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Target Tracking Using KALMAN Filters

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ABSTRACT: Kalman filtering was very popular in the research field of navigation and aviation because of its magnificent accurate estimation characteristics. Now a day's electrical engineers make a wide usage of its advantages in target tracking systems. Due to its filtering capabilities, it has evolved as a best technique in the estimation and redundant errors resolving process in target tracing.

This paper proposes a system for tracking a target (ball) in video streams, returning its body and head bounding boxes. The system use above has varied Stauffer's adaptive algorithm along with Spacio-tempor learning parameters and a feedback path comprising of Kalman tracker. The adaptive background module helps to attain evidence of the object to the Kalman track in the feed-forward path. The learning parameters of the adaptive background module are adapted by the Kalman tracker in the feedback path.

Only detection by background subtraction which is considered to be the ground truth is done by former.kalman filter will be fed by the deflection output by later the actual ground truth position (green) will then be compared with the predicted position from the Kalman filter (red).

Surveillance, security, smart spaces, pervasive computing and human-machine interfaces are a few applications of target tracking systems. In the above applications human bodies or vehicles are the targets. The main problem with this targets is that sooner or later they show some movement this identifies them as foreground targets and distinguishes them from the background.

KEYWORDS: Kalman Filter, Tracking, Target Tracking Systems

I.INTRODUCTION

We humans have been filtering things for virtually our entire history. Water filtering is a simple example. We can filter impurities from water as simply as using our hands to skim dirt and leaves off the top of the water. Another example is filtering out noise from our surroundings. If we paid attention to all the little noises around us we would go crazy. We learn to ignore superfluous sounds (traffic, appliances, etc.) and focus on important sounds, like the voice of the person we're speaking with.

There are also many examples in engineering where filtering is desirable. Radio communications signals are often corrupted with noise. A good filtering algorithm can remove the noise from electromagnetic signals while still retaining the useful information. Another example is voltages. Many countries require in-home filtering of line voltages in order to power personal computers and peripherals. Without filtering, the power fluctuations would drastically shorten the useful lifespan of the devices.

II.BACKGROUND

Kalman filtering is a relatively recent (1960) development in filtering, although it has its roots as far back as Gauss (1795). Kalman filtering has been applied in areas as diverse as aerospace, marine navigation, nuclear power plant instrumentation, demographic modeling, manufacturing, and many others. In the field of motion estimation for video coding many techniques have been applied. It is now quite common to see the Kalman filtering technique and some of its extensions to be used for the estimation of motion within image sequences. Particularly in the pixel-recursive approaches, which suit very much the Kalman formulation, one finds various ways of applying this estimation technique both in the time and frequency domains. On a very general perspective, we find use of

Kalman filter (KF), which implies linear state-space representations and the extended Kalman filter (EKF), which uses the linearized expressions of non-linear state- space formulations. Moreover, the parallel extended Kalman filter (PEKF) which consists of a parallel bank of EKF's, is often encountered in practice.

III. KALMAN FILTER

A.INTRODUCTION

In 1960, R.E. Kalman published his famous paper describing a recursive solution to the discrete-data linear filtering problem. Since that time, the Kalman filter has been the subject of extensive research and application, particularly in the area of autonomous or assisted navigation. The Kalman filter is a mathematical power tool that is playing an increasingly important role in computer graphics as we include sensing of the real world in our systems.

B.WHAT IS A KALMAN FILTER

Theoretically, the Kalman Filter is an estimator for what is called the *"*linear quadratic problem*"*, which focuses on estimating the instantaneous "state" of a linear dynamic system perturbed by white noise. Statistically, this estimator is optimal with respect to any quadratic function of estimation errors. In practice, this Kalman Filter is one of the greater discoveries in the history of statistical estimation theory and possibly the greatest discovery in the twentieth century. It has enabled mankind to do many things that could not have been done without it, and it has become as indispensable as silicon in the makeup of many electronic systems

In a more dynamic approach, controlling of complex dynamic systems such as continuous manufacturing processes, aircraft, ships or spacecraft, are the most immediate applications of Kalman filter. In order to control a dynamic system, one needs to know what it is doing first. For these applications, it is not always possible or desirable to measure every variable that you want to control, and the Kalman filter provides a means for inferring the missing information from indirect (and noisy) measurements. Some amazing things that the Kalman filter can do is predicting the likely future courses of dynamic systems that people are not likely to control, such as the flow of rivers during flood, the trajectories of celestial bodies or the prices of traded commodities.

