

Need precision
16 bit and 32 bit float points. During testing

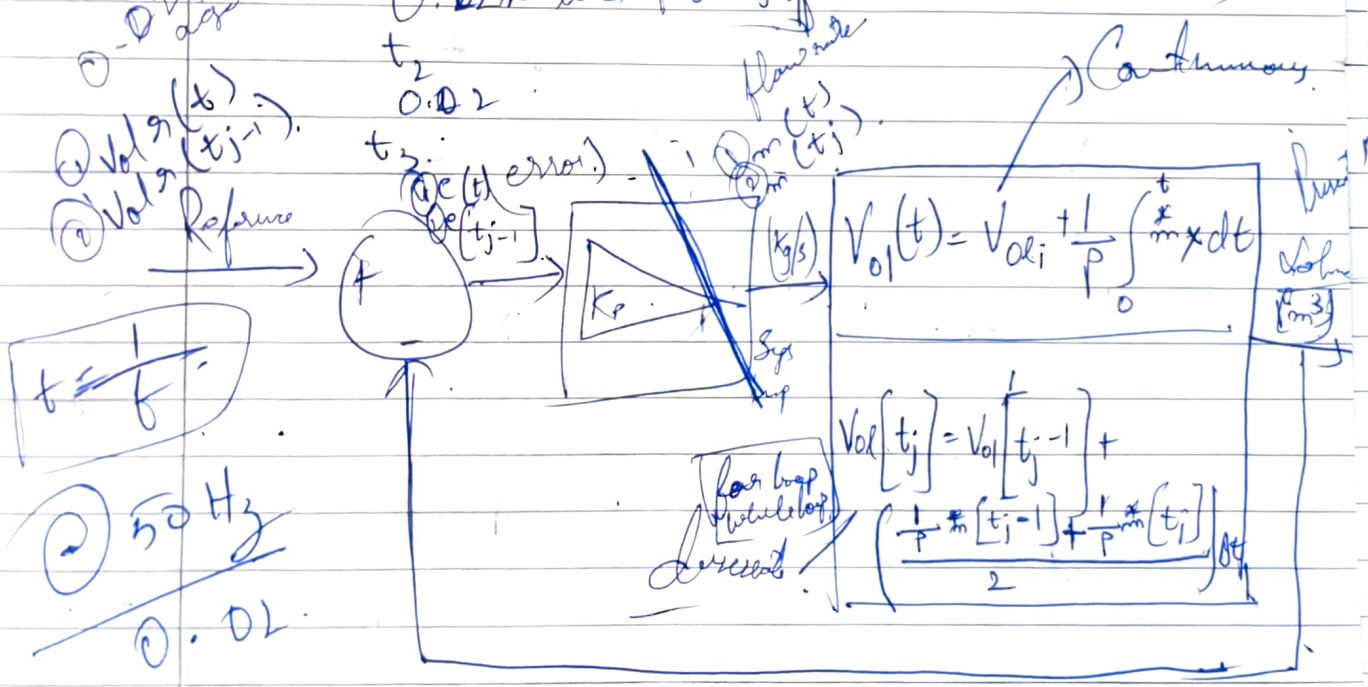
to make it run faster and use less memory. Compute

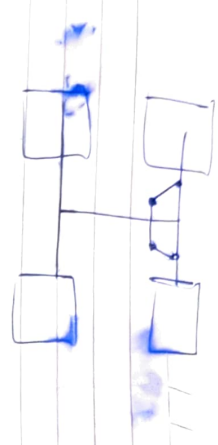
GPU compatible to 7.0 @ 100 Hz for better performance.
using 1000 GPU.
V100 @ 100 Hz for 7.0 @ 100 Hz.
T4, A100

Compare history.

