Multi-object Tracking of Vehicles using Kalman and Particle Filters

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***Abstract*—In this report, we detail a system capable of simultaneously tracking multiple vehicles in a highway scene, from a fixed camera above the road. We use a mixture of Gaussians to segment the scene into foreground and background pixels. Blob detection is used to extract the bounding box and centroid of the blobs, which are then passed to a filter. We present two methods of tracking — multiple Kalman filters, or a modified particle filter. The filters are able to process video at a rate of 5 and 2 frames per second respectively, with good results when the environment is uncomplicated. Performance degrades in night scenes, and when occlusions occur.**

I. Introduction

The tracking of vehicles is an active area of research. Over the past two decades, a large number of different techniques have been developed or employed for the purpose of vehicle tracking. Broadly speaking, there are two different scenarios which are often encountered. First, we have the case in which the camera is mounted on a moving vehicle, and we attempt to track the motion of target vehicles, in order to assist the driver, or to give as input to an autonomous driving system. The other case is that in which we have a fixed camera looking at a portion of road, and we wish to track the vehicles entering and exiting the field of view of the camera, also known as traffic surveillance. Previous research in traffic surveillance deals with tracking and classification [3, 8], and traffic flow and vehicle speed calculation [4, 1]. Numerous methods are used in order to extract the relevant data. For example, lane-dividing lines can be used to eliminate problems relating to shadows [3], and using a-priori road information to improve the tracking quality [7]. In order to extract information from the image, some visual processing is required. There are several methods that have been used to extract vehicles from images, including 3D detection and description [6], Gaussian mixture models for background and foreground extraction [9], and methods using optical flow [5].

Systems which extract and process this information can be used in intelligent transport systems in order to monitor traffic conditions and attempt to reduce congestion. The simplest useful system is one which tracks the position and velocity of vehicles in the image, and we will discuss our implementation of such a system in the subsequent sections.

II. Object Extraction

A. Mixture of Gaussians

The first step after obtaining a video to process is to extract the objects of interest in the image. Our approach uses Gaussian mixture models technique developed by Stauffer [9]. This technique allows the separation of background pixels and foreground pixels by using multiple Gaussians. Each pixel is represented by some K Gaussians, and the persistence and variance of these are used to determine whether a certain pixel is a background or foreground pixel in any given image of the sequence. As each pixel can have multiple surfaces present within it, and the illumination can also change, multiple Gaussians are required to fully represent the possible range of background pixel values. We make the assumption that Gaussian noise is added to the value of the pixel which is measured by the sensor, either due to random noise, or due to small fluctuations in the illumination. For each pixel in the image, the probability of observing its current value is [9]

$$P(X_t) = \sum_{i=1}^{K} w_{i,t} \cdot \eta(X_t, \mu_{i,t}, \Sigma_{i,t}) \tag{1}$$

where X_t is the pixel value, $\mu_{i,t}$ and $\Sigma_{i,t}$ are the mean and covariance of the ith Gaussian at time t, η represents the normal distribution. $w_{i,t}$ is a weight assigned to each Gaussian which estimates how much of the data that has been seen so far is accounted for by this Gaussian. Since we are dealing with colour images, the Gaussians are multivariate, but we make the assumption that each colour is independent and has the same variance, and therefore the covariance for each Gaussian is

$$\Sigma_{k,t} = \sigma_k^2 \mathbf{I} \tag{2}$$

At each timestep, the Gaussian closest to the current pixel value is computed. If it is within 2.5 standard deviations (computed using the Mahalanobis distance), then we update the mean and covariance of the matched Gaussian as follows

$$\mu_t = (1-\rho)\mu_{t-1} + \rho X_t \tag{3}$$
$$\sigma_t^2 = (1-\rho)\sigma_{t-1}^2 + \rho(X_t - \mu)^T(X_t - \mu) \tag{4}$$

where ρ is a learning rate

$$\rho = \alpha\eta(X_t \mid \mu_k, \sigma_k) \tag{5}$$

The parameters of other Gaussians are not updated, but their weight is updated according to

$$w_{k,t} = (1-\alpha)w_{k,t-1} + \alpha(M_{k,t}) \tag{6}$$

where α is another learning rate, which "describes an exponentially decaying envelope that is used to limit the influence of old data" [11]. We set α to 0.01. The weights are normalised after this operation. If it is the case that none of the current distributions matches the pixel, then the one with the lowest probability is replaced with a Gaussian with a mean corresponding to the current pixel value, a high variance, and a low weight.