IV. TARGET TRACKING

A. TRACKING

The block diagram of the tracking system is shown in Figure1. It comprises three modules: adaptive background, measurement and Kalman filtering. The adaptive background module produces the foreground pixels of each video frame and passes this evidence to the measurement module. The measurement module associates the foreground pixels to targets, initializes new ones if necessary and manipulates existing targets by merging or splitting them based on an analysis of the foreground evidence. The existing or new target information is passed to the Kalman filtering module to update the state of the tracker, i.e. the position, velocity and size of the targets. The output of the tracker is the state information which is also fed back to the adaptive background module to guide the spacio-temporal adaptation of the algorithm

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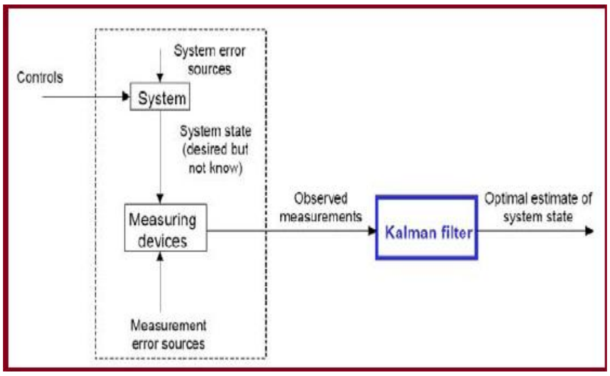

Figure 1:Target tracking system

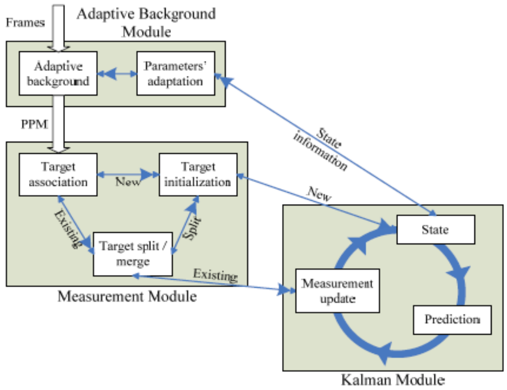

Figure 2. Block diagram of the complete Feedback tracker architecture

STEPS FOR TARGET TRACKING

There are two major components of a visual tracking system, namely,
• Target Representation and Localization
• Filtering and Data Association

B. TARGET REPRESENTATION AND LOCALIZATION

This involves identifying and tracking features. These features are what the tracking algorithm locks onto and follows in every frame. Features are selected because they are bright/dark spots, edges or corners depending on the particular tracking algorithm.

Each feature represents a specific point on the surface of a real object. As a feature is tracked it becomes a series of two-dimensional coordinates that represent the position of the feature across a series of frames. This series is referred to as a **track**. Once tracks have been created they can be used immediately for 2D motion tracking, or then be used to calculate 3D information.

Target Representation and Localization is mostly a bottom-up process. Typically the computational complexity for these algorithms is low. The following are some common target Representation and Localization algorithms:

- **Blob Tracking:** Segmentation of object interior
- **Kernel-based Tracking (Mean-shift Tracking)**: An iterative localization procedure based on the maximization of a similarity measure
- **Contour Tracking:** Detection of object boundary
- **Visual Feature Matching:** process of transforming the different sets, of data
- Acquired by sampling the same scene or object at different times, or from different perspectives, into one coordinate system.

C.KALMAN FILTER FOR TARGET TRACKING

In target tracking applications, the most popular methods for updating target positions incorporate variations of the Kalman filter/state estimator. The Kalman filter assumes that the dynamics of the target can be modeled, and that noise affecting the target dynamics and sensor data is stationary and zero mean. In cases where the target is actively maneuvering, the plant disturbance is not zero mean, and the performance of the Kalman filter degrades. To compensate, it is important to minimize sensor noise, such that the sensor data gains will be higher and the reliance on the model dynamics will be reduced. This is of considerable importance when tracking people, whose erratic movements are poorly y matched to any model of more than second order