Automatic
under
system
Controller.
0.02 sec
ago

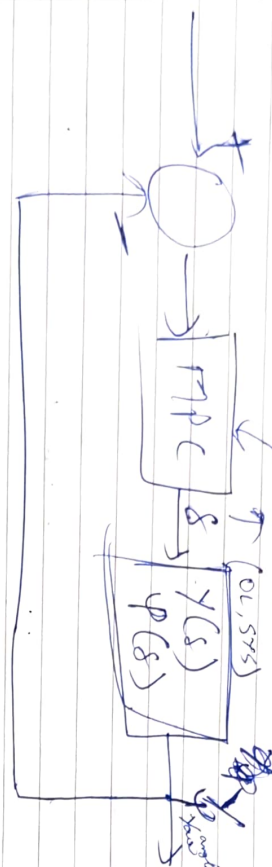
$$Vol[t_j] = Vol[t_j - 1] + \left(\frac{\frac{1}{p} * m[t_j - 1] + \frac{1}{p} * m[t_j]}{2} \right) \Delta t$$



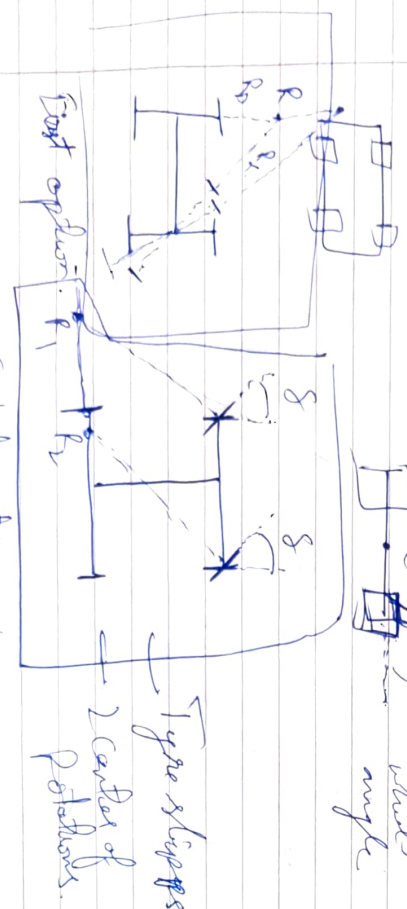


MPC (Model Predictive Control)

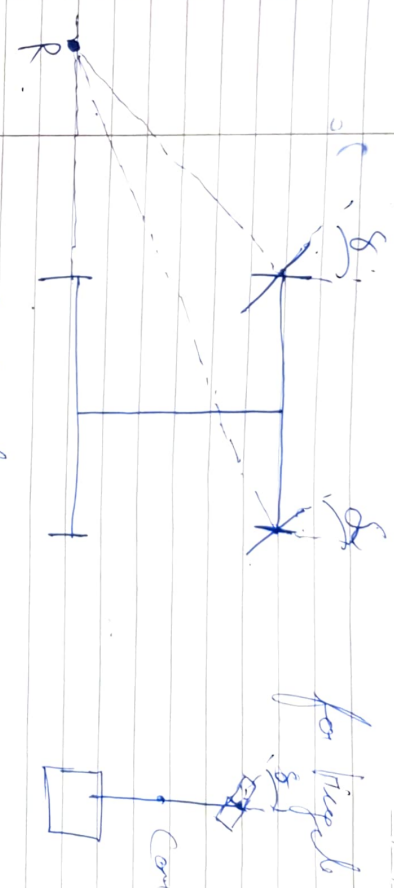
→ MPC Control.
→ Scalable.



Controlled vs Bicycle Model

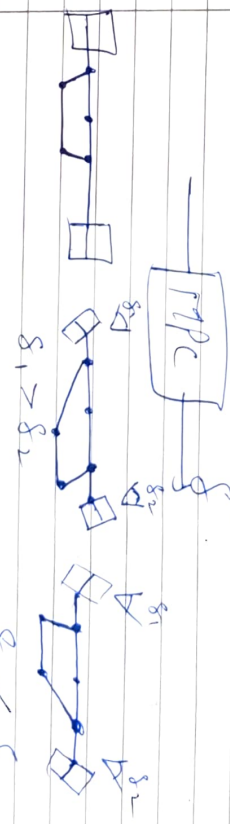


Second option.



Third option.

