ISSN 2278 – 1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 1, Issue 1, March 2012

Efficient Object Tracking Using K means and Radial Basis Function

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ABSTRACT— ***In the present article, an efficient method for object tracking is proposed using Radial Basis Function Neural Networks and K-means. This proposed method starts with K-means algorithm to do the segmentation of the object and background in the frame. The Pixel-based colour features are used for identifying and tracking the object. The remaining background is also considered. These classified features of object and extended background are used to train the Radial Basis Function Neural Network. The trained network will track the object in next subsequent frames. This method is tested for the video sequences and is suitable for real-time tracking due to its low complexity. The objective of this experiment is to minimize the computational cost of the tracking method with required accuracy.***

Keywords— **object tracking, k-means segmentation, neural networks, radial basis function neural networks**

I INTRODUCTION

Tracking is used in several computer applications, e.g., video monitoring systems, traffic monitoring, etc. Object tracking can be defined as the problem of estimating the trajectory of an object in the image plane as it moves around a scene. Several challenges have been encountered in visual tracking such as non-rigid objects, complex object shapes, occlusion and appearance change of the objects and real-time processing. Many experiments are carried out to address these challenges [1]. In the existing algorithms, segmentation is done on each video frame to determine the object. Hence computational cost increases.

With popularity of ANN due to its ability to learn, solution to complex non-linear problem and generalization, attracted much attention. One of the most popular neural network models is the radial basis function network. The learning based algorithms were rarely used for object tracking due to difficulty in adapting the neural network [2].

Here a fast tracking algorithm is proposed that uses k-mean colour segmentation for detecting an object.

1) In first frame the object is manually selected.
2) Next the colour features from object and background are extracted.
3) Segmentation is done.
4) The neural network is trained by these features.
5) Separate the object from the background in other frames by the using the trained network.

Next section describes the proposed algorithm that presents k-means segmentation, feature extraction, background extension and radial basis function neural network.

The paper is organized as follows: Section II describes the proposed algorithm that presents k-means segmentation, feature extraction, background extension, radial basis function neural network and object location. The experimental results are detailed in Section III and the conclusions and future work are given in Section IV.

II PROPOSED ALGORITHM

Fig. 1 shows the process of the proposed method:-

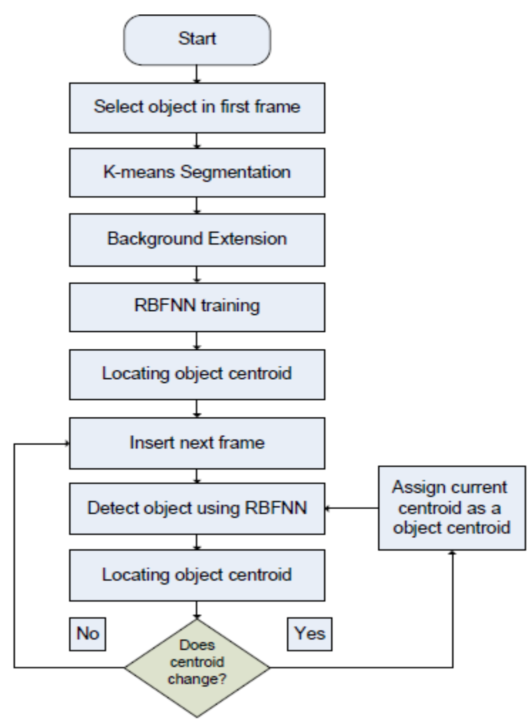

Fig 1: Procedure for Tracking

ISSN 2278 – 1021

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A. Object Selection

This is the first step of the proposed algorithm which is used to develop a model for tracking the object of interest from the given initial video frame. For tracking an object of interest, the approximate object is manually selected from the initial video frame. This is object selection [3].