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To estimate the background model, we need to find which of the Gaussians in the model are most likely to represent background pixels, heuristically those with the lowest variance, and most supporting evidence [9]. When some object is static, the variance in its pixels is very low, generally coming only from noise. This results in the Gaussians building up a large body of evidence to suggest that this is a background pixel, represented by their weights. When a moving object comes into the scene and occludes the background, it will either be attached to one of the existing Gaussians, increasing its variance, or it will be too dissimilar and therefore a new distribution will be created to account for it. To deal with these issues, we choose some part of the mixture model to represent the background; the rest will represent dynamic objects in the image. Gaussians are ordered according to the value w/σ, a value that increases the lower the variance, and the more supporting evidence the Gaussian has. The background model is chosen as

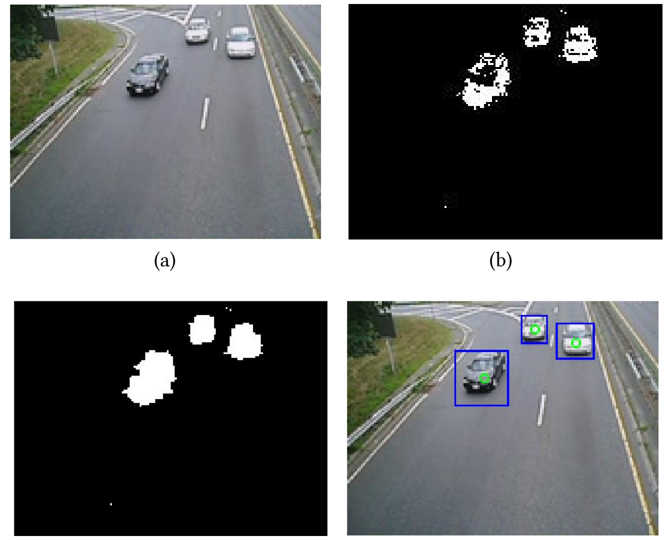
$$B = \underset{b}{arg\ min} \left(\sum_{k=1}^{b} w_k > T \right) \tag{7}$$

T defines the proportion of the image that should be considered as background data. The value B gives the index of the last Gaussian that should be considered part of the background model — all subsequent Gaussians are part of the foreground. The value of T depends on the video that is being processed. If there are a large number of foreground objects, then its value may be quite low. In our case, we have found that a value of approximately 0.6 is appropriate. Using this and the value we choose for α, the number of frames τ taken for an object to be considered background is [11]

$$\tau = \frac{\log(0.6)}{\log(1 - 0.01)} \approx 51 \tag{8}$$

B. Morphological Operations and Blob Detection

Once the foreground pixels have been determined, we perform further processing to extract objects from the image and transform the pixel data into something which can be used for tracking. An example of the image received from the mixture of Gaussians can be seen in Figure 1b. The extracted foreground pixels do not fully cover the object — this is likely because some parts of the vehicles have colours which are similar to the background pixels. We would like to fill in these holes and receive a uniform blob to work on. First, we need to apply some morphological operations in order to make the second stage of the process easier. Morphological operations are “a tool for extracting image components that are useful in the representation and description of region shape” [2]. We are particularly interested in the operations of erosion, dilation and filling. Erosion is an operation that shrinks or thins regions in a binary image. This allows us to get rid of some of the smaller features that might be present in the image that are not relevant to what we are trying to extract. Dilation is the opposite to erosion. Instead of shrinking regions, it grows or thickens them. This allows us to connect regions that were not connected for whatever reason. The filling operation, as the name suggests, fills holes in an image. The holes must be surrounded by 8-connected boundaries [2]. Two pixels are 8-connected if one can be reached from the other by taking a 1-pixel step in horizontal or diagonal directions.



(a) (b) (c) (d)

Fig. 1: Steps in the object extraction process. a) shows one frame of the video being processed. b) shows the results of applying the mixture of Gaussians technique to extract the foreground pixels. c) is the image obtained after applying dilation, filling and erosion to b). d) shows the centres and bounding boxes of the extracted blobs.