Active Plan Steering



$\theta_1 < \theta_2 < \theta_3 < \delta$

Equations of motions.



$$\sum F = ma$$

$$\sum M = I \alpha$$

angular acceleration

X

$$\sum F = ma_y$$

$$F_{gx} + F_{yt} = ma_y$$

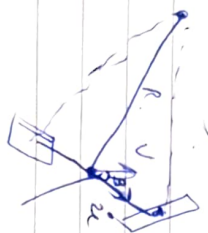
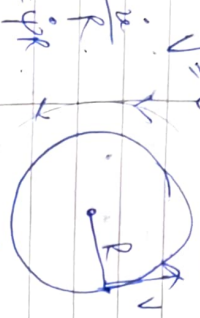
$$F_{yt} - F_{gx} \cdot \sin \theta = I \ddot{\theta}$$

$$a_y = \ddot{y} + r \ddot{\theta}$$

center of mass acceleration

If Bicycle is turning

then use sharp turn centripetal acceleration.



$$d = r \dot{\theta}$$

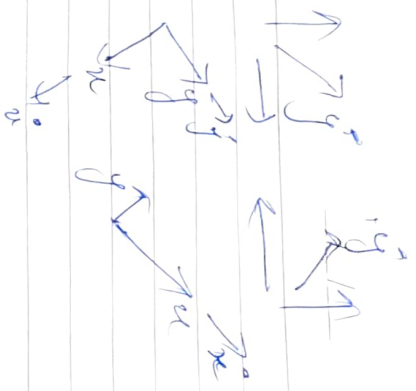
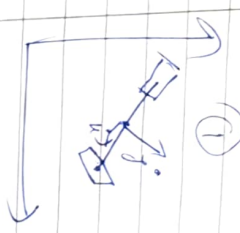
$$\dot{d} = r \ddot{\theta}$$



$$d = r \dot{\theta}$$

$$F_{yt} + F_{gx} = m (\ddot{y} + r \ddot{\theta})$$

$$a_y = \ddot{y} + r \ddot{\theta}$$



Presence of \dot{y} m/s -

indicates there might be slipping in the turn wheel. usually the very left \dot{y} m/s presence states there is more slip.

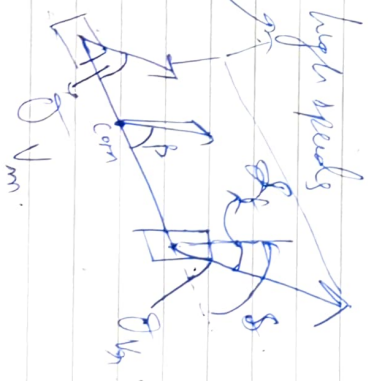
$$\dot{y} = 0 \text{ m/s}$$

2 hrs

$$F_{yt} + F_{gx} = m (\ddot{y} + r \ddot{\theta})$$

$$F_{yt} - F_{gx} \cdot \sin \theta = I \ddot{\theta}$$

during high speeds due to tyre deformation



$$\delta_f = \delta - \theta$$

$$\delta_n = 0 - \theta$$

$$= -\theta$$

$$F_{yt} \propto \delta_n$$

axial (on line)
but only if
the axle is
connected
to the body
connecting
stiffness

$$F_{yf} = 2 C_{sf} \cdot \delta_f$$

$$F_{yn} = 2 C_{sn} \cdot \delta_n$$

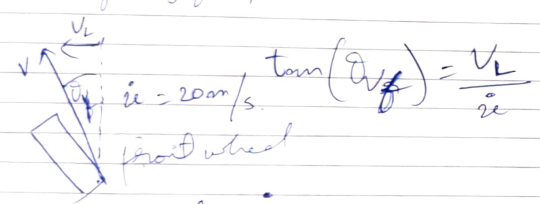
$C_{sf} \rightarrow$ slope
N/mad
only for small slip angles