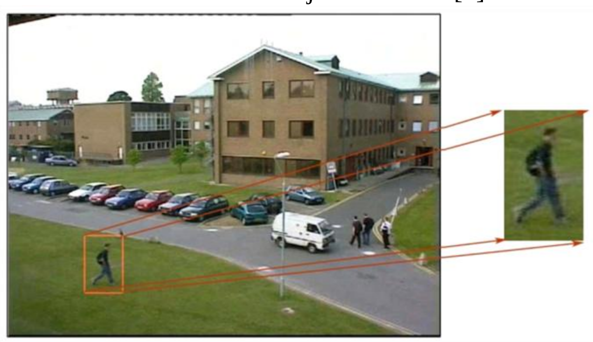

Fig 2: Object Selection

Next, k-means color segmentation is separating the object from background this results in a binary image. The features used for k-means segmentation are simple pixel color based features, which correspond to the values in colour spaces R-G-B.

B. Segmentation

Here the selected image is segmented to separate the object and the background. K-means algorithm with two classes for segmentation (class 1: Object pixels, class 2: Non-object pixels) is used. This is pixel based and should be computationally fast and simple.

K-means segmentation is one of the popular algorithms in clustering that we use it for segmentation. Hence we use three color features (R-G-B) . Thus we have feature points {x1, x2, ….., xn} where (xi = {Ri, Gi, Bi}).

- **Step 1**: Choose 2 initial cluster centres z_1 and z_2, randomly from the n points
- **Step 2**: Assign point x_i to cluster c_j if $\| x_i – z_j \| < \| x_i – z_p \|$ where p =1, 2 and j ≠ p
- **Step 3**: Compute new cluster centres z_i *:

$$z_i^* = \frac{1}{n}\sum_{x_j \in c_i} x_j$$

  where n_i is the number of elements belonging to cluster c_i
- **Step 4**: If $z_i * = z_i$ where i=1, 2 then terminate, else repeat from Step 2.

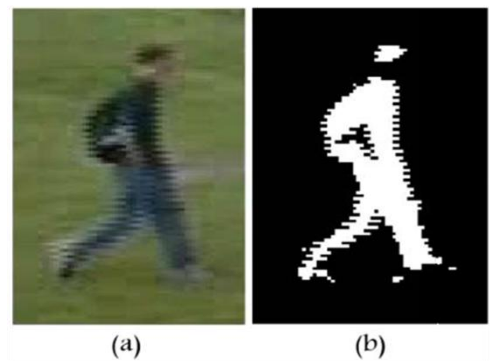

Fig 3: (a) Manually selected object
(b) Using K-means segmentation

Fig. 3 shows the manually selected object and Fig. 4 shows k-means colour segmentation result.

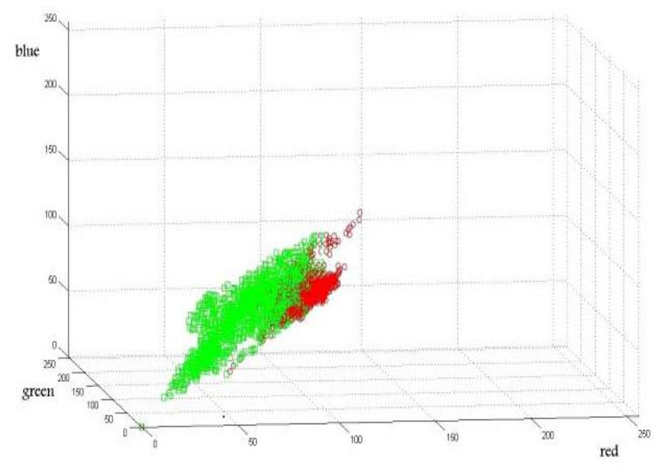

Fig 4: K-means segmentation

C. Background Extension

In segmentation, the colour features of object and background are extracted. These can be used to train RBFNN. But these are unreliable if background changes in consecutive frames. Hence, use the new proposed algorithm. We consider randomly distributed work points in the whole feature space except object space. This process is named as background extension.