The first operation we apply is dilation, in order to bridge gaps in the vehicles, which are often caused by the windscreen. Then, we fill holes in the image, which are again usually caused by the windscreen. Finally, to disconnect regions that should not be connected which may have been connected by the dilation operation, or to remove noise pixels and other very small regions, we use erosion. Once these operations have been done, we obtain something which looks like Figure 1c.

Once the morphological operations have been applied, we extract information about the blobs in the image. Blob extraction is done by finding connected components in an image using 8-connectivity. We use the built in MATLAB algorithm to perform blob extraction. Since we have a thresholded image with only two colours, either black or white, this operation is relatively simple as we do not have to define measure of pixel similarity. We receive the centroids and bounding boxes of the blobs in the image from the algorithm. The blob detection only returns blobs which have a size larger than 100 pixels, but this is adjustable depending on the situation in which the system is being used. An example of overlaying the results onto the original image can be seen in Figure 1d.

III. Kalman Filter

A. Basic Formulation

The first of the two filtering methods that we used in our implementation is the Kalman filter. It uses a multivariate Gaussian to represent the state of the system, and a process model R and measurement model Q to represent the noise in the system. The basic Kalman filter is a linear estimator, which means that it assumes that the evolution of the system follows some sort of linear equations. The extended Kalman filter allows the use of nonlinear equations in the state evolution. However, in our system we make the assumption that objects are moving in a linear fashion. This is a reasonable assumption, since in the vast majority of highway scenes vehicles will be moving in straight lines.

First, we define the state vector $\mathbf{x}$ of the system as

$$\mathbf{x}^T = [x\ y\ w\ h\ \dot{x}\ \dot{y}] \tag{9}$$

where x and y are the position of the centre of the object in the image, w and h are the width and height of the bounding box of the object, and $\dot{x}$ and $\dot{y}$ are the velocities of the object centre in the x and y directions. In our case, the origin is in the top left of the image. We have included the bounding box dimensions in our state vector as this allows us to attempt to estimate the change in size of the bounding box as the system evolves, and to maintain a better estimate of the bounding box even if the measurement received is not accurate.

Our measurement vector $\mathbf{z}$ is

$$\mathbf{z} = [c_x\ c_y\ b_w\ b_h] \tag{10}$$

where (c_x, c_y) is the centroid received from the blob detection, and b_w and b_h are the width and height of the bounding box. The blob detection can extract several different blobs, so several of these vectors can be received in each timestep.

The Kalman filter process has two major steps; the prediction step and the update step. In the prediction step, the next state of the system is predicted using the previous state and the state transition matrix A and the process model as follows

$$\bar{\mu}_t = A\mu_{t-1} + Bu_{t-1} \tag{11}$$

$$\bar{\Sigma}_t = A\Sigma_{t-1}A^T + R \tag{12}$$

In most systems, there is some control input that is received by the system to modify its state, but in this case we have no control input, so $B = 0$, and that term is not relevant in the update — we rely purely on the state transition model to modify the state. The prediction step computes the predicted mean $\bar{\mu}$ and covariance $\bar{\Sigma}$ for the tth timestep. At any point in time, the value of Σ indicates the uncertainty in the system, and μ indicates the point around which the Gaussian is centred, that is, the most probable current state. We have set A as

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & dt & 0 \\ 0 & 1 & 0 & 0 & 0 & dt \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{13}$$

where dt is the time elapsed between updates. Since we process every frame, this is generally 1. The process model R is dependent on the particular video sequence that is being processed, and is of the form

$$R = \begin{bmatrix} \sigma_x^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_y^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_w^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_h^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{\dot{x}}^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_{\dot{y}}^2 \end{bmatrix} \tag{14}$$

The measurement model is dependent on the efficacy of the blob detection, and the quality of the camera, and is of the form

$$Q = \begin{bmatrix} \sigma_{c_x}^2 & 0 & 0 & 0 \\ 0 & \sigma_{c_y}^2 & 0 & 0 \\ 0 & 0 & \sigma_{b_w}^2 & 0 \\ 0 & 0 & 0 & \sigma_{b_h}^2 \end{bmatrix} \tag{15}$$