$$F_{yf} = 2 C_{sf} (\delta - \theta_{vf})$$

$$F_{yn} = 2 C_{sn} (-\theta_{vn})$$

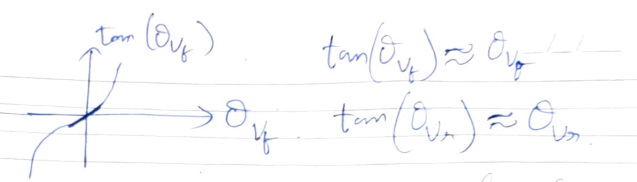
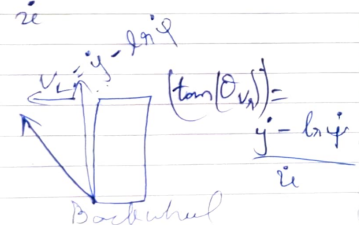
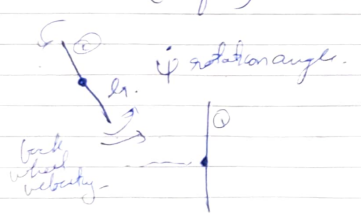
intensity of $\dot{\psi} \rightarrow \dot{\psi}$

θ_{vf}
 θ_{vn}



$$V_L = \dot{y} + l_f \dot{\psi}$$

$$\tan(\theta_{vf}) = \frac{\dot{y} + l_f \dot{\psi}}{u}$$



$$\theta_{vf} = \frac{\dot{y} + l_f \dot{\psi}}{u} \quad \text{only when they are small}$$

$$\theta_{vn} = \frac{\dot{y} - l_n \dot{\psi}}{u}$$

$$m(\ddot{y} + \dot{\psi} u) = 2 C_{sf} (\delta - \theta_{vf}) + 2 C_{sn} (-\theta_{vn})$$

$$m \ddot{y} + m \dot{\psi} u = 2 C_{sf} \cdot \delta - 2 C_{sf} \theta_{vf} - 2 C_{sn} \theta_{vn}$$

$$\ddot{y} = \underbrace{\left[\frac{-2 C_{sf}}{m u} - \frac{2 C_{sn}}{m u} \right]}_a \ddot{y} + \underbrace{\left[\frac{-u - 2 C_{sf} l_f}{m u} + \frac{2 C_{sn} l_n}{m u} \right]}_b \dot{\psi} + \frac{2 C_{sf} \delta}{m}$$

$$\begin{bmatrix} \ddot{y} \\ \ddot{\psi} \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} \dot{y} \\ \dot{\psi} \end{bmatrix} + \begin{bmatrix} e \\ f \end{bmatrix} \delta$$

$$I \ddot{\varphi} = l_f + l_f^2 C_{sf}(s - \partial_{\varphi_s}) + l_m^2 C_{sn}(\partial_{\varphi_n})$$

$$\ddot{\varphi} = \underbrace{\begin{bmatrix} -l_f + l_f^2 C_{sf} + l_m^2 C_{sn} \\ I \ddot{u} \end{bmatrix}}_c \dot{y} +$$

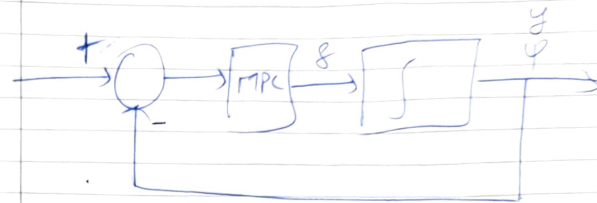
$$\underbrace{\begin{bmatrix} -l_f^2 C_{sf} - l_m^2 C_{sn} \\ I \ddot{u} \end{bmatrix}}_d \dot{\varphi} +$$

$$\underbrace{\begin{bmatrix} l_f + l_f^2 C_{sf} \\ I \end{bmatrix}}_f \cdot s \quad \text{longitudinal velocity is const.}$$

$\therefore a, b, c, d, e, f$ are const.

$$\begin{bmatrix} \ddot{y} \\ \ddot{\varphi} \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} \dot{y} \\ \dot{\varphi} \end{bmatrix} + \begin{bmatrix} e \\ f \end{bmatrix} s$$

$$\begin{cases} \ddot{y} = a \cdot \dot{y} + b \dot{\varphi} + e s \\ \ddot{\varphi} = c \cdot \dot{y} + d \dot{\varphi} + f s \end{cases} \quad \begin{matrix} \text{State space} \\ \text{equations} \\ \text{First order diff} \\ \text{equations} \end{matrix}$$



$\dot{\varphi}, \dot{y} \rightarrow$ states

variables
to describe how
sys behaves.