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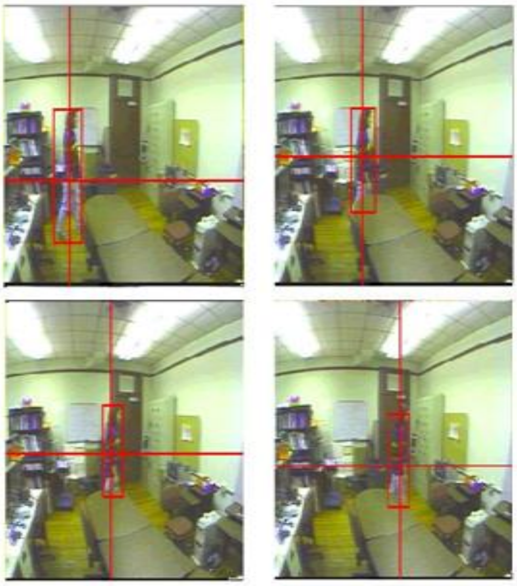

Fig3 : Tracking a Person Walking

Fig4:Position Estimate while Tracking a face

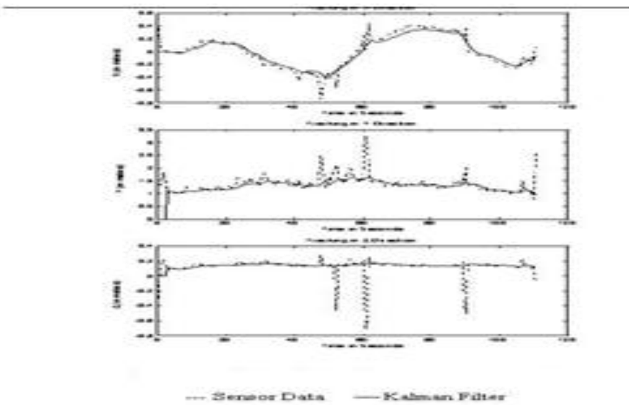

Fig5:target Tracking of a face in 3D

D. TRACKING MULTIPLE TARGETS

The Kalman Filter can be used to track the position of multiple targets. To do this, an object-oriented approach was used: a plane class was created containing the iterate method and all the data associated with the plane. Two instances of the plane class were created upon running the program, one for each target being tracked. The main class read in the data and called the iterate method in each of the plane instances, passing the data to them as parameters. The new data points were then retrieved from both planes and printed out.

This object-oriented approach greatly simplified the problem of managing data from both targets and also allowed for more targets to be added and tracked, as new plane instances could easily be created.

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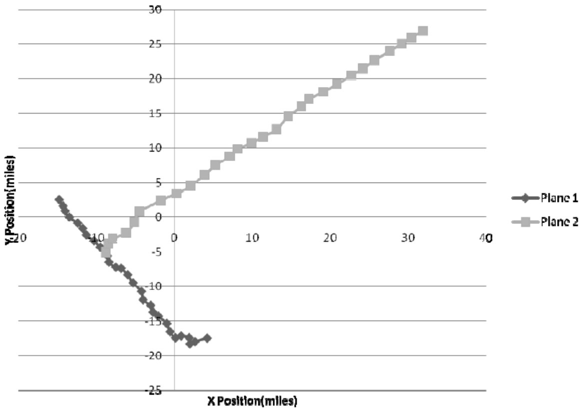

Figure 6: shows the two planes being tracked as they travel in a line.

V.PROPOSED IMPROVEMENTS

A. The linear motion model that is used to describe the motion of the object being tracked does not accurately represent the actual motion of the objects in the simulations, this leading to the sharp ‘peaks’ in the error estimation curves.

Solution: There are two ways to solve this problem; the obvious one is to use a motion model which is more accurate. This might not always be possible because the motion might not conform to one model throughout the simulation. To compensate for this the ‘Extended Kalman Filter’ or one of its many variations may be used, the scope of which are much beyond what’s covered in this project.

As was shown from the results with high values of process noise covariance matrix ‘Q’, the errors are minimized to almost negligible because the Kalman Filter trusts the measured values more than the state equation obtained values. But in case of very noisy measurements (magnitude of error comparable to magnitude of measurement), the high ‘Q’ value will result in high errors in estimated values because of the weight given to the measured values. This situation is optimized by using a mid value of Q when we are not sure whether the measurements or the state equation estimated values are more correct.

B. The measurement error covariance matrix R is given a constant value, calculated beforehand by running the filter offline. This ‘R’ value is obtained only by the minute errors caused by the measurement function implemented. In truth, the R matrix should also include for the noise caused by perturbations in the sensor (camera) position etc. Similar to point 1, a small value of R implies more weight to the measurements while a large value means less importance to measured values while calculating the estimated state values.
Solution: An optimum value of Q and R matrices must be chosen keeping in mind the presumed correctness of the measurement and the state equations (estimation model).

