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Neural Network Controllers for Trajectory control

Mobile Autonomous robots

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Technical Aspects of Multimodal Systems

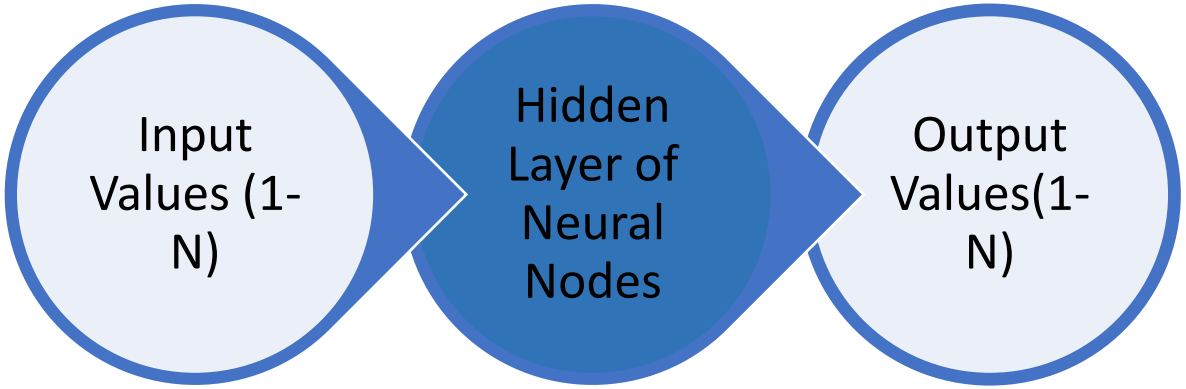
Motivation

- Getting an insight of Neural Network.
- Outlining basic expectation from a Neural Network system.
- Explore few different design of Neural Network Controllers and compare their results with classical Non-linear Non-adaptive Controllers.

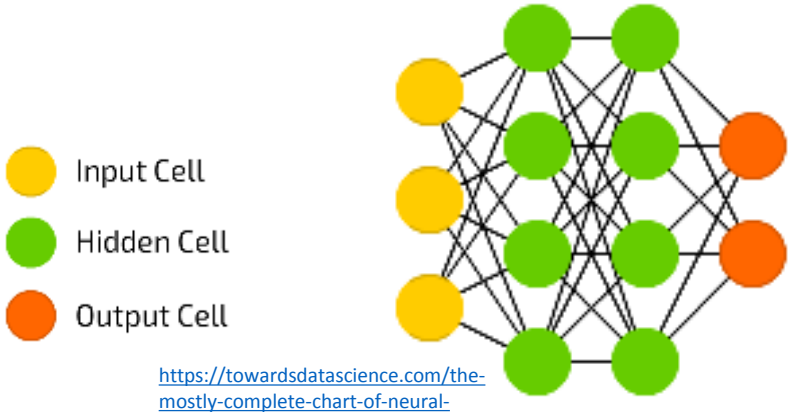
Content

Neural Network in a Nutshell

- The basic expectation



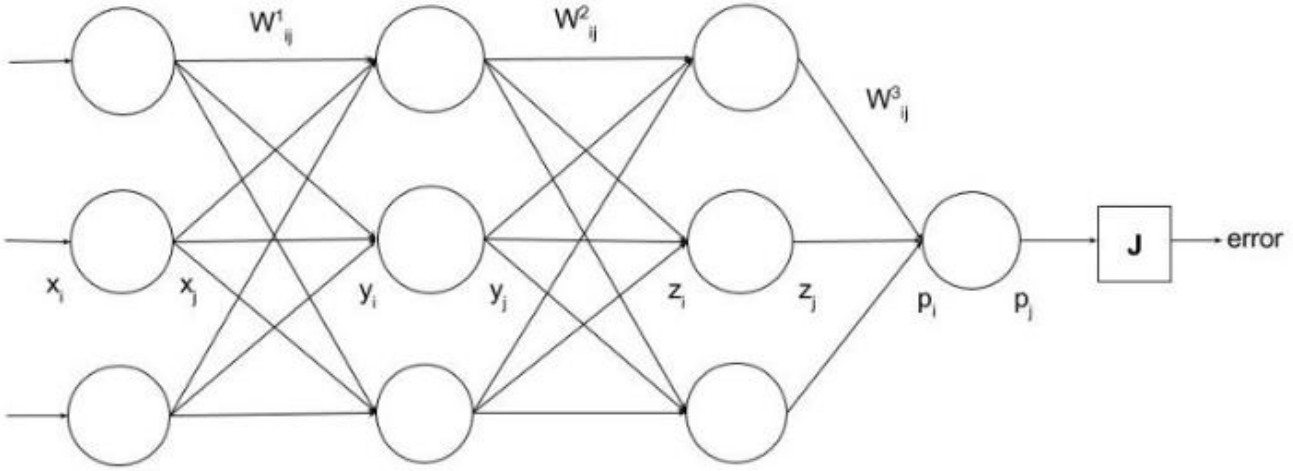
Function Approximation



https://towardsdatascience.com/the-mostly-complete-chart-of-neural-networks-explained-3fb6f2367464