Since multiple measurements may be received, it is necessary to associate the correct measurement with the filter in order to choose which measurement to use in the update step. There may be multiple measurements, but we are only interested in the measurement which is closest to the state of the filter after the prediction step. Association is done by comparing all measurements obtained to the mean of the filter and choosing the one with the lowest Mahalanobis distance. This process can also be used to compute outliers. An observation model H is defined which allows us to transform the state vector into a form that can be compared with the measurements. As the measurement and the state vector contain essentially the same parameters, this matrix is simply

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix} \tag{16}$$

After incorporating the measurement uncertainty into the uncertainty after the prediction step, we compute the innovation ν, which is the difference between the predicted measurement and the one received $\hat{z}_t$. This is then used to compute the Mahalanobis distance D. This is passed into a Gaussian to compute the probability Ψ of taking that measurement. Outliers are those measurements for which $D > \lambda_M$, where λ_M is a value sampled from the inverse χ^2 distribution with 4 degrees of freedom, which gives a boundary on the Mahalanobis distance below which we expect most measurements to fall [10]. We make the assumption that our measurements are accurate, and so $\lambda_M = \text{Inv-}\chi^2(0.99, 4)$.

$$S_t = H\bar{\Sigma}_t H^T + Q \tag{17}$$

$$\nu_t = z_t - H\bar{\mu}_t \tag{18}$$

$$D = \nu_t^T S_t^{-1} \nu_t \tag{19}$$

$$\Psi = \frac{1}{2\pi \det(S)^{\frac{1}{2}}} \exp^{-\frac{1}{2}D} \tag{20}$$

The process in Equations (17)–(20) is repeated for each measurement, and the measurement which corresponds to the maximum value of Ψ is the one which is used in the measurement update.

Finally, the measurement chosen is incorporated into the filter to update the belief and obtain the final values of μ_t and Σ_t. μ_t is then used to represent the state of this object.

$$K_t = \bar{\Sigma}_t H^T S^{-1} \tag{21}$$

$$\mu_t = \bar{\mu}_t + K_t \nu_t \tag{22}$$

$$\Sigma_t = \bar{\Sigma}_t - K_t H \bar{\Sigma}_t \tag{23}$$

B. Extension to Multiple Objects

In order to extend the Kalman filter to track multiple objects, it is necessary to introduce additional distributions into the model somehow. This could be done using a mixture of Gaussians, where the posterior is represented by a multimodal Gaussian distribution [10], but this is not a good match for our application as it seems to imply that there is a single object about whose position we have multiple hypotheses. In actual fact, we have multiple distinct objects, about which we have a single hypothesis. In that sense, a multimodal distribution to represent a single object seems to be unnecessary. As such, we have decided to assign a single Kalman filter to each object as it is detected.

At each timestep, all existing Kalman filters are updated. Each update results in the computation of outliers, which give information about measurements which are far from the expected measurements given the filters that are currently active. Each of the measurements that is an outlier is considered to be an object which has appeared onto the scene and that has not yet been assigned a filter. New filters are initialised with the centroid from one of the outlier measurements. The initial parameters for each filter are

$$\mu_0 = [c_x \; c_y \; 0 \; 0] \tag{24}$$

$$\Sigma_0 = \begin{bmatrix} 5 & 0 & 0 & 0 & 0 & 0 \\ 0 & 5 & 0 & 0 & 0 & 0 \\ 0 & 0 & 5 & 0 & 0 & 0 \\ 0 & 0 & 0 & 5 & 0 & 0 \\ 0 & 0 & 0 & 0 & 100 & 0 \\ 0 & 0 & 0 & 0 & 0 & 100 \end{bmatrix} \tag{25}$$

The velocity is not known when the measurement is received, so we assign a high variance to it in order to accommodate possible velocities. The other parameters, the centroid and the bounding box parameters are comparatively accurate, so they are assigned a lower variance.

In addition to creating new filters to track newly detected objects, filters which were created as a result of spurious measurements or for those objects which have left the scene are deleted. This is done by keeping a count of the number of consecutive frames in which the filter was not updated as a result of unreliable or non-existent measurements corresponding to that filter. Filters are deleted if they are not updated within 2 frames of the last update.