C. The object recognition methods used in the simulation are very basic, with little innovation involved. The prerequisite of the camera being stable or fixed in position are not always satisfied in real world problems.

Similarly, in the simulation where the camera position is not the same throughout, it is assumed that the background very nearly is. This again is not true on every situation, even in the cases of tracking in the sky and sea; there may be differences in the background with changing camera view, differences which may result in wrong object detection.

D. The simulations all depend on only one camera as the sensor. Although this doesn’t pose any problems for the concerned simulation cases and their accuracy, but in applications where characteristics of the object like size, distance from the camera etc. need to be considered, the one camera method falls short. A minimum of two cameras are required for characteristics like depth, size and distance to be measured.

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Solution: Using two cameras as sensors, placing the cameras at positions where it is geometrically possible from the two views to calculate the distance and size of the object. This is achieved by co-relating the two sensor inputs using co-ordinate transforms, i.e. .translating the two different views to one combined view.

V1.CONCLUSION

A. The Kalman Filter estimation has errors due to the fact that the motion of the objects is not accurately represented by the linear motion model assumed.

Also, for increasing values of the State noise covariance matrix Q, the errors reduce dramatically with estimation error peaks(in pixels) in the RADAR simulation for the first object in falling from 27 to 5 to 0.33 for values of Q (the state noise standard deviation actually) increasing by a factor of 10 for each case.

B. This trend of decreasing errors with larger values of Q is visible in each of the four simulations.For high values of Q, the Kalman filter estimates the states with a very low degree of error, even though the model is not accurate, this shows the high level of accuracy of the Kalman Filter in almost any case of implementation.

C. In the final simulation, i.e. the video simulation, the results are as close to perfection as can be.This is because unlike the other simulations where the object movements are human defined, the movement of the objects (the airplane) is much closer to reality, and also there are no rapid turns.

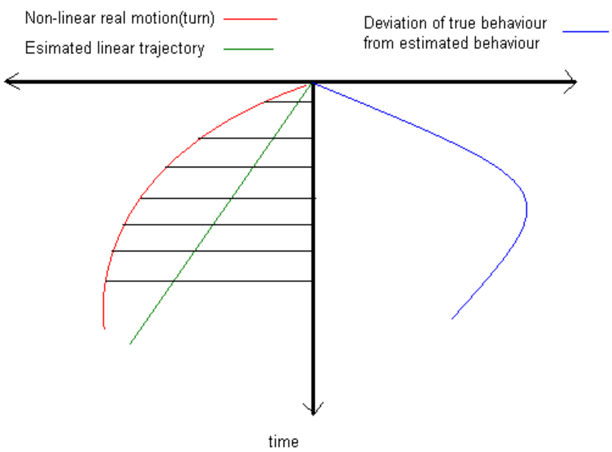

Figure 7. Diagram showing how the error depends on the path of the object

D. The peaks in the estimation error curves are due to turns which the object undertakes. The Kalman Filter is vulnerable to tracking objects which take sharp turns in their trajectory.For this the Extended Kalman Filter or other variations are used. The turns mean that there’s a deviation from the linear motion model.

In case of the video tracking simulation, there are no turns, but the peaks are present. This is due to the fact that the targets (planes) are changing in one frame duration, the Kalman filter converges only after multiple iterations.
5. Another observation related to the peaks is that there’s a gradual fall in the error after the peak is reached, this fall will continue until another turn or change of objects is encountered.This reduction of errors with multiple iterations is the result of the **Kalman Gain,**This is the ability of the Kalman Filter to adapt to the change and reduce the error with each iteration

REFERENCES

[1]Simon, Dan. “Kalman Filtering”, Embedded Systems Programming, June 2001
[2]University of North Carolina at Chapel Hill
[3]Theory and Practice” Upper Saddle River, NJ USA, Prentice Hall.

[4]Lacey, Tony. "Tutorial: The Kalman Filter", Georgia Institute of Technology
[5]Kramer, K.A., Stubberud, Stephen C. "Tracking of Multiple Target Types with a Single Neural Extended Kalman Filter".
[6]Tang, Li, Venkataraman V.B., Fan G. "Multi-aspect Target Tracking in Image
[7]Welch, Greg, Bishop, Gary(2006). "An Introduction to the Kalman Filter"

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