Non linear
State space
equation
(Dumpling example)

$$\begin{cases} \ddot{x}_1 = a \cdot x_1 + (x_2^2 + d x_3^2 + v_1) \\ \ddot{x}_2 = c^2 \cdot u_1 + \sin(x_2) + v_1 + v_2 \\ \ddot{x}_3 = f \cdot u_1^3 \end{cases}$$

Dumpling example

$\dot{y} = u_1$	$\ddot{y} = \ddot{y}$	$\ddot{y} = a u_1 + b u_3 + f \cdot u$
$\dot{\varphi} = u_2$	$\ddot{\varphi} = \ddot{\varphi}$	$\ddot{\varphi} = u_3$
$\dot{\varphi} = u_3$	$\ddot{\varphi} = \ddot{\varphi}$	$\ddot{\varphi} = (x_1 + d u_3 + f \cdot u$
$y = u_4$	$\ddot{y} = \ddot{y}$	$\ddot{y} = x_1 (a f(u_2) + 2 \sin(x_2))$
$s = u$	$s = u$	

State space
equation

$$\ddot{y} = a \dot{y} + b \dot{\varphi} + f s$$

$$\ddot{\varphi} = \ddot{\varphi}$$

$$\ddot{\varphi} = c \dot{y} + d \dot{\varphi} + f s$$

$$\ddot{y} = y \cos(\varphi) + \ddot{u} \cdot \sin(\varphi)$$

3 mgs

Future state prediction

$$\vec{x}_1 = A \vec{x}_0 + B \delta_0$$

$$\vec{x}_2 = A \vec{x}_1 + B \delta_1$$

$$\vec{x}_3 = A \vec{x}_2 + B \delta_2$$

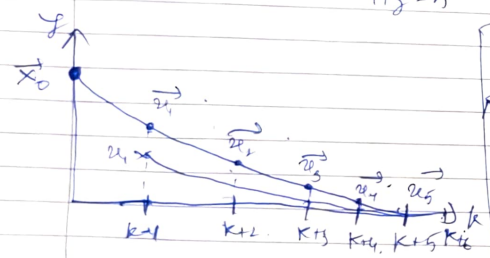
$$\vec{x}_4 = A \vec{x}_3 + B \delta_3$$

$$\vec{x}_5 = A \vec{x}_4$$

$$\vec{x}_5 = A^5 \vec{x}_0 + A^4 B \delta_0 + A^3 B \delta_1 + A^2 B \delta_2 + A B \delta_3 + B \delta_4$$

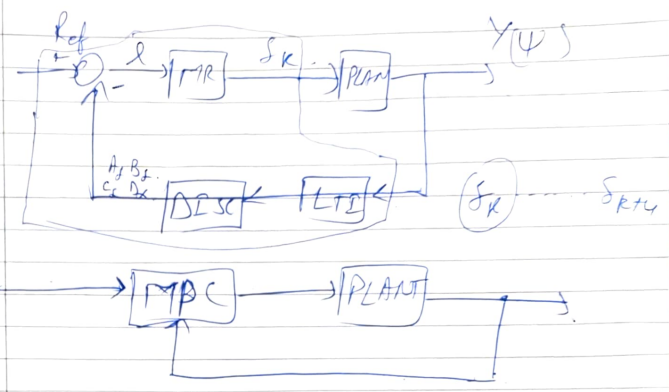
$$\vec{x}_k = A^k \vec{x}_0 + [A^{k-1} B \quad A^{k-2} B \quad \dots \quad A B \quad B] \begin{bmatrix} \delta_0 \\ \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \end{bmatrix}$$