IV. Particle Filter

A. Basic Formulation

The particle filter is another common state estimation method, but it is fundamentally different from the Kalman filter in the sense that it does not represent its posterior by a Gaussian approximation, but instead uses a representative sample from a proposal distribution described by a number N of particles p_i^t. This means that it can easily represent multiple hypothesis situations, such as those occurring in the problem of localisation. By using another type of filter for the same task we are able to compare the two approaches.

Much like the Kalman filter, the particle filter has two stages; a propagation step in which particles are moved according to the process model and the control action applied. The second step is the measurement update, in which particles are assigned weights w_i^t according to their correspondence with received measurements. After weights are assigned, particles are resampled — particles are carried over to the next timestep with a probability proportional to their weight, with the exact proportion dependent on the resampling scheme used. The particle filter uses the same state vector and receives the same measurements as the Kalman filter, shown in equations (9) and (10). The position of the object centre is shifted according to the velocities, while velocities and bounding boxes remain the same. The details of this stage differ somewhat to the Kalman filter, however. While the Kalman filter only has a single state vector and covariance matrix for each instance, the particle filter has a comparatively large number of particles it uses to represent the posterior. As a result, the state transition must be applied to each particle, which is a complete representation of a possible state of the system. Herein lies the main computational difference between the Kalman filter and particle filter; the particle filter needs to update large numbers of particles in order to represent its belief state, and as a result computations are often slower.

Before starting the filter it is necessary to initialise the particles according to our belief about the system state. It is common to distribute particles uniformly across the whole operational space. In our case, we have decided to avoid initialisation until measurements have been received, as if there are no objects in the image frame there will be nothing to track, and so moving particles around will be pointless. Each particle is initialised by

$$p_i^t = \begin{bmatrix} U_x w_k + x_k \\ U_y h_k + y_k \\ w_k \\ h_k \\ \dot{x}_i \\ \dot{y}_i \end{bmatrix} \tag{26}$$

where $U_x, U_y \sim U(0,1)$ are numbers in the range $[0,1]$ independently sampled from a uniform distribution, w_k and h_k are the width and height of the bounding box given by the kth measurement, and (x_k, y_k) is the centroid of that bounding box. $\dot{x}_i, \dot{y}_i \sim \mathcal{N}(0, \sigma_v^2)$ are numbers drawn from a zero-mean normal distribution with variance σ_v^2. This initialises particles uniformly within the bounding box of each of the k measurements, with normally distributed velocities, which can be either positive or negative, meaning that objects moving upwards and downwards through the image can be tracked.

Since multiple measurements may be received at initialisation, particles are split between different objects according to the proportion of the total area of all bounding boxes which the bounding box for the object occupies. The number of particles n assigned to the kth measurement is

$$n_k = N \cdot \frac{w_k h_k}{\sum_{i=1}^{b} w_i h_i} \tag{27}$$

where b is the total number of measurements received. To ensure that large boxes do not receive a disproportionate number of particles, there is a lower limit on the number of particles that can be assigned to any given object. This is set in the initialisation of the filter and depends on the number of objects that are expected to be visible in any given frame.

To perform the propagation step, each particle is updated using

$$p_i^{t+1} = p_i^t + \begin{bmatrix} 0 & 0 & 0 & 0 & dt & 0 \\ 0 & 0 & 0 & 0 & 0 & dt \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} p_i^t + \mathcal{N}R \tag{28}$$

where $\mathcal{N}$ is a 6×1 column vector containing zero mean normally distributed random numbers. R is the process noise matrix, identical to (14). The matrix is used to modify the x and y position of the particle according to the velocities and the time dt which has elapsed from the previous update, which is usually 1, as we do per-frame updates.

After prediction, particles need to be re-weighted in preparation for resampling. The re-weighting is done based on the distance of the particle to its closest measurement. We compare only the position and the size of the bounding box for each measurement and particle, as we do not know the velocity of measured objects. To save on computation time we use the city block distance. Distances are computed between every particle and measurement. A matrix ν is constructed which contains the differences between each particle and its closest measurement in its columns. The weight of each particle is then computed by

$$w_i^t = \frac{1}{(2\pi)^2 \det(Q)^{\frac{1}{2}}} \exp\left(-\frac{1}{2}\nu_i^T Q^{-1} \nu_i\right) \tag{29}$$

where Q is the measurement model, identical to (15), and ν_i is the ith column of ν. The weights are normalised to ensure that they sum to 1.