Learning:
Takes Input and output -> Identifies relationship between the 2

Neuron and Networks



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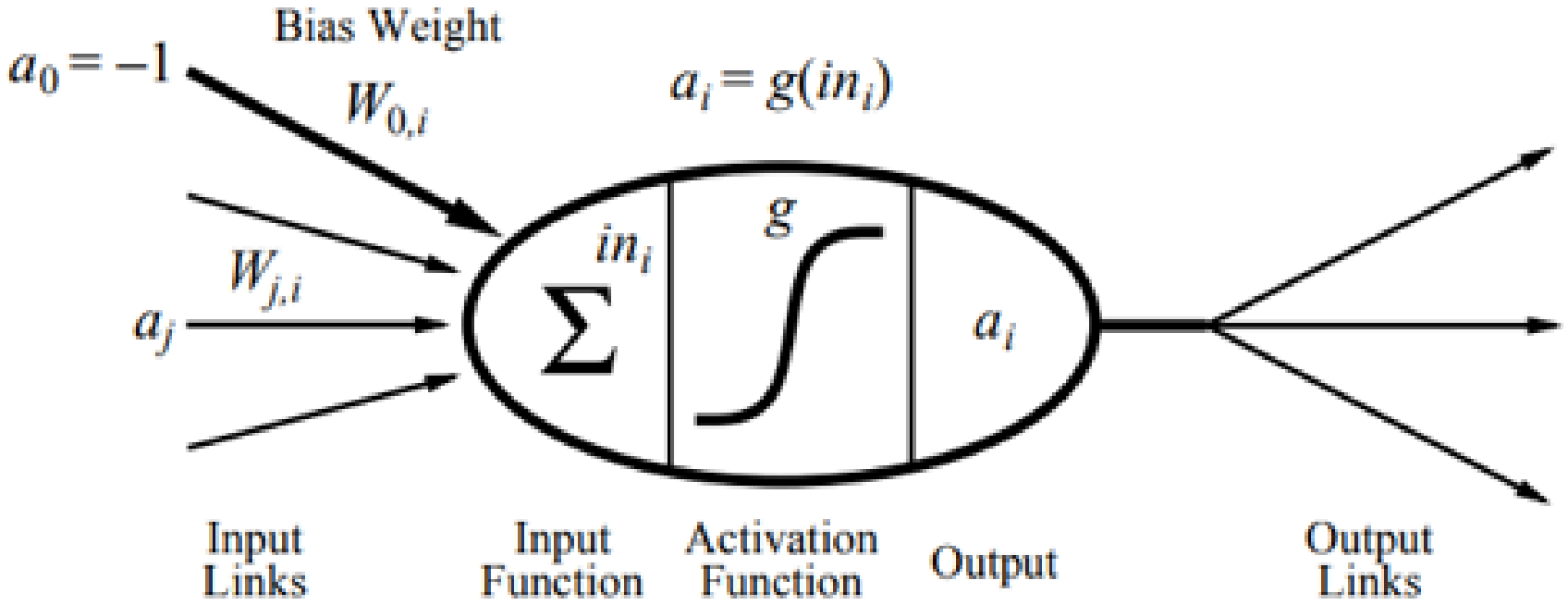
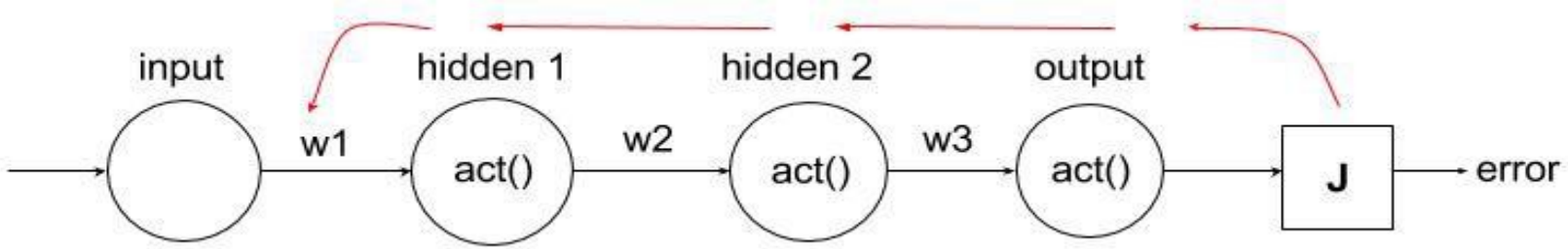


http://aima.eecs.berkeley.edu/slides-pdf/chapter20b.pdf

Backpropagation



$$error = J = \frac{1}{2}(\vec{p} - \vec{a})^2$$

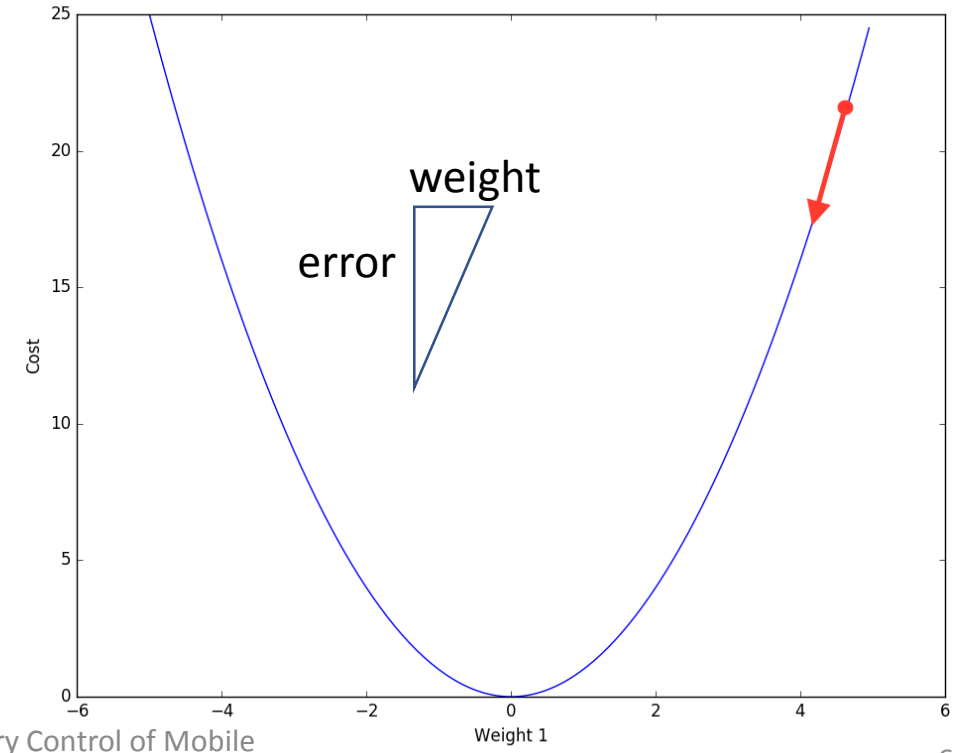
vector **p** = predicted output,
vector **a** = actual output

$$\frac{\partial error}{\partial w1} = \frac{\partial error}{\partial output} * \frac{\partial output}{\partial hidden2} * \frac{\partial hidden2}{\partial hidden1} * \frac{\partial hidden1}{\partial w1}$$

$$output = act(w3 * hidden2)$$

$$hidden2 = act(w2 * hidden1)$$

$$hidden1 = act(w1 * input)$$



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Optimization algorithm

https://skymind.ai/wiki/neural-network

Some examples of optimization algorithms include:

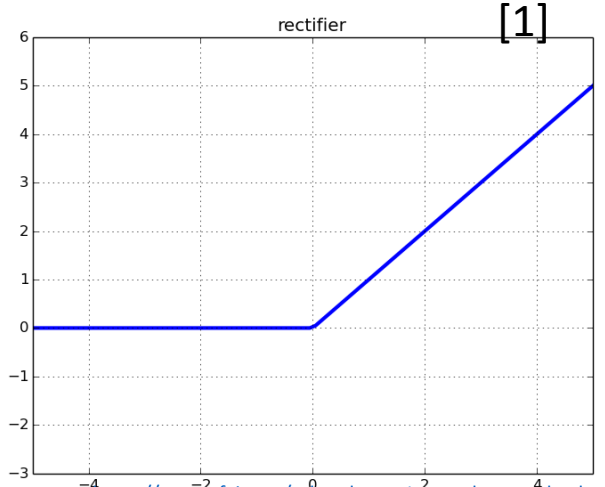
- ADADELTA
- ADAGRAD
- ADAM
- NESTEROVS
- NONE
- RMSPROP
- SGD
- CONJUGATE GRADIENT
- HESSIAN FREE
- LBFGS
- LINE GRADIENT DESCENT

Activation Function

Some examples include:

