



Bayesian Filter based Object Tracking in Computer Vision


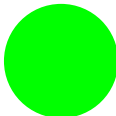
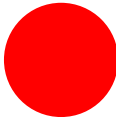

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Content

-  **Introduction**
-  **Particle Filter based Object Traction**
-  **Kalman Filter based Simultaneous Localization and Mapping (SLAM)**
-  **Conclusion**

Introduction

- Camera is the most widely used sensor.
- Camera is very cheap
- An Image contain lots of information.

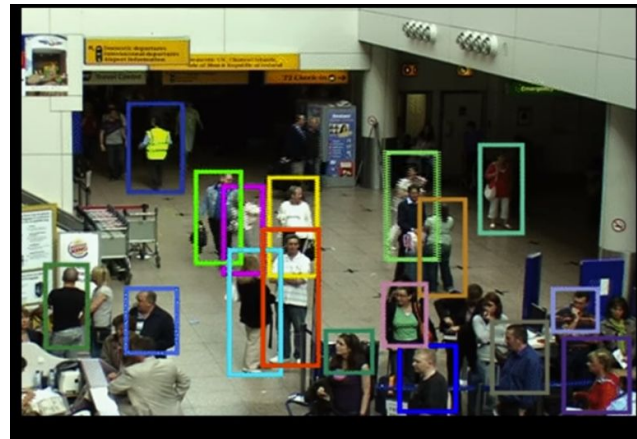
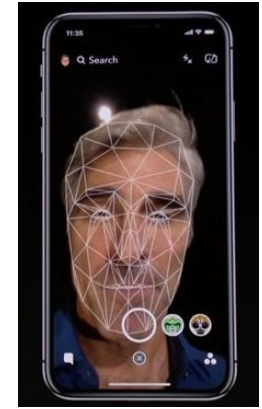
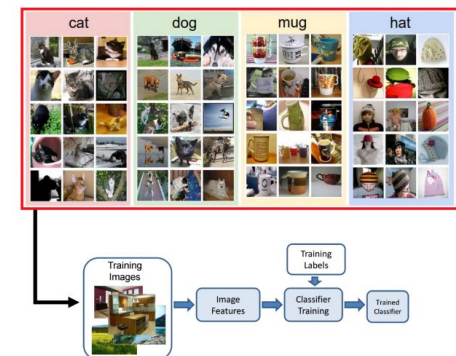