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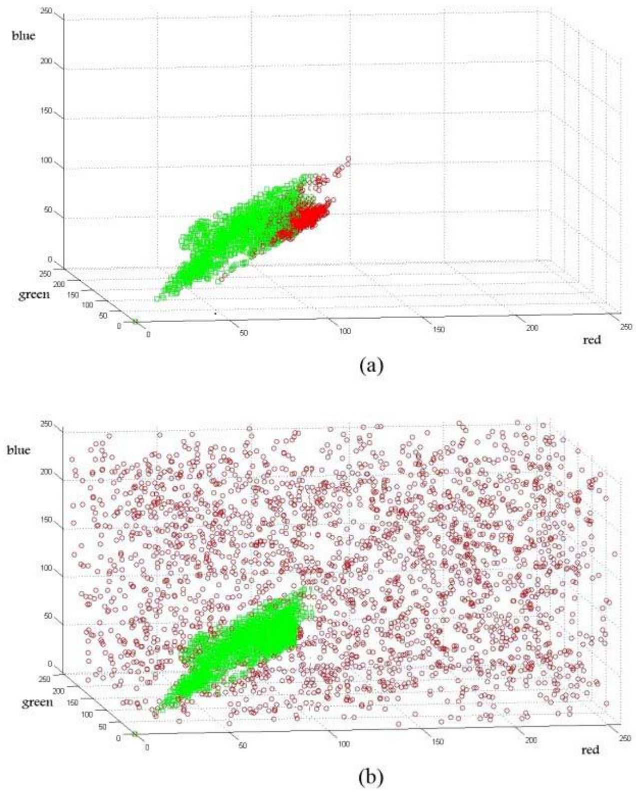

Fig. 5: (a) Object and background R-G-B colour space
(b) Object and extended background feature space

D. RBF Neural Network

The object features and extended background features are used to train the neural network which is having the radial basis function as its transfer function. This takes less computational effort over those which use segmentation in every frame. The trained ANN is used to find the new location of the tracked object from the pixel values based on its experience. Input to the ANN will be the R-G-B values of the pixels of object and extended background.

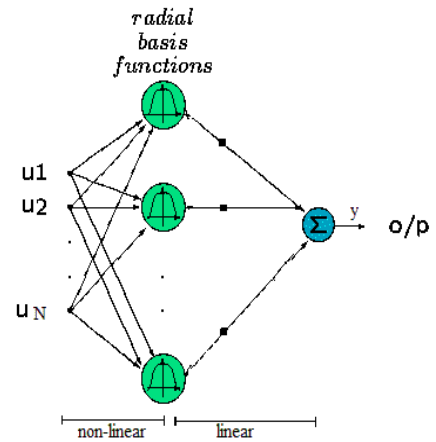

Fig 6: RBF ANN

The radial basis function neural network is three layered feed-forward neural network. The first layer is linear and only distributes the input signal, while the next layer is nonlinear and uses Gaussian functions. The third layer linearly combines the Gaussian outputs. Only the weights between the hidden layer and the output layer are modified during training.

5 parameters of optimization:

- The weights between hidden layer and output layer.
- The activation function.
- The centre of activation functions.
- The distribution of centre of activation functions.
- The number of hidden neurons.

The activation function selected is commonly a Gaussian kernel for pattern recognition application. The centre of activation functions should have characteristic similar to data so random number between [0,255] is used for centre of activation functions. The distribution of centre of activation functions is chosen random number between [0,255] similarly.

Using universal approximation property, one can say that the single hidden layer feed-forward network with sufficient number of hidden neurons can approximate any function to any arbitrary level of accuracy.

In Fig 6, U is N*3 dimensional input feature vector which 3 representing R-G-B features and *N* is number of pixels. Let μ_i and σ_i be the centre and width of i^{th} Gaussian hidden neuron and α_i be the interconnection weight. The i^{th} output (y) of RBF Neural Network with neurons has the following form:

$$y = \sum_{i=1}^{k} \alpha_i \exp\left(- \frac{\| U - \mu_i \|^2}{2\sigma_i^2} \right)$$

In matrix form, $Y = \varphi_k \alpha$ where

ISSN 2278 – 1021

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$$\varphi_k(\mu,\sigma,U)=\begin{bmatrix}\varphi_1(\mu_1,\sigma_1,U_1) & \ldots\ldots\ \ldots & \varphi_k(\mu_k,\sigma_k,U_1)\\ \vdots & & \vdots\\ \vdots & & \vdots\\ \varphi_1(\mu_1,\sigma_1,U_N) & \ldots\ldots\ \ldots & \varphi_k(\mu_k,\sigma_k,U_N)\end{bmatrix}$$

To find the weights between hidden and output layer:
$Y=\varphi_k\alpha=T$ where T is the known output while training then $\alpha=\varphi_k{}^{+}T$ where $\varphi_k{}^{+}$ is pseudo-inverse= $(\varphi_k{}^{T}\varphi_k)^{-1}$ also called as Moore-Penrose generalized pseudo inverse [3].