- CUBE
- ELU
- HARDSIGMOID
- HARDTANH
- IDENTITY
- LEAKYRELU
- RATIONALTANH
- RELU
- RRELU
- SIGMOID
- SOFTMAX
- SOFTPLUS
- SOFTSIGN
- TANH

[1]



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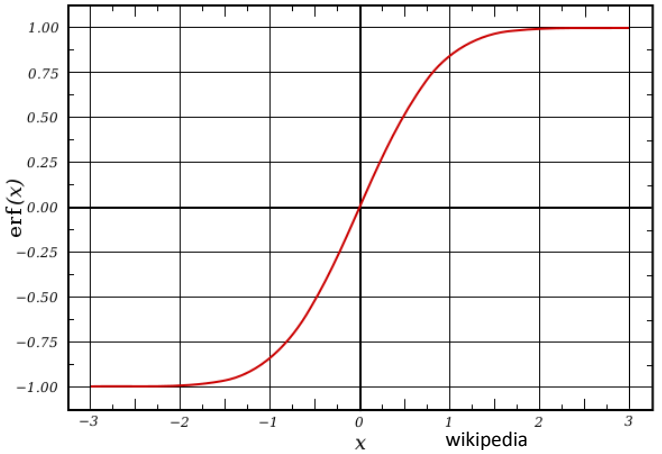

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2. Robot Trajectory Control : Problem Statement
3. Neural Network controller
   - A Basic Model (on Robot Manipulator)
   - Model Based on Quadrotors(Focus Model)
   - Additional Model on Mobile wheeled Robot
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Problem Statement

Employing Neural Network in Trajectory control of Robot(Mobile autonomous).

https://robotacademy.net.au/lesson/paths-and-trajectories/

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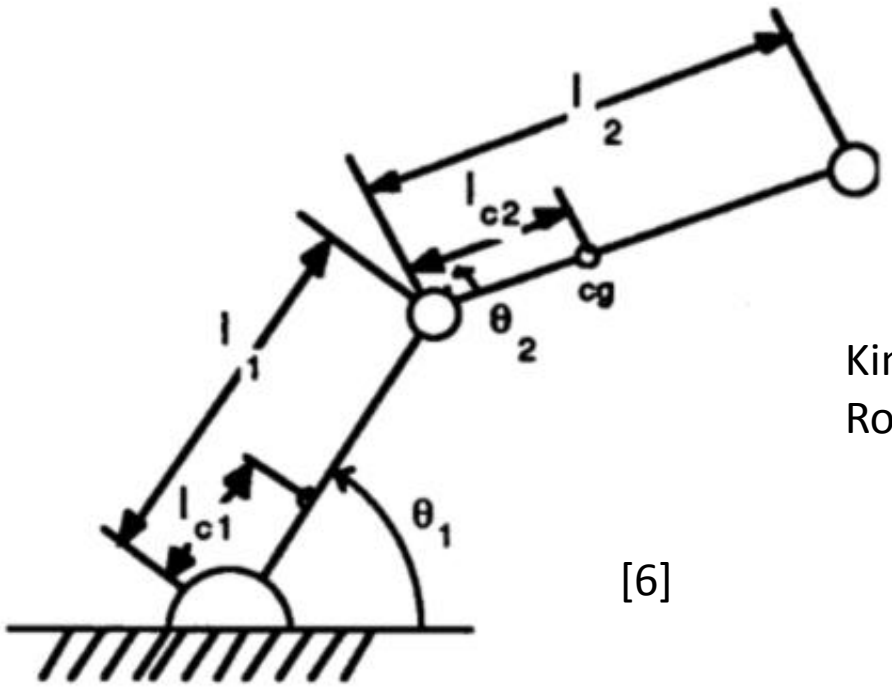
Trajectory control of End effector of Robot Manipulator

- Inverse Kinematics(Jacobian) by Neural Network
- FNN with Back propagation



Kinematics of Robot Arm

[6]

PARAMETER	VALUE
l_1	0.39 m
l_2	0.42 m
l_{c1}	0.35 m
l_{c2}	0.20 m
M_1	10.0 kg
M_2	3.0 kg
I_1	0.0597 kg-m^2
I_2	0.0494 kg-m^2

$$J^{-1} = \frac{1}{l_1 l_2 \sin\theta_2}\begin{bmatrix} l_2\cos(\theta_1+\theta_2) & l_2\sin(\theta_1+\theta_2) \\ -(l_1\cos\theta_1 + l_2\cos(\theta_1+\theta_2)) & -(l_1\sin\theta_1 + l_2\sin(\theta_1+\theta_2)) \end{bmatrix}$$