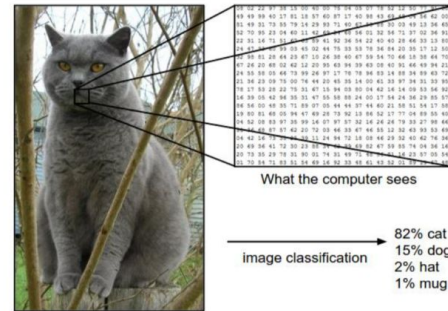
Image Classification Pipeline



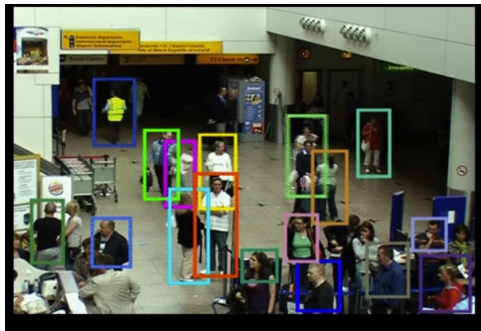
Introduction

- Images are Numbers

Images are Numbers



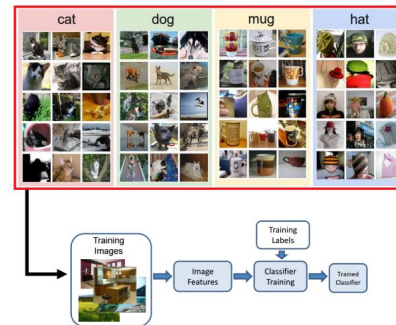
Object Traction



Moving Object: Kalman Filter

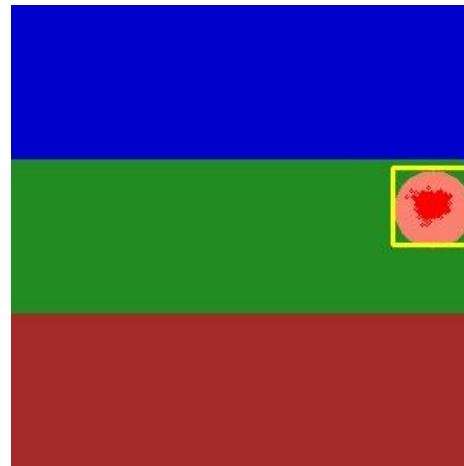
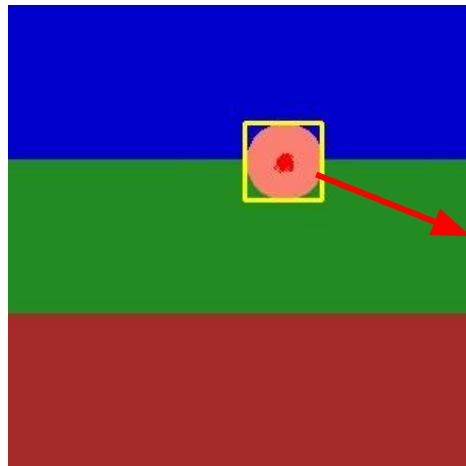
Object Classification/reconsization

Image Classification Pipeline

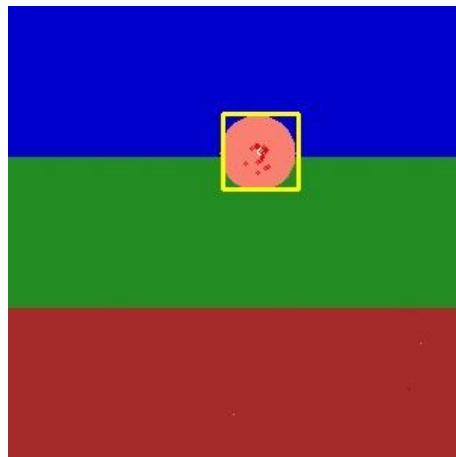


Deep Learning

Particle Filter based Object Tracking



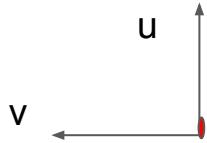
Object



1. Object is the “thing” that is actually being tracked.
2. $x(t)$ represent the state of the model at time t .
3. A dynamic model $p(x(t)|x(t-1))$ distribution of the state at time t given the state at $t - 1$
4. a measurement $z(t)$ that somehow captures the data of the current image.
5. a sensor model $p(z(t) | x(t))$ that gives the likelihood of a measurement given the state.

