for extended targets. Here, the two Kalman filters are used in visual tracking systems to predict the object motion depends on it size. Cognitive Perceptor unit measurement is processed from environment field to make representation of external world. Cognitive Control Unit described a set of actions and it evaluates the hidden variable by Hidden Markov Model. However, object tracking was difficult and consume more time in outdoor environments. In addition to, redundant and unwanted information were not removed with higher signal to noise ratio. The performance of object tracking accuracy was not efficiently enhanced.

In order to solve the above problems, Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme is proposed for object tracking to increase the accuracy for tracking the object. Bayesian approach is used for state estimation to reduce the signal to noise ratio. Initially, the Bayesian State Estimator using Monte Carlo Particle Simulation (MCPS) is estimated the set of particles (i.e. objects) with associated weighted via posterior density. As a Bayesian estimator, particle simulation considered two main steps namely prediction and update by using particle information filter for object tracking. Then, Monte Carlo Particle State Estimator algorithm is employed for achieving the object tracking accuracy from state estimation by removing unwanted and redundant information. Finally, the Gaussian Information Filter scheme is applied with the estimated state to track the original object with noise reduction. Gaussian Information Filter scheme is described by information matrix and information vector to detect the multiple moving objects. The performance of proposed Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme is analyzed against with the following metrics such as Signal-to-noise ratio, Object tracking accuracy and Mean square error with respect to number of objects.

KEYWORDS

Cognitive Control Inspired Approach (CCIA), Monte Carlo Particle Simulation (MCPS)

1. INTRODUCTION

Detection and tracking of moving objects are a significant research area in a multiple system. Object tracking is exploited in several applications such as video compression, surveillance, robot technology and so on. Recently many researches have been developed for moving object detection. The object detection process is utilized to identify the moving object areas with dissimilar size of objects and video progression. Moving object detection is utilized to enlarge the image processing analysis. The perfect detection and classification of moving objects is a significant feature of advanced assistance scheme.

There are many approaches used in object tracking system such that

- Point-based approach
  - ➢ Kalman filter
  - ➢ Particle filter
- Contour-based approach
  - ➢ Shape matching
- Kernel-based approach
  - ➢ Generative methods
  - ➢ Discriminative methods
  - ➢ hybrid methods
  - ➢ Mean shift method
  - ➢ Support vector machine

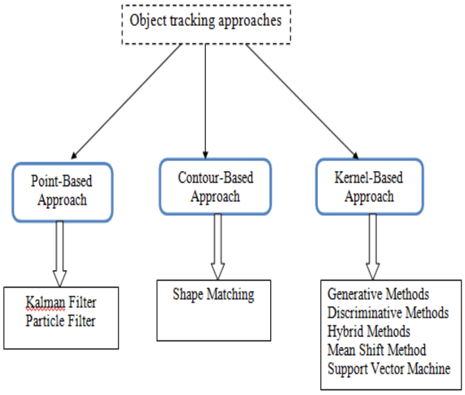

Figure. 1 Object Tracking Approaches

Visual feature extraction is the origin of content-based object identification technique where both text-based features (key words, annotations) and visual features (color, texture, shape, etc.) are involved. Under visual feature extent, the features are again categorizedinto low-level features and high-level features. Feature selection is one of the main objectives of content-based object identification systems for characterizing an image. Due to observation subjectivity and the difficult composition of visual data, it present number of representation techniques for a given visual feature and all feature represented from a varied perspective.

A unique approach is designed in which user input is employed for identifying distances between different media types. The unique approach utilized min-Hash, A Priori, and image signature containers for activating despite size, type or representation. Additionally, incorporation of other high and low level feature types into the image signature was also performed for extracting additional information that the dataset image and videos incorporated to enhance the performance of unique approach.

The content based object tracking systems was investigated to address the problems for object segmentation and key frame selection. The inclusion of content based object tracking system to utilize both low level features for video representation. In content based object tracking in video retrieval systems, video stream was categorized into separate shots. Subsequently, features were mined for video shots representation and a similarity metric with an efficient algorithm to improve query similar videos results. The main objective of the analysis was to review and analyze the interesting features mined from video data to index and retrieval with similarity measurement methods.