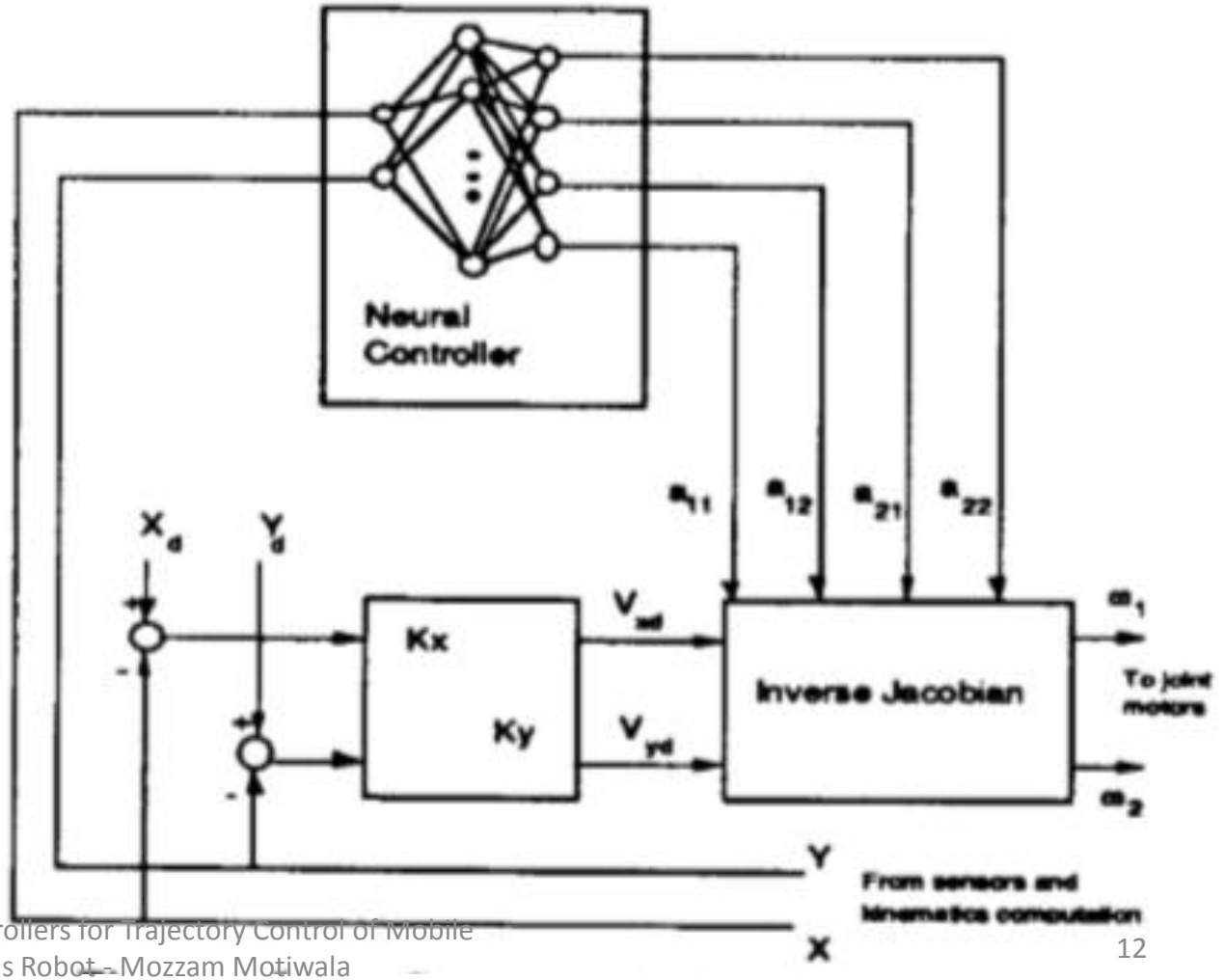
Neural Network design

- 2 angles as input and 4 components of Jacobian as output

TABLE II
VALUES OF θ_1 AND θ_2 USED TO CONSTRUCT TRAINING SET USED TO TRAIN THE INVERSE JACOBIAN NEURAL NETWORK

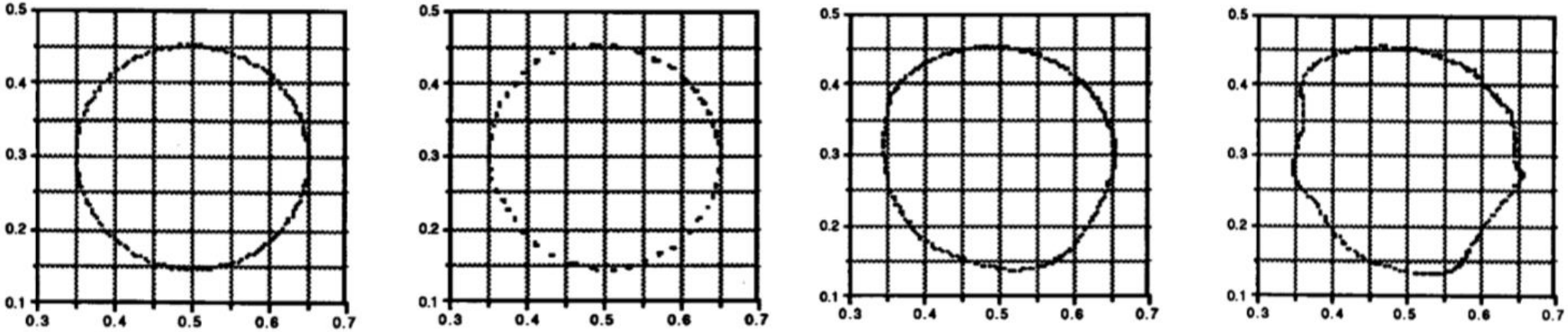
θ_1 (degrees)	θ_2 (degrees)
10	-135
30	-105
50	-75
70	-45
90	-15
110	15
130	45
150	75
170	105
	135

[6]



Functionality and result

- Desired position is compared with the actual position which can be inferred from joint angle measurements. The position error vector is used to scale a desired velocity which gives the direction in which the robot must move to drive the error to Zero.
- 2 input, 4 output, 2 hidden layers of 32 neurons each. 5000 cycles for upto 2.5 – 3 % RMS error.



[6]

0.26 m/s

0.59 m/s

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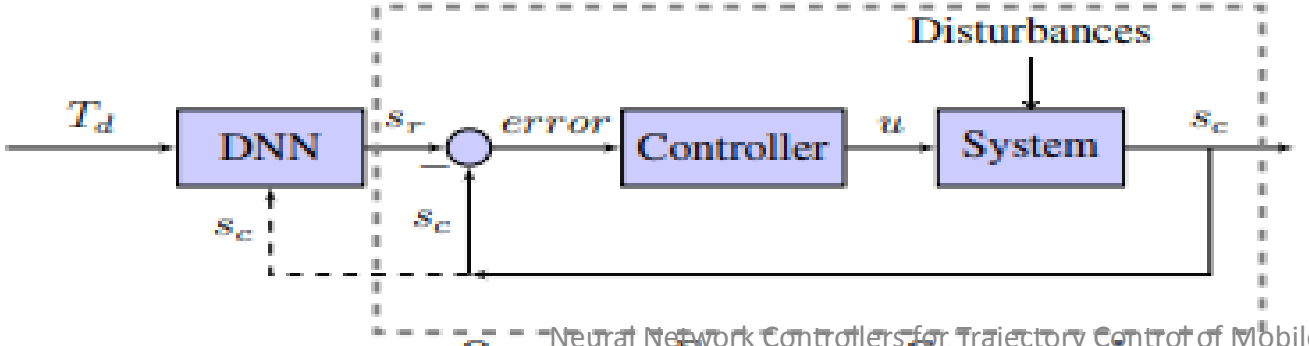
Trajectory Control of Mobile Autonomous Robot(Deep Neural Networks for Quadrotor trajectory)[Video]

- **WHY** : precision of quadrotors can be affected by many factors like
  - Including uncertainty in the turn-rate-to-thrust map
  - unquantifiable time delays
  - aerodynamic effects
  - other unpredictable factors such as friction in the actuators etc.
- **What is does**: Approximate relationship between desired and actual trajectory (highly nonlinear) of baseline controller to reduce it.
- **How:** The proposed method modifies the control system design by adding a DNN block in front of the controller
- A feed-forward DNN with rectified linear units (ReLU) as activation Function



ORIGINAL FEEDBACK CONTROL LOOP

[7]

Experiment Setup

- **The full state of the quadrotor(S)** consists of 13 components.
  - translational position of the quadrotor's centre of mass(X,Y,Z)
  - attitude, represented by Euler angles roll, pitch and yaw(ϕ, θ, ψ)
  - translational velocity($\dot{x}$, $\dot{y}$, $\dot{z}$)
  - rotational velocity, ω = (p, q, r).
  - translational accelerations ($\ddot{z}$)

Input: Current State + 'L' Future Desired State

Output: 1 Reference state (fed to Baseline PD controller as current state by freq 1 /10)

Error Function: Root-mean-square (RMS)

$$E(T_c, T_d) = \sqrt{\frac{1}{N}\sum_{t=1}^{N} \|\mathbf{p}_{c,t} - \mathbf{p}_{d,t}\|^2},$$