$$Bel(x_t) \propto p(z_t|x_t)p(x_t|u_t, x_{t-1})Bel(x_{t-1})$$

Particle Filter based Object Tracking

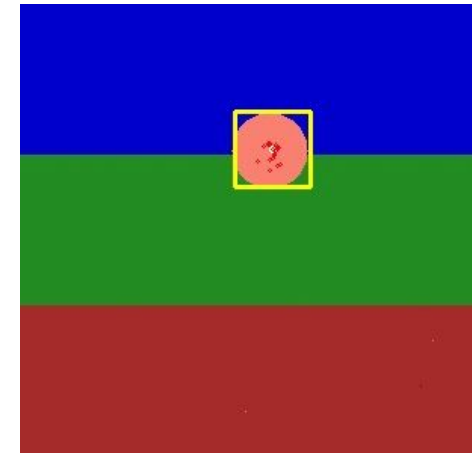
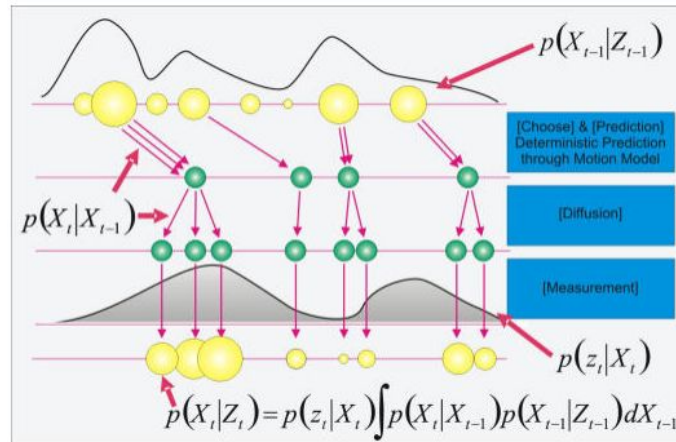


Each Particle have 4 states.
u, v, u speed, v speed.

$$MSE(u_p, v_p) = \frac{1}{mn} \sum_{u=1}^m \sum_{v=1}^n (Template(u, v) - Image^t(u + u_p - m/2, v + v_p - n/2))^2$$

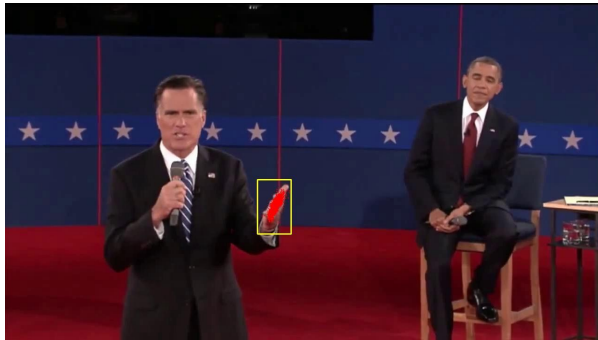
Important sampling

$$p(z_t | x_t) \propto \exp\left(-\frac{MSE}{2\sigma_{MSE}^2}\right)$$



Particle Filter based Object Traction

Objects are Changing



$$Template(t) = \alpha Best(t) + (1 - \alpha)Template(t - 1)$$

where $Best(t)$ is the patch of the best estimate or mean estimate. It's easy to see that by recursively updating this sum, the window implements an exponentially decaying weighted sum of (all) the past windows.

