Assignment 2

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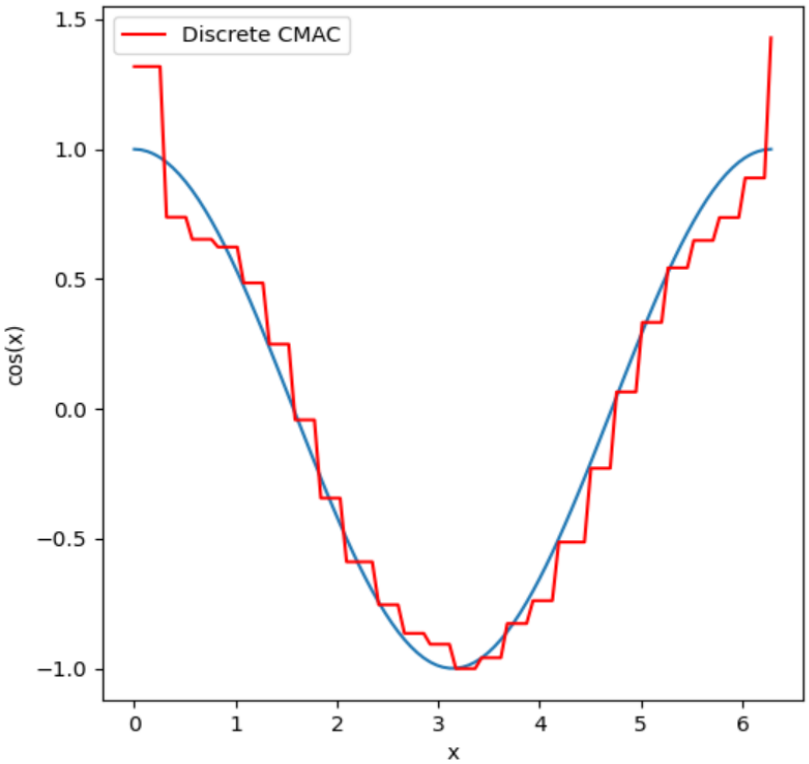
Q1.

I. Task using Machine Learning: Fault detection in unmanned UAV's using Support Vector Machine (Supervised Multiclass classification).
II. The inputs are the features on which the SVM model will be trained. As future predictions regarding the type of error are based on the training data, it is supervised learning approach.
III. The inputs are linear, angular acceleration of an aircraft. The command given by the control system to drive the UAV are also considered.
    - Inputs:
        1. linear acceleration in x direction
        2. linear acceleration in y direction
        3. linear acceleration in z direction
        4. angular acceleration in x direction
        5. angular acceleration in y direction
        6. angular acceleration in z direction
        7. pitch command
        8. roll command
        9. yaw command
    - Output:
        1. No failure
        2. Engine failure
        3. Left aileron failure
        4. Right aileron failure
        5. Rudder left failure
        6. Rudder right failure
        7. Both ailerons failure
        8. Elevator failure

Using SVM, we can supervise the unmanned UAV if there is any of the given faults.
Based on the model predicted by SVM, the respective faults will be detected.

Q2. For discrete CMAC, performed the following steps.

I. The 1-D function selected is cos(x).
II. The number of weights is selected as 35 and generalization factor as 10
III. The data of 100 coordinates of x and corresponding cos(x) is selected.
IV. It is then divided into a ratio of 70:30 for training and testing.
V. M_matrix is created to map the input data to number of weights - generalization factor + 1
VI. Corresponding Association map is created where the weights are initialized to 1 and then corrected based on the error of calculated and actual output.
VII. Finally the test data is predicted based on the test data points and accuracy is calculated.



The accuracy is found is

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Discrete Accuracy 0.9871430442013438
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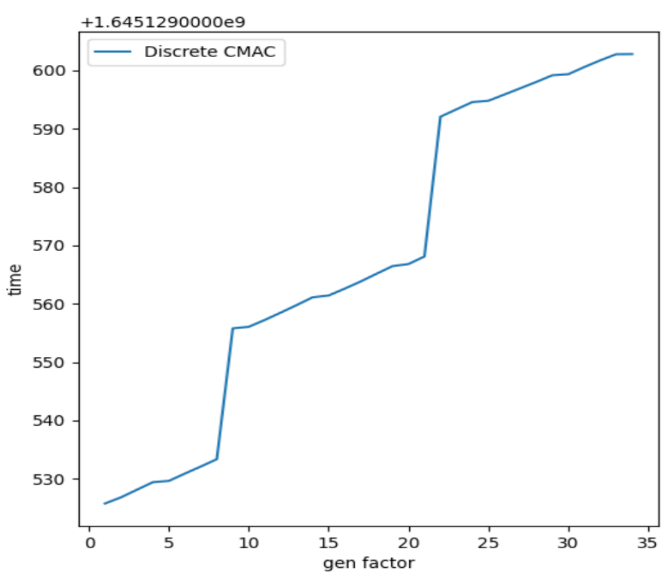
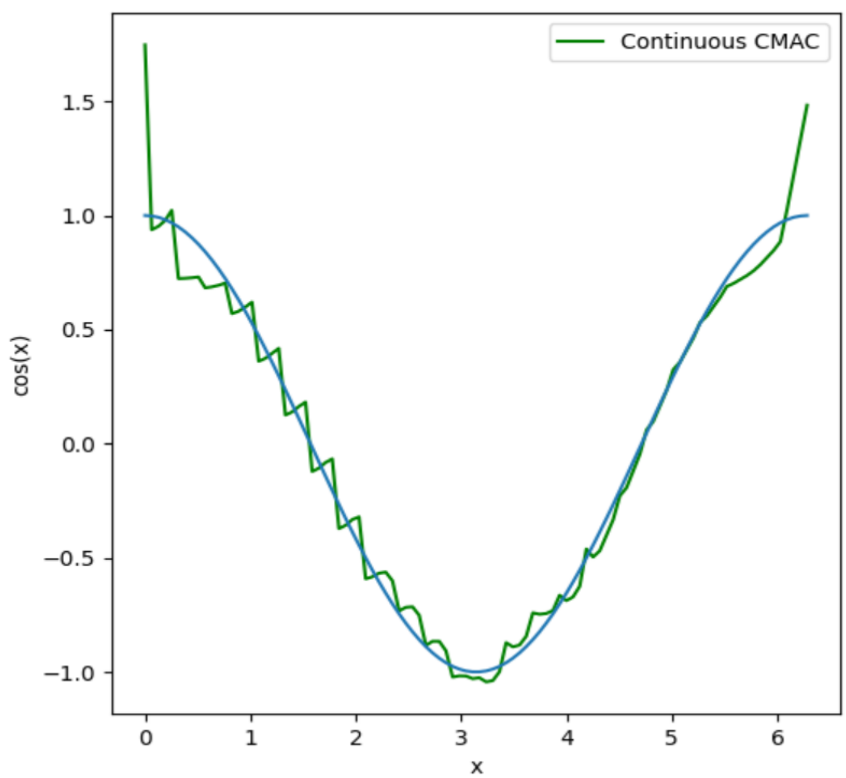
Time of Convergence

As the generalization factor increases, the overlap between the weights of the association increases, which results in slower convergence (the convergence time increases).



Q