Accuracy Measure:

$$I(T_{\text{w/ DNN}}, T_{\text{w/o DNN}}) = \left(1 - \frac{E_{\text{w/ DNN}}}{E_{\text{w/o DNN}}}\right) \times 100\%,$$

[7]

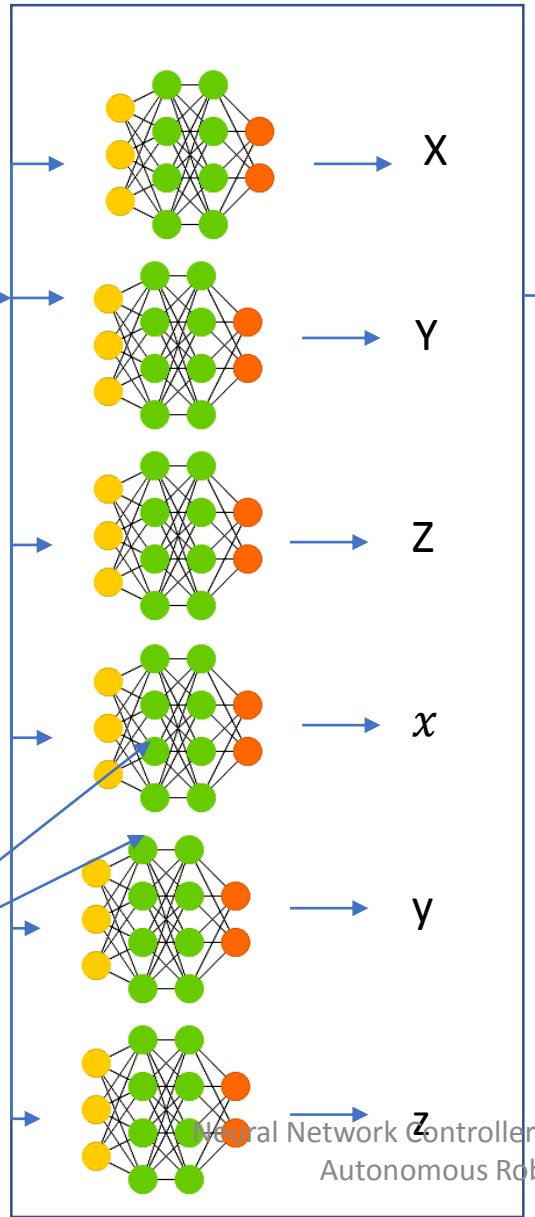
DNN Network design

2L+1 Inputs

1 current state +
L future desired state +

L sets of desired positions relative to the current current position {pd,t+Δ1 −pc,t, . . . , pd,t+ΔL −pc,t}

4 Fully connected Hidden Layer with 128 Neurons Each.



https://towardsdatascience.com/the-mostly-complete-chart-of-neural-networks-explained-3fb6f2367464

1 output for each component

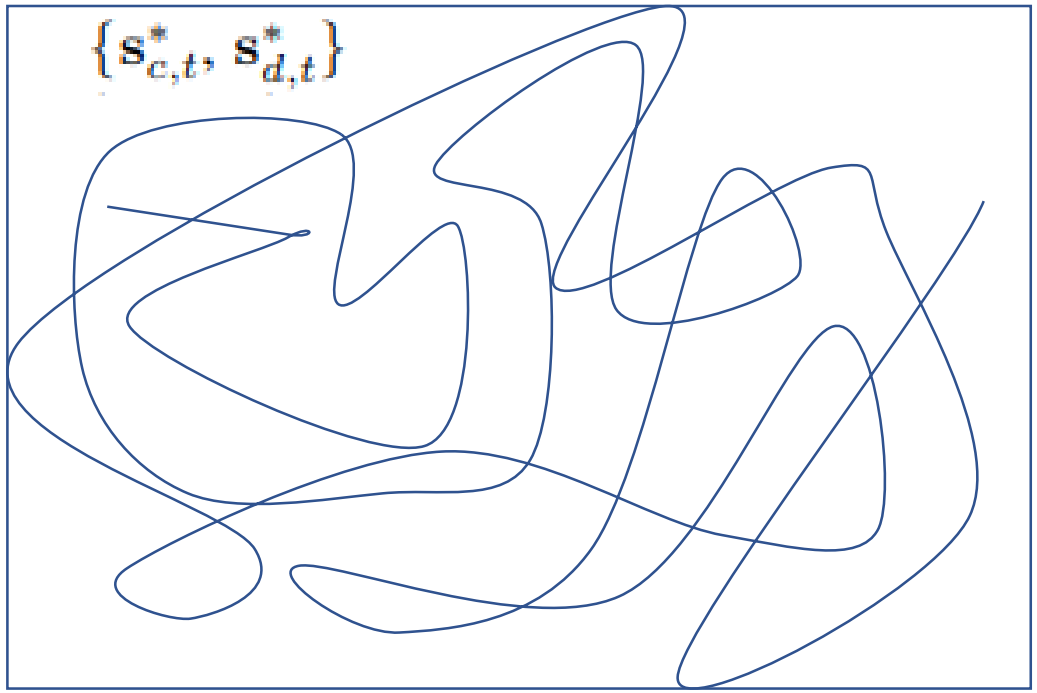
One Neural Net for each of the position and velocity elements of the reference state.

Other elements , {ϕ, θ, ψ, p, q, r, z¨} -> Constant.

Adam optimizer is used to tune the weight and bias parameters in the DNNs,

[7]

DATA Collection and DNN Training



[7]

- a 400-second trajectory of Baseline controller recorded.
- Approximately 10,000 ordered raw data pairs are collected at a 7 Hz rate

- **Input 1** : the current State at time t.
- **Input 2**: the L actual states already traced as L desired states (t+1 -> t+L+1)