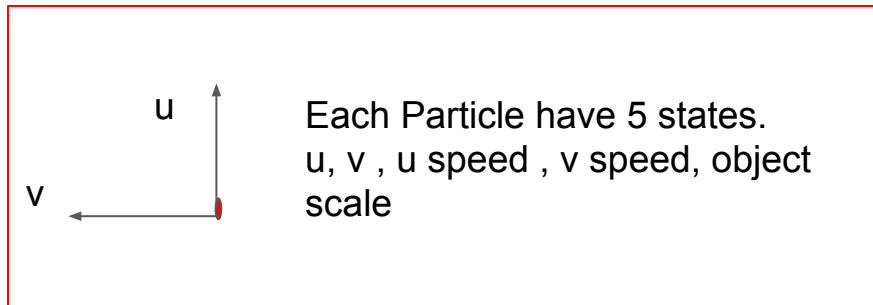


Particle Filter based Object Traction



Particle Filter based Object Traction

Objects are Changing, and the scale of object also change, and occlusion



Particle Filter based Object Tracking



Particle Filter based Object Tracking

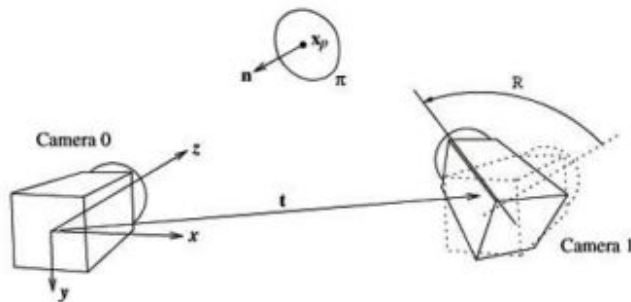
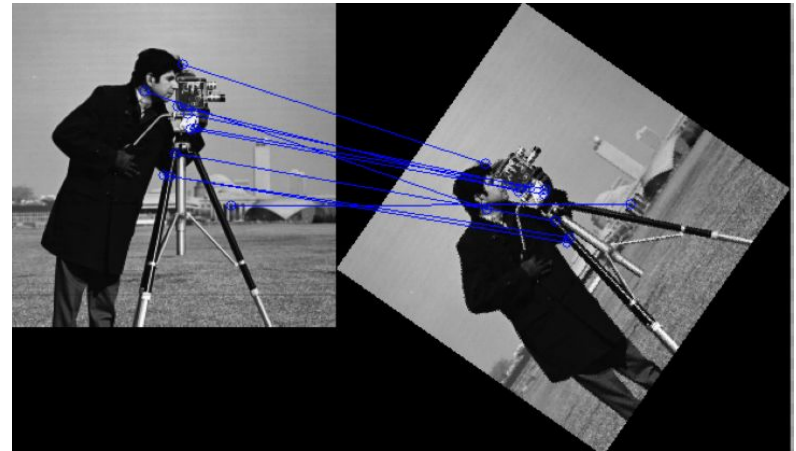
Multi Object Tracking



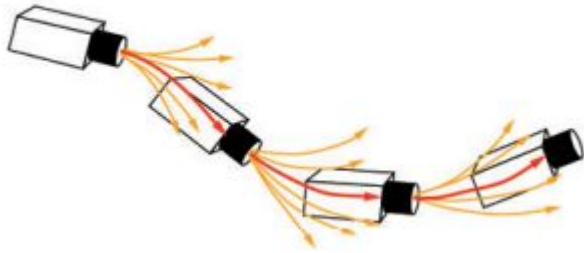
Kalman Filter based Simultaneous Localization and Mapping (SLAM)

Scale-invariant feature transform (SIFT)

Can we use those Key points to estimate the camera's location?



Kalman Filter based Simultaneous Localization and Mapping (SLAM)



$$\mathbf{f}_v = \begin{pmatrix} \mathbf{r}_{new}^W \\ \mathbf{q}_{new}^{WR} \\ \mathbf{v}_{new}^W \\ \omega_{new}^R \end{pmatrix} = \begin{pmatrix} \mathbf{r}^W + (\mathbf{v}^W + \mathbf{V}^W)\Delta t \\ \mathbf{q}^{WR} \times \mathbf{q}((\omega^R + \Omega^R)\Delta t) \\ \mathbf{v}^W + \mathbf{V}^W \\ \omega^R + \Omega^R \end{pmatrix}.$$

$$\mathbf{x}_v = \begin{pmatrix} \mathbf{r}^W \\ \mathbf{q}^{WR} \\ \mathbf{v}^W \\ \omega^R \end{pmatrix}.$$