Finally, the resampling step is applied. In this step, we select which particles should carry through to the next timestep based on their weight as a proportion of the total. We use systematic or low variance sampling which reduces the likelihood of particle deprivation, which is important when using particle filters, as deprivation can result in the loss of accurate tracking in comparison to the simple multinomial sampling. We also considered the use of stratified sampling, but there appeared to be no improvement in the tracking performance of the filter if it was used. One issue that could possibly arise is the particle deprivation in one cluster due to very low weights, as systematic sampling works through the whole particle cloud, so if the total weight of one cluster is very low, then it may be the case that these clusters are lost, but in practice we did not notice such issues.

B. *Dealing with New Objects*

While the particle filter is designed in such a way that it deals easily with multiple hypotheses, in its basic form it does not deal with new objects. The filter does not place any particles in regions where particles are not already present. This means that even if a new object was to appear and a measurement for it was received, if there are no particles in that region, then the object will go “unnoticed” by the filter. Thus, we need some method of introducing particles into these regions in such a way that allows the consideration of new objects.

A standard technique in many particle filter implementations which attempts to mitigate the effects of particle deprivation is to add some small proportion of particles into the scene at random. This gives the filter a chance of creating new particle clusters in areas of interest that were previously devoid of particles. This method is not robust enough, however. In order to reliably catch all new objects entering the scene a large proportion of the total number of particles would have to be assigned to this randomly reinitialised group. This would reduce the accuracy of the filter in places where there was an object of interest, and also wastes computation time and particles on regions of the space which are completely uninteresting.

In [8], Meier and Ade propose an extension to the particle filter which allows it to include new objects in the tracking. This extension ensures that regions in which measurements appear are populated with some particles, which allows the tracking of the object if measurements of it continue to be made.

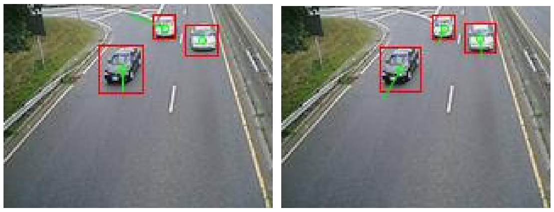
The first modification is the addition of an initialisation step to the filter. Usually, the initialisation step is done once, at the beginning of tracking. In this case, however, a portion of particles are re-initialised at the beginning of each step of the filter. Taking some M particles, we initialise them directly on measurements that were received in the previous timestep. The other particles are the $N - M$ particles which were selected from the resampling step. This direct initialisation allows new any new objects to be added to the tracking. If the previous timestep has no measurements, then all N particles are initialised based on the measurements, as in the first timestep. When initialising on top of measurements, we considered initialising particles only on those measurements which were new, that is, those measurements for which there were no corresponding clusters, but tests indicated that this led to some particle deprivation issues on existing clusters.

The propagation step is done as usual. When this step is completed, some of the M particles which were initialised around measurements corresponding to new objects are likely to have moved into a region close to that in which the measurement in the current timestep has been received.

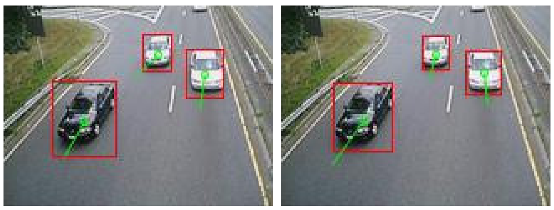
A suggestion is also made to weight particles according to

$$w_i^t = \begin{cases} e^{-\frac{1}{2\sigma^2}u^2} & u < \delta \\ \rho & \text{otherwise} \end{cases} \tag{30}$$

$$u = \min_k \mid p_i^t - z_m^t \mid \tag{31}$$



(a) Frame 65



(b) Frame 70

Fig. 2: Tracking results 5 frames apart, using the particle filter with 10000 particles (left), and Kalman filter (right). The green velocity vector is exaggerated and not adjusted for perspective.

in order to allow those objects which are missing a measurement in a timestep to continue on to the next and allow continued tracking. However, in our testing of this weighting scheme, we noticed that it resulted in a large degradation in performance due to a resulting high spread of particles over the space, and the difficulty of extracting reliable clusters from which to extract tracking information. As a result, we have kept the original weighting procedure detailed in (29).