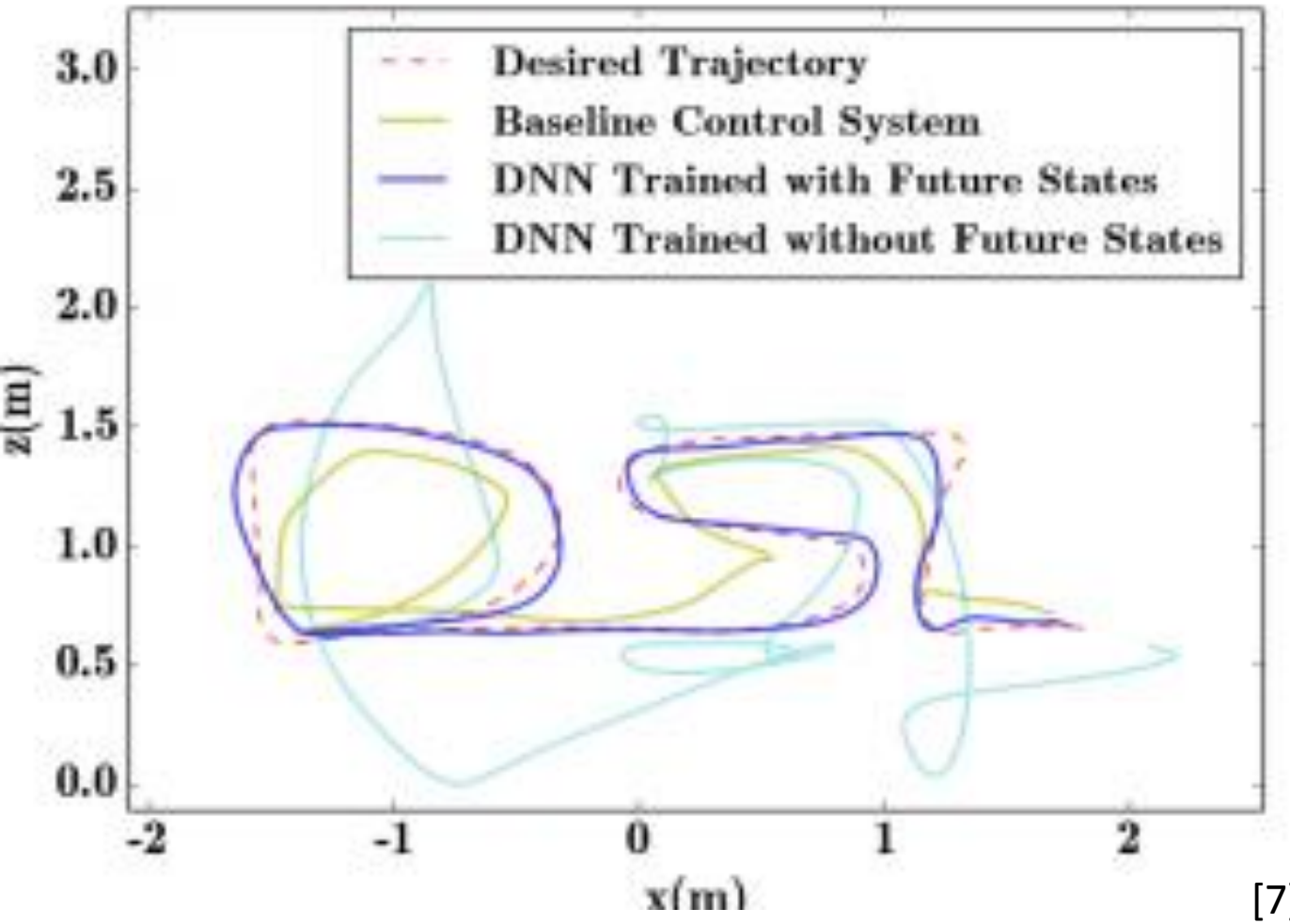
$$\{\mathbf{s}^*_{c,t}, \mathbf{s}^*_{c,t+\Delta_1+1}, \cdots, \mathbf{s}^*_{c,t+\Delta_L+1}\}$$

- **Output** : Current Desired State of Controller

$$\mathbf{s}^*_{d,t}$$

Approximation between Actual states based on desired states of Baseline controller

Results



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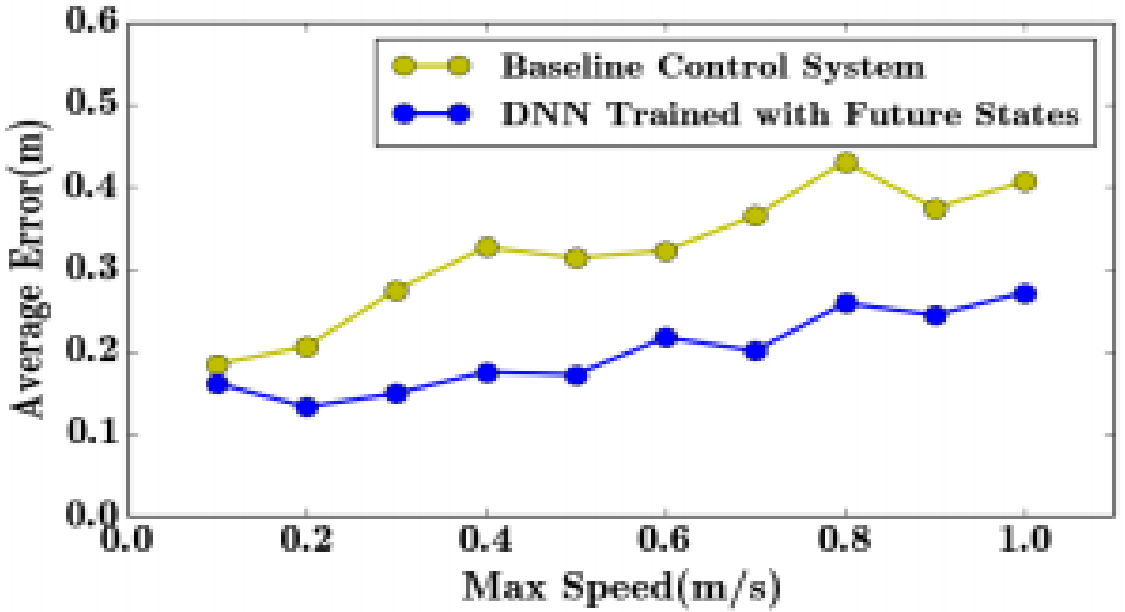

TABLE I

TRACKING ERRORS ON ONE TRAJECTORY FOR THREE DIFFERENT CONTROL SYSTEMS

	Baseline Controller	DNN without Feedback	DNN with Feedback
RMS Error, E (m)	0.360	0.232	0.144
Peak Error (m)	0.605	0.497	0.356
Improvement, I (%)	-	35.6	59.9

Additions done in next paper on this topic

To Identify

- conditions in which the “add-on DNN” can improves performance
- rules for the DNN feature selection.
- conditions to improve efficiency of the training.