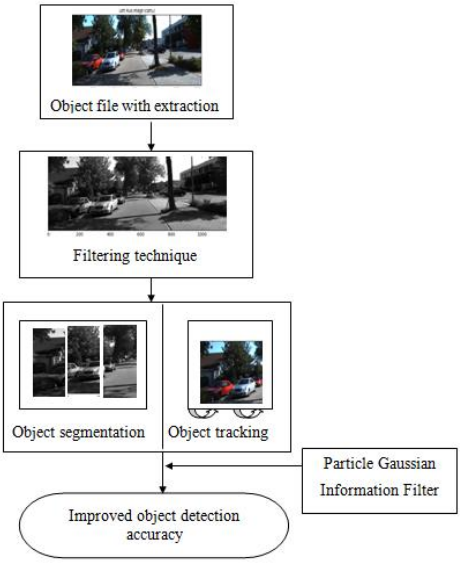

Figure. 2 Particle Gaussian Filter For Object Tracking

2. EXISTING SYSTEM

The Cognitive Control Inspired Approach (CCIA) was implemented for achieving targets object results. Cognitive Perceptor unit measurement is performed from environment field to make representation of external world. Although, a sub-optimal implementation was applied on several challenging datasets that decreases the square error after the Q function is learned for tracking of small object. Followed by, the redundant and unwanted information were not removed. The existing approach was not effectively reduced the information overload and signal to noise ratio. Therefore, object tracking of existing approach was very complicated in real time system and takes more time in outdoor environments.

To address the above issues, Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme is presented to increase the accuracy for tracking the object. The MCPS is computed for set of particles (i.e. objects) with associated weight via posterior density. Hence, Bayesian approach is used to extent the object with noise removal. Then, applied Monte Carlo Particle State Estimator algorithm is used to successfully track the single moving object in the presence of occlusion with improved accuracy. To minimize the signal-to-noise ratio, Gaussian Information filter is used for each samples of object. Jaechan Cho et al (2019) proposed moving object detector was designed using hardware description language (HDL) and its real-time performance was evaluated using an FPGA based test system.

3. PROPOSED SYSTEM

Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme is employed to track the object with higher accuracy. Monte Carlo Particle for state estimation is determined to maintain the graphs structure for producing different outcomes and their chances of occurrence for state estimation. In Bayesian estimator, prediction and update is used through particle information filter for object tracking. The particle filter employs the set of weighted particle to calculate the system state and exploits sequential significance sampling method to update the particle set. Then probability is calculated for each particle (i.e. objects) set.

An optimal investigation model is developed which includes a rigorous probabilistic formulation and providing an indication of the informative content of estimations using information filtering system. A rigorous probabilistic formulation is addressed by likelihood function of each sample. After, training and testing samples are considered by Gaussian Information Filter to select the position, RGB value and measure space color probability. In order to perform information matrix and information vector while minimum error occurring in filter scheme through estimated state functions. To achieve accurate visual object tracking and overcome the difficulties brought by the object deformation, occlusion, and illumination variations, a particle filter for object tracking algorithm is used.

4. IMPLEMENTATION

Bayesian Monte Carlo Employing Particle Gaussian Information Filter for Object Tracking

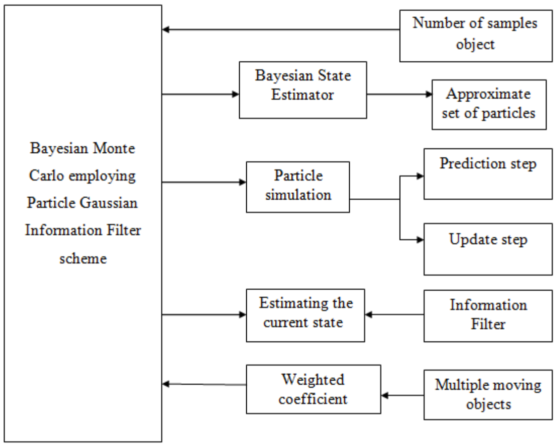

Figure. 3 Architecture Diagram For Bayesian Monte Carlo Employing Particle Gaussian Information Filter Scheme

Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme is provided by three proposed modules such as,

- Bayesian State Estimator
- Monte Carlo Particle State Estimator algorithm
- Gaussian Information Filter
- Bayesian State Estimator

Bayesian approach is used to preserve the occlusion, disappearance of objects, modify some changes in object velocity and alters in object color profile and size. Bayesian approach is to determine correspondences between moving objects over frames and effectively resolves difficult tracking cases. Initially, number of samples object is considered as input sequences. The basic idea followed Bayesian State Estimator using Monte Carlo Particle Simulation (MCPS) is to approximate a set of particles (i.e. objects) with associated weighted via posterior probability density function (pdf) such as the object position by using samples or particles. Monte Carlo

Particle for state estimation maintains graphs of different outcomes and their chances of occurrence for state estimation.

Since a Bayesian estimator, particle simulation contains two main steps namely prediction and update depending on particle weight. Prediction is performed by propagating samples (i.e. frames) based on the system model. Update step is performed by measuring weight of each samples based on observation. The observation model is employed to compute the observation likelihood of the samples. Several observation models are constructed for particle filtering tracking. Thus, the rigorous probabilistic formulation is addressed using likelihood function. The likelihood of the estimated target's state proposes that the estimate is appropriately reliable. The objective of a Bayesian estimator is to approximate the conditional pdf depending on measurements.

- Monte Carlo Particle State Estimator algorithm

From that, Object tracking accuracy is achieved for state estimation by removing unwanted and redundant information using Monte Carlo Particle State Estimator algorithm. The implementation of Monte Carlo Particle State Estimator algorithm is described as follows,

- ➢ Step 1. Frame initialization
- ➢ Step 2. Prediction based on system model
- ➢ Step 3. Particle update
- ➢ Step 4. Resample

➢ Step 1. Frame initialization

Start with weighted set of samples for each frame, and then new samples are generated based on the previous and new measurements

➢ Step 2. Prediction based on system model

Applying Probabilistic system transition model, the Particles or frames are predicted for each time't'. It is performed by propagating all particle based on the transition.

➢ Step 3. Particle update

Particle update based on particle (i.e. frame) weight is made by measurement of likelihood function of each sample.

To obtain estimation of state of tracked object

➢ Step 4. Resample

It produces new samples for next iteration based on weight. The resample step decreases number of samples with low weight and increase number of high weight sample. To attain Expectation approximation for target (object) tracking

- Gaussian Information Filter

Gaussian Information Filter scheme is used with the estimated state to track the original object with efficiently removes the noises. Filtering is concerned with estimating the current state presented all previous measurements. The posterior distribution of the current state is determined from the previous state of distribution. This Information Filter is described by information matrix and information vector. The vector represents the corresponding objects based on its state (color, shape, and size).

Initially, the training and testing samples are considered by Gaussian Information Filter to select the position and RGB value. Then, measure H space color probability of every particle between training and testing samples. In the position of the training samples, the RGB value and the corresponding H space color probability of results is attained through state estimation of tracking particles at the initial moment. Based on optimal results, the parameter combination set with minimum error is selected

Algorithm for Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme
Input: Taken number of samples objects
Output: Improved Object tracking accuracy
Begin:
Step 1 : Apply Bayesian State Estimator to corresponding moving object
Step 2 : Using Monte Carlo Particle Simulation for set of particles
Step 2.1: Measure Prediction based on appearance condition
Step 2.2: Update target object depends on the observation model
Step 3 : Measure the weight update factors depends on the likelihood function from measurement model
Step 4 : Resample particles based on weight results
Step 5 : Calculate probability density function
Step 6 : Perform Gaussian Information Filter with the estimated state to calculate information matrix and vector to corresponding objects
Step 7 : Measure Euclidean distance among real sample objects and test sample objects
Step 8 : Determine weighted coefficient between testing and training sample
Step 9 : To obtain the tracked object with information filter
Step 10 : Remove unwanted information
End

Markov chain Monte Carlo filtering methods are different from conventional PF's on at least two accounts. Firstly, MCMC schemes are primarily designed to produce a Markov chain and hence the obtained particles are by definition statistically dependent.