$H_3 = 5$



$$\begin{bmatrix} \vec{x}_1 \\ \vec{x}_2 \\ \vec{x}_3 \\ \vec{x}_4 \\ \vec{x}_5 \end{bmatrix} = \begin{bmatrix} B & \dots & \dots & \dots & \dots \\ AB & B & \dots & \dots & \dots \\ A^2 B & AB & B & \dots & \dots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A^{n-1} B & A^{n-2} B & \dots & AB & B \end{bmatrix} \begin{bmatrix} \delta_0 \\ \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \end{bmatrix} + \begin{bmatrix} A \\ A^2 \\ \vdots \\ A^n \end{bmatrix} \vec{x}_0$$

LTI
ABCD \rightarrow $\begin{matrix} A & B \\ C & D \end{matrix}$



Reformulating the Cost fn

$$J = \frac{1}{2} \int_{k=N}^T \vec{e}_{k+N}^T + \frac{1}{2} \sum_{i=0}^{N-1} \left[\vec{e}_{k+i}^T \phi \vec{e}_{k+i} + \vec{f}_{k+i}^T R \vec{f}_{k+i} \right]$$

$$J^* = \frac{1}{2} \vec{e}_{k+N}^T \int \vec{e}_{k+N} + \frac{1}{2} \left[\vec{e}_k^T \phi \vec{e}_k + \vec{f}_k^T R \vec{f}_k + \vec{e}_{k+1}^T \phi \vec{e}_{k+1} + \vec{f}_{k+1}^T R \vec{f}_{k+1} + \dots + \vec{e}_{k+N-1}^T \phi \vec{e}_{k+N-1} + \vec{f}_{k+N-1}^T R \vec{f}_{k+N-1} \right]$$

$$J = \frac{1}{2} \vec{e}_{k+N}^T \int \vec{e}_{k+N} + \frac{1}{2} \sum_{i=0}^{N-1} \left[\vec{e}_{k+i}^T \phi \vec{e}_{k+i} + \vec{f}_{k+i}^T R \vec{f}_{k+i} \right]$$

1 Long (Car lane change)

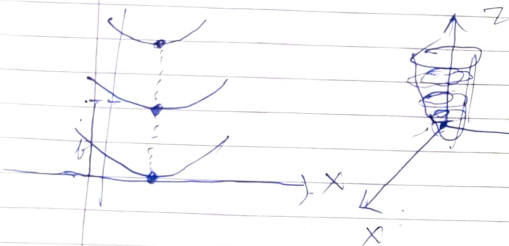
$$J = \frac{1}{2} [\vec{x}_{k+N} - \tilde{C} \vec{x}_{k+5}]^T (\vec{x}_{k+N} - \tilde{C} \vec{x}_{k+5})$$

$$+ \frac{1}{2} \sum_{i=0}^{k+1} \left[(\vec{x}_{k+i} - \tilde{C} \vec{x}_{k+5})^T \right] \left(\vec{x}_{k+i} - \tilde{C} \vec{x}_{k+5} \right)$$

$$+ \Delta \vec{s}_{k+1}^T R \Delta \vec{s}_{k+1}$$

$$y = ax + b$$

$$y = a(x - x_0) + b$$



$$z = (u, v)^T + \frac{1}{2} (y - y_0)^2 + b^2$$

Swarm Analysis 41

NIST 52, 56

Business Caffe 53, 57

Abstract 60, 61, 62, 63, 69

data source file

LipNet ✓

CNN Image Classifier ✓

Edge detection (openCV) ✓

IRIS Tracker ✓

Face recognition app ✓

Deep audio classifier ✓

GAN ✓

ESRGAN (Superes) ✓

Broof file

RTCV with TensorFlow.js and React + 7 projects

LipNet ✓

Water tank ✓

PID ✓

Boat ✓

MPC Car automation (lateral) ✓

Skunkit (NLP)

Best predict

Landmark detection.

Installing Facemesh (Pretrained deep learning library)

Building the facemesh app. (react up model)

Detecting 70 face in Real time (detection)

How it works.

- ① Create a webcam stream inside of front end react app.
- ② Tensorflow.js (load facemesh.) (make detection from stream)
- ③ Draw keypoints and triangle on javascript canvas.