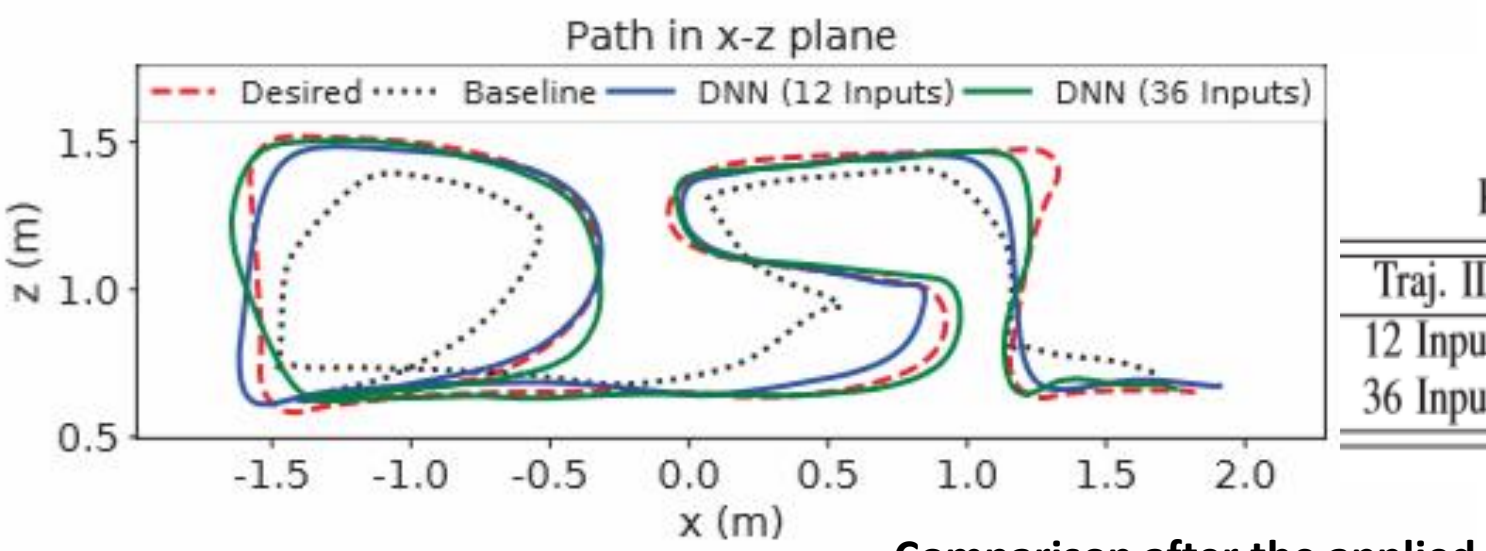

TABLE I

PERCENTAGE REDUCTION IN RMS TRACKING ERROR

Traj. ID	‘DSL’	2	3	4	5	Avg.
12 Inputs	52.4%	48.4%	42.0%	46.6%	36.9%	45.2%
36 Inputs	55.6%	61.4%	39.7%	43.9%	26.6%	45.5%

[8]

Comparison after the applied results with the original system

Future scope and limitation of this Idea

- The DNN serves as a pre-block outside the feedback control loop, the proposed method can be generalized as an add-on to any “Blackbox”, stable feedback control system.
- **More effective Neural Network design can be implemented to enhance the performance.**
- **Improvement mostly depends on the training.**

[7], [8]

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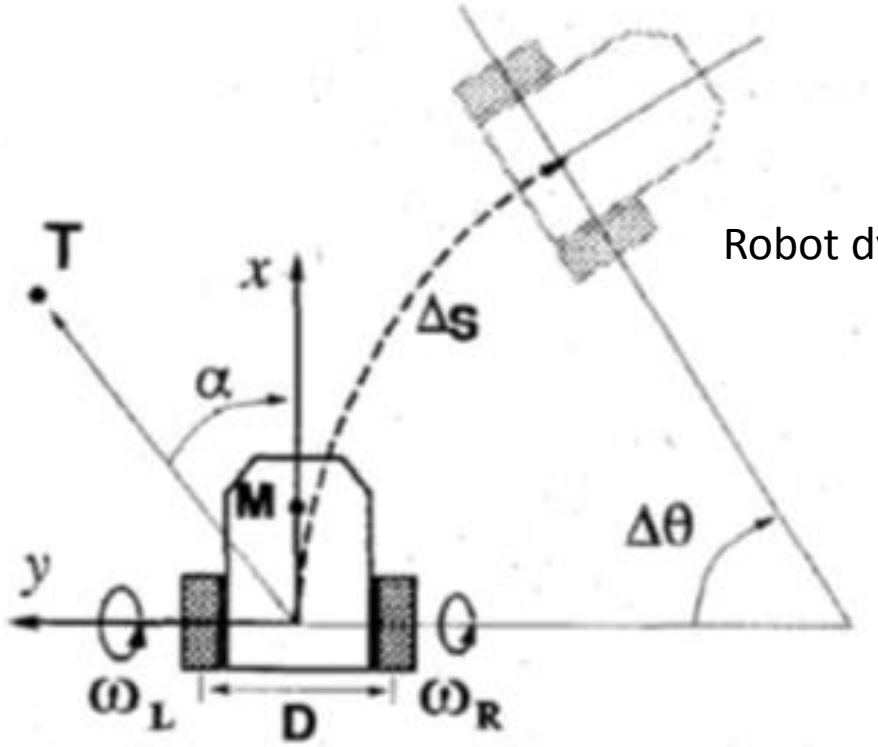
Bonus architecture(in case of extra time)