5. RESULTS

The performance measure of the proposed Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme is conducted.
Performances metrics

- Signal-to-noise ratio
- Mean square error
- Object tracking accuracy

Signal-to-noise ratio

Signal-to-noise ratio is defined as the ratio of the power of meaningful information and the power of background noise or unwanted information. Signal-to-noise ratio is measured in terms of decibels (dB).

$$SNR = \frac{P_I}{P_N}$$

Or

$$SNR_{dB} = 10log\frac{P_I}{P_N}$$

SNR is evaluated with 'P_I' denotes the power of meaningful information and 'P_N' indicates the power of background noise.

Table. 1 Samples Object Vs Signal-To-Noise Ratio (SNR)

Samples object	**Signal-to-noise ratio (dB)**	
	Existing CCIA	**Proposed Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme**
20	25	16
40	29	19
60	32	22
80	36	29
100	41	33

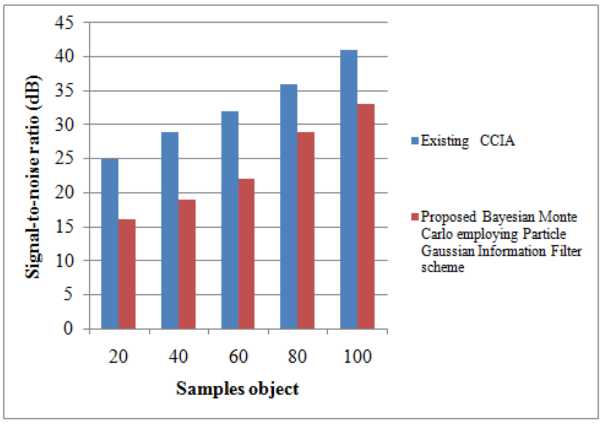

Figure. 4 Comparison Of Signal-To-Noise Ratio Using Proposed And Existing Approach

Figure 4 demonstrates the Signal-to-noise ratio. X axis represents the samples object whereas Y axis denotes the Signal-to-noise ratio using both the Existing Cognitive Control Inspired Approach (CCIA) and the proposed Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme. When the samples object is increased, Signal-to-noise ratio gets increased consequently. But comparatively, the Signal-to-noise ratio is reduced by the existing CCIA and the proposed Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme. The Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme achieves 38 to 41% high performance when compared with existing approach.
Mean square error

Mean square error is measures the ratio of number of samples particles (i.e. frame) to difference between the actual frame size and the estimated frame size. It is measured in terms of decibel (dB).

$$Mean\ square\ error = \frac{\text{Actual frame size} - \text{Estimated frame size}}{Number\ of\ \text{samples particles}}$$

Table. 2 Samples Object Vs Mean Square Error

Samples object	**Mean square error (dB)**	
	Existing CCIA	**Proposed Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme**
20	45	33
40	51	39
60	56	42
80	61	49
100	65	52

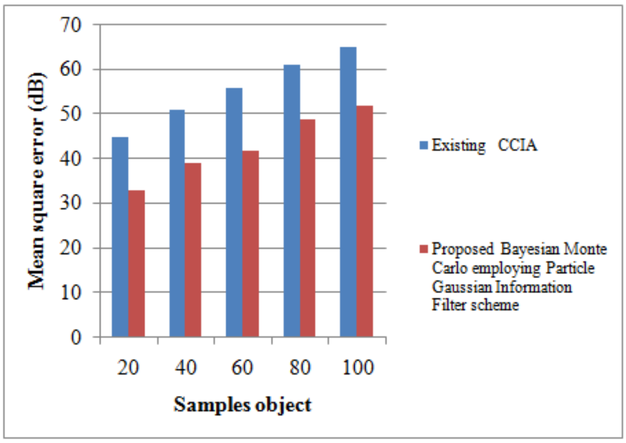

Figure. 5 Comparison Of Mean Square Error Using Proposed And Existing Approach

Figure 5 shows the Mean square error. X axis signifies the samples object but Y axis denotes the Mean square error using both the Existing Cognitive Control Inspired Approach (CCIA) and the proposed Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme. When the samples object is increased, Mean square error is increased accordingly. But comparatively, the Mean square error is reduced by the existing CCIA and the proposed Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme. Therefore, the Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme achieves 28 to 30% high performance when compared with existing approach.

Object Tracking Accuracy

Object tracking accuracy is defined as the ratio of number of objects tracked correctly to the total number of objects on each frames. Object tracking accuracy is measured in terms of percentage (%) and it is formulated as,

$$\text{Oject tracking accuracy} = \frac{No.of\ objects\ tracked\ \text{correctly}}{Total\ number\ of\ objects\ on\ each\ frames} * 100$$

Table. 3 Samples Object Vs Object Tracking Accuracy

Samples object	Object tracking accuracy (%)	
	Existing CCIA	Proposed Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme
20	55	65
40	62	72
60	67	78
80	71	82
100	75	86

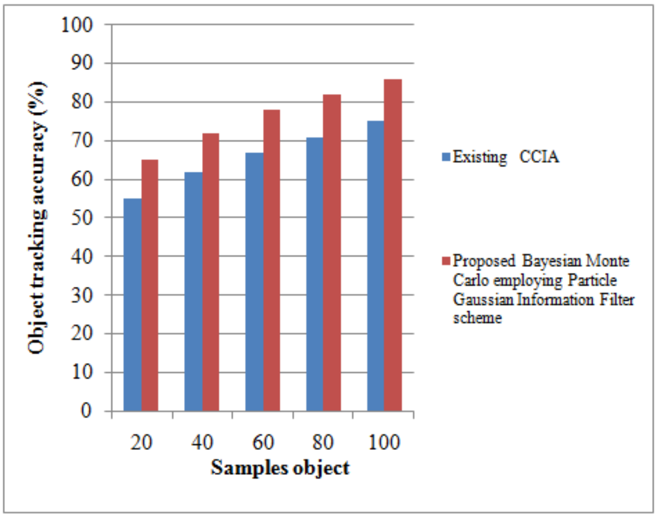

Figure. 6 Comparison Of Object Tracking Accuracy Using Proposed And Existing Approach

Figure 6 display the Object tracking accuracy. X axis signifies the samples object but Y axis represents the Object tracking accuracy using both the Existing Cognitive Control Inspired Approach (CCIA) and the proposed Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme. While the samples object is increased, Object tracking accuracy is enhanced subsequently. But comparatively, the Object tracking accuracy is increased by proposed Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme than existing CCIA. As a result, the Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme is improves the Object tracking accuracy by 12 to 14 % of high accuracy while compared with existing approach.

6. Conclusion & Future Enhancements

Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme is introduced for efficient object tracking with enhanced accuracy of tracking object. First, the Bayesian State Estimator using Monte Carlo Particle Simulation (MCPS) is estimated with associated weighted via posterior density based on samples particles. Based on state estimation, particle simulation includes prediction and update for target object tracking with adjusts position. The object position is evaluated by the minimum mean square estimation. Afterward, Monte Carlo Particle State Estimator algorithm is used for achieving the object tracking accuracy by removing unwanted and redundant information. Finally, the Gaussian Information Filter scheme is designed with the estimated state to track the original object with noise reduction. As a result, the Bayesian Monte Carlo employing Particle Gaussian Information Filter scheme is effectively achieves the better performances than the existing approach.

Future enhancement can be done to expand the scheme to provide efficient detection and tracking on real time. A novel approach is developed for real time object detection and tracking on high resolution camera. Further, joint probabilistic data association filter may be carried out to achieve the low computation cost, it appropriate for multi target tracking, and its robustness to noisy environments.

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