The final change required is to modify the resampling step. In the standard formulation, N particles are chosen based on weight to replace the N particles in the previous step. However, we instead resample only $N-M$ particles. This still results in a fair representation of the posterior, but allows for the addition of the M particles which are randomly initialised at the measurement positions at the start of the next timestep.

V. Results

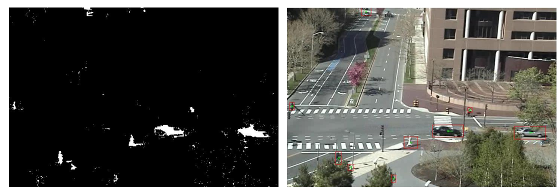
To evaluate the performance of the two filters, we used video from various sources[1]. Due to the lack of ground truth, it was not possible to perform a quantitative analysis of the performance, but by looking at various situations we were able to perform a qualitative analysis.

Figure 2 shows an example of the output of the two filters. The particle filter has some issues with regard to the variance of the velocity vector tracking, which can be seen in one of the images. This is most likely in part due to the addition of random particles to all clouds, which introduces some error into the vector. When given enough time the filter generally fluctuates around the correct vector, but it is not as accurate as is desirable. The Kalman filter on the other hand, as can be seen from the images is very consistent in its estimates of the velocity. Both of the filters have little problem tracking the vehicle centroid.

[1]Datasets from http://www.ee.cuhk.edu.hk/~xgwang/MITtraffic.html, http://www.edmontontrafficcam.com, and MATLAB computer vision toolbox.

(a) Dark scenes

(b) Occluding vehicles



(c) Minimum blob too small

Fig. 3: Causes of filter issues. a) shows some of the problems of dark scenes. The vehicle in the bottom centre is treated as two blobs, and one of these has its centroid in between its headlights and car itself. In the bottom left there is a vehicle which is only visible by its headlights. b) shows the effect of two vehicles close to each other on blob detection — they are detected as a single blob, which leads the tracking to see both vehicles as only a single one. c) shows the result of a minimum blob size which is too low. The filters also track pedestrians.

Many of the problems encountered are a result of the difficulty of getting good measurements from the blob extraction. In night scenes, the background and foreground have very similar colours, and headlights cause significant problems. In scenes with a large number of vehicles which occlude each other, some blobs end up covering two or more cars. Sometimes two blobs may represent the same vehicle, and this reduces the accuracy as well. these problems account for the vast majority of tracking losses. In these difficult scenes, both filters are still able to detect some vehicles, but the accuracy of both the Kalman filter and particle filter are significantly reduced. Specifying a minimum blob size results in the tracking of unwanted objects, some of them objects which might be useful to track, such as people or cyclists, but it also results in the tracking of spurious blobs. Figure 3 shows some of these issues.

Average processing time on one run of 160×120 pixel video with Kalman filter is 0.215 frames/sec, compared to 0.487 frames/sec for the particle filter with 10000 particles. The timing includes foreground and blob extraction, filter processing and then image display.

VI. Conclusion

In this report, we have presented a system for the tracking of multiple vehicles in a highway environment using augmented versions of the Kalman filter and particle filter. Video frames are separated into foreground and background pixels using a mixture of Gaussians. Foreground pixels are processed using morphological operations and then a blob detection algorithm is run to extract the centroid and bounding box of the blob. This information is used by the filters to track different objects in the image.

The system is able to process videos of approximately 160×120 pixels at a rate of 5 frames/sec with the Kalman filter, and 2 frames/sec with the particle filter using 10000 particles, on an Intel i7-3520M at 2.9 GHz. This includes application of mixture of Gaussians, blob extraction, morphological operations and insertion of bounding boxes and centres into the image. As we had no ground truth, it was not possible to do a quantitative investigation of the errors, but qualitative investigation indicates that the Kalman filter is generally very accurate, whereas the particle filter suffers from some issues with regards to the velocity of vehicles, which has a high variance.

There are numerous ways in which the system could be improved. First, improved blob extraction and a more reliable mixture of Gaussians could result in better measurements being received by the filters. Reduction of blob merging and issues with shadows could be done by applying the lane dividing technique suggested in [3]. Initial velocity estimates for objects could be improved using a-priori road information, as suggested by [7].

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