\mathbf{r}^W

3D position vector

\mathbf{q}^{WR}

orientation quaternion

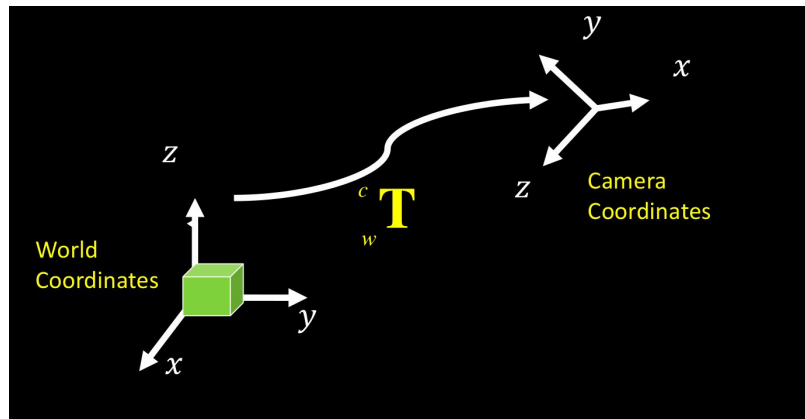
\mathbf{v}^W

velocity vector

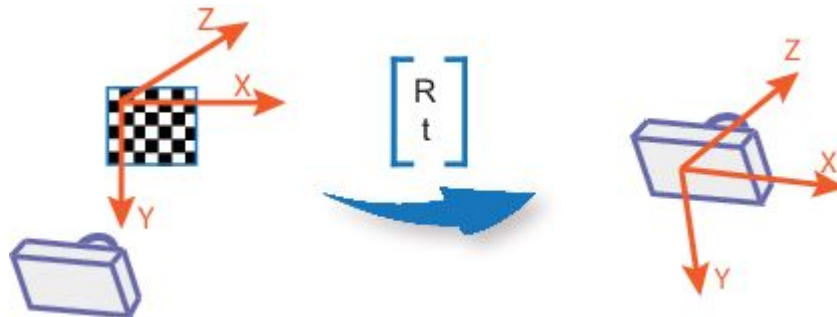
ω^R

angular velocity vector

Kalman Filter based Simultaneous Localization and Mapping (SLAM)

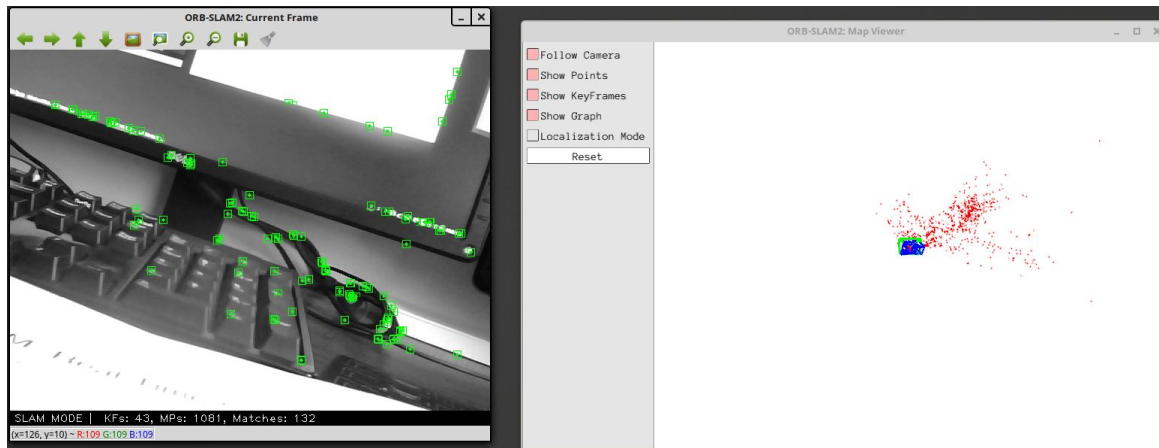
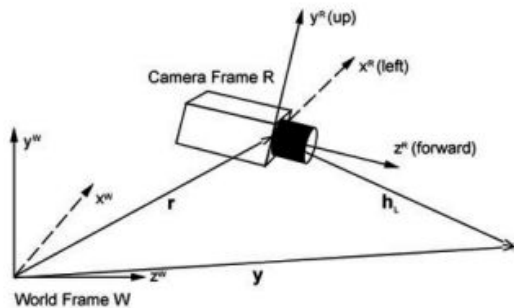