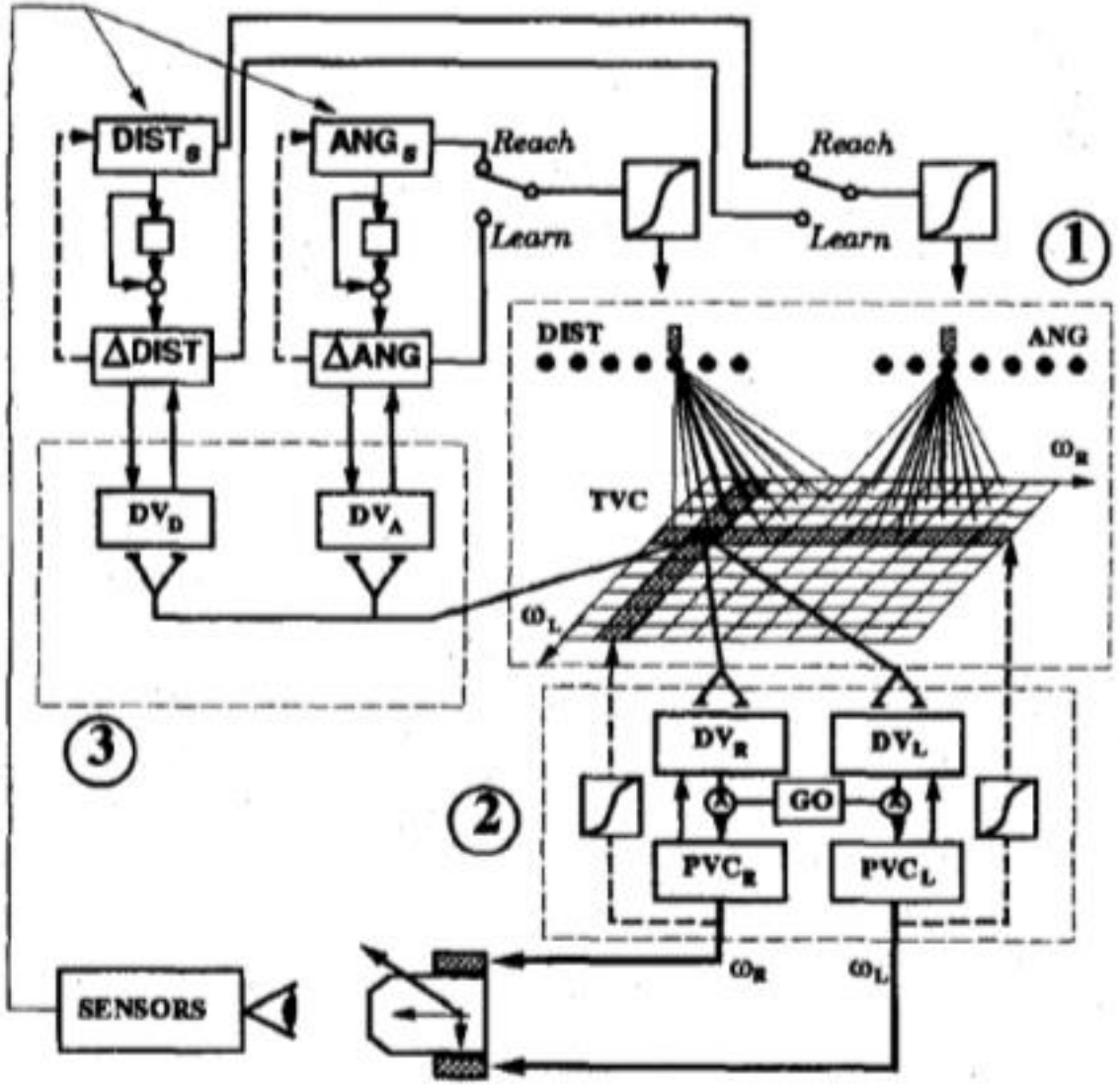


Robot dynamics

1. Adaptive Inverse Odometric Transformation.
2. Velocity Look up Transformation.
3. Adaptive Forward Odometric Transformation.

[9]

Robot Neural Controller Architecture

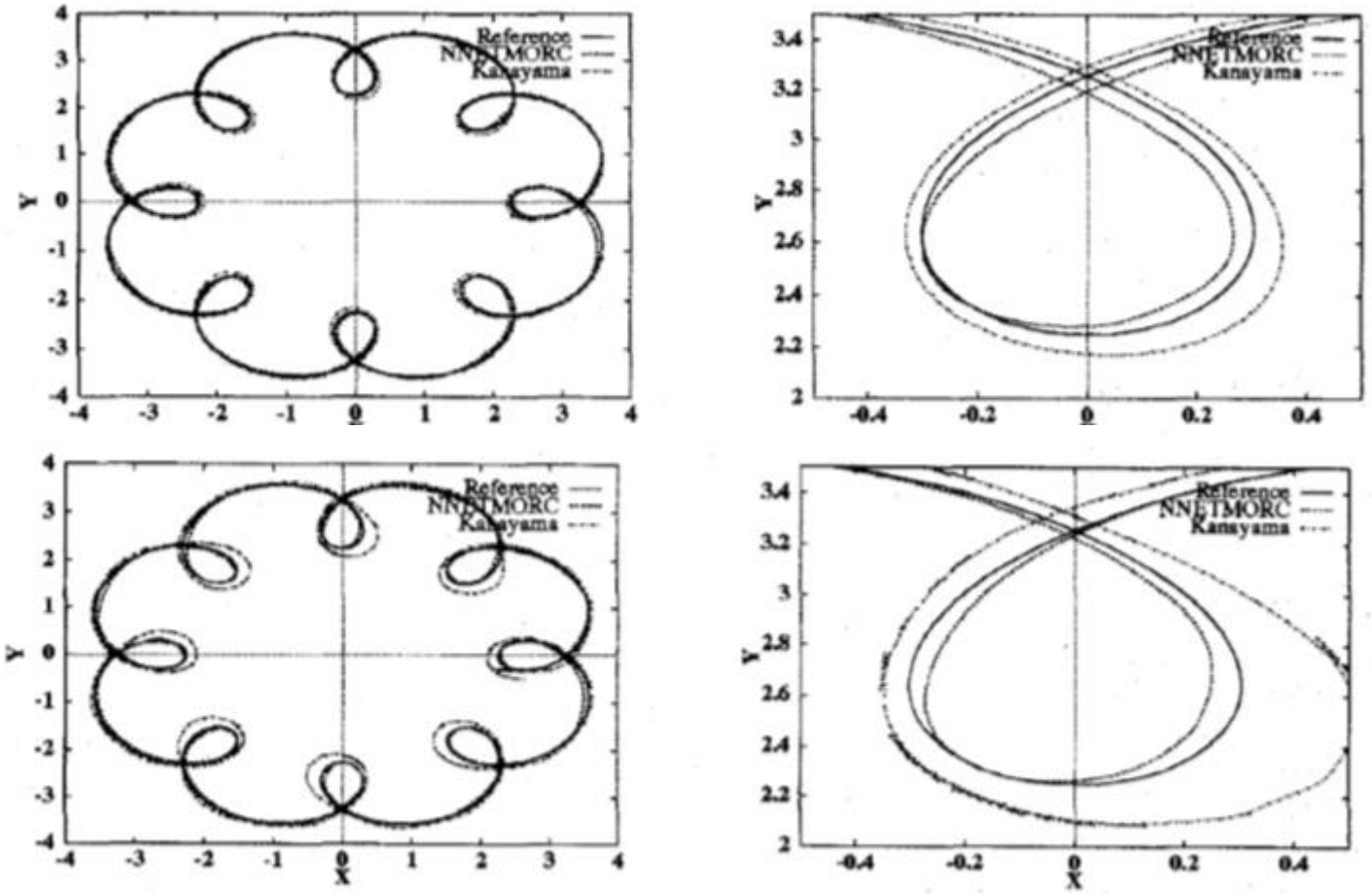


Advantages

- Can operate without sensory information.
- Wheel Slippage
- On line Adaptation.

Without noise

With noise



[9]

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Conclusion

What can be expected out of Neural Network controllers?

- NNs can provide a good approximation of Noise.
- NNs controllers can improve performance as well as accuracy.
- Can provide generalized approximated result even in failure condition.

Cons:

- Their efficacy is directly based on their training in similar environment. Thus, Training has to be comprehensive.

References

Literature:

- [6] Gardner, Brandt, Luecke (1991): “Application of Neural Network for Trajectory control of Robots” in Fifth International Conference on Advanced Robotics 'Robots in Unstructured Environments
- [7] Q. Li, J. Qian, Z. Zhu, X. Bao, M. K. Helwa, and A. P. Schoellig, “Deep neural networks for improved, impromptu trajectory tracking of quadrotors,” in IEEE Intl. Conf. on Robotics and Automation (ICRA), 2017, pp. 5183–5189.
- [8] Siqi Zhou, Mohamed K. Helwa, and Angela P. Schoellig, “Design of Deep Neural Networks as Add-on Blocks for Improving Impromptu Trajectory Tracking”, in 2017 IEEE 56th Annual Conference on Decision and Control (CDC) December 12-15, 2017, Melbourne, Australia
- [9] Paolo Gaudiano, Eduardo Zalama, and Juan L6pez Coronado, “An Unsupervised Neural Network for Low-Level Control of a Wheeled Mobile Robot: Noise Resistance, Stability, and Hardware Implementation ”, in IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS-PART B: CYBERNETICS, VOL. 26, NO. 3, JUNE 1996