This overcomes many issues in traditional gradient algorithms such as stopping criterion, learning rate, number of epochs and local minima.

E. Object Location

After object detection in first frame, the object in next frames is found by feature extraction and testing it with the RBFNN classifier. Finding the object starts at the centre of the segmented object. The displacement of the object is given by the shift in the centroid which is achieved by iteratively seeking the object centroid using RBF ANN. It terminates when centroid location for any two consecutive iterations remains unchanged [6].

III RESULTS

The proposed algorithm has been tested on complex video sequences. In the example demonstrated below, the object to be tracked is surrounded by a rectangle with orange border.

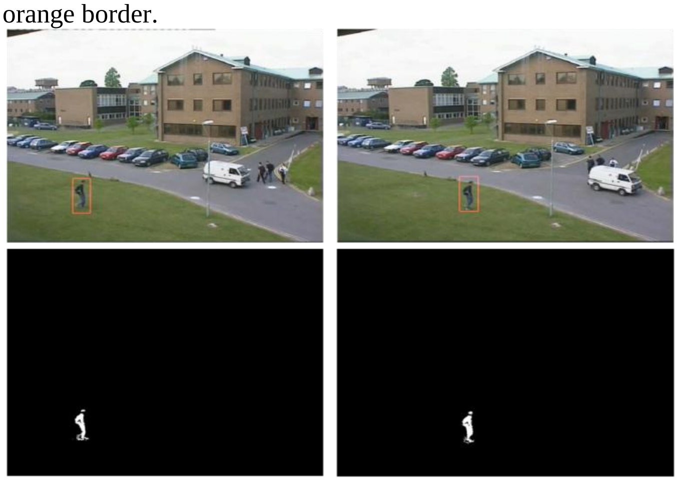

Fig. 7: Tracking result of proposed algorithm (Frame 1 & 2)

As the object walks such that his body undergoes partial occlusion, as well as, appearance and illumination and background changes, over time. It is observed that the proposed algorithm can track an object even if the background changes or partial occlusion takes place.

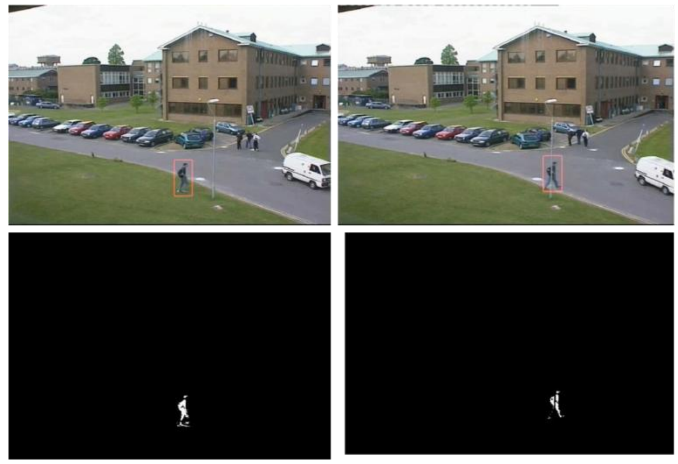

Fig. 8: Tracking result of proposed algorithm (Frame 3 & 4)

IV SUMMARY AND FUTURE WORK

- Achieved improved object tracking in terms of accuracy.
- Lower computational complexity as compared to any other learning based object tracking algorithm as K-means is applied only in the initial frame.
- Achieves optimized results in lesser iterations.
- But the pixels whose R-G-B values are very close are not clearly distinguished as shown in figures below.

Fig. 9: Tracking result of proposed algorithm-less accuracy (Frame 5 & 6)

Hence the object and the background (road) are not clearly distinguished. By segmenting the frame into 3 classes i.e. object background and extended background, can help lessen this error which is the future scope of this experiment.

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