Extrinsic Camera Calibration

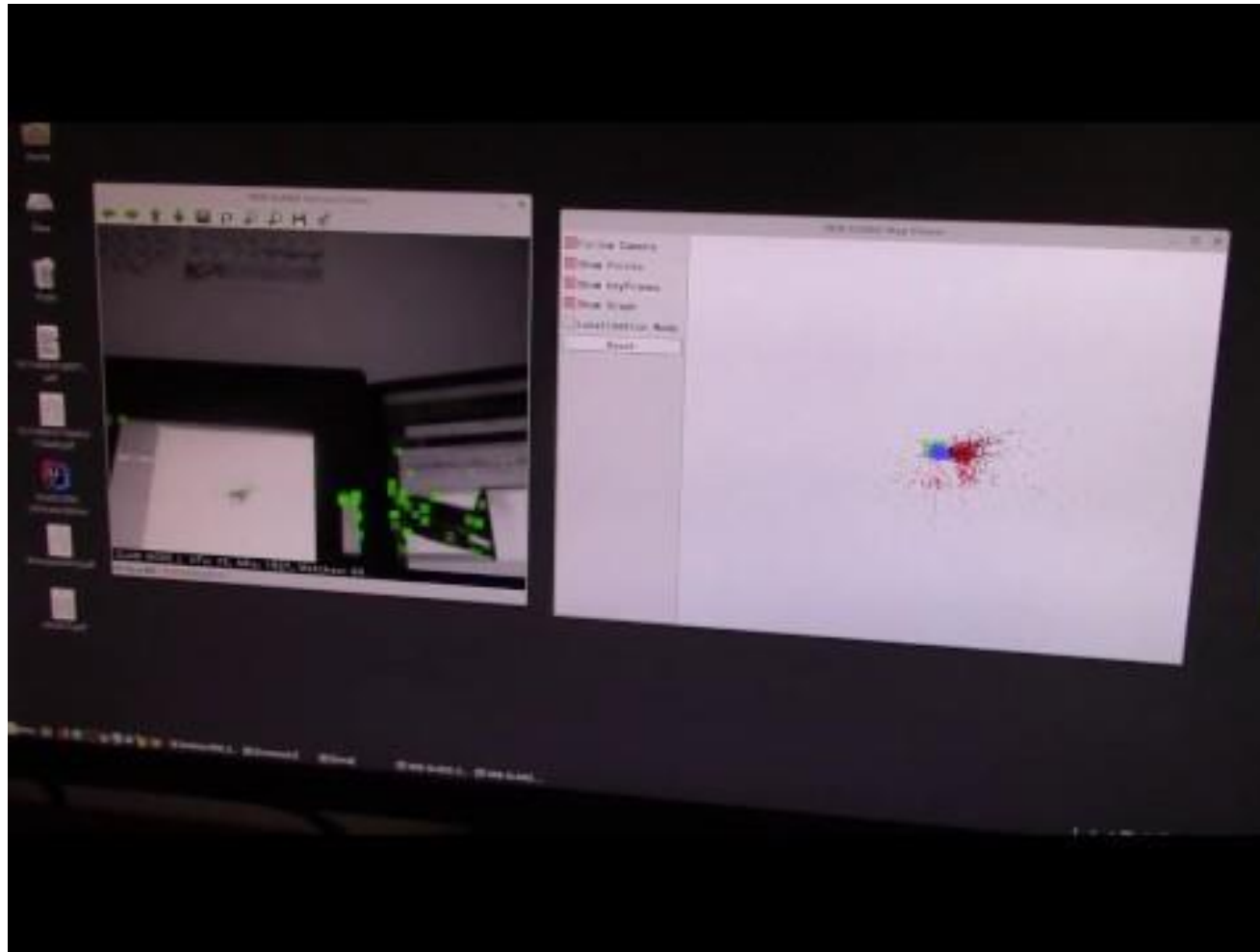


Intrinsic camera calibration

Kalman Filter based Simultaneous Localization and Mapping (SLAM)



Kalman Filter based Simultaneous Localization and Mapping (SLAM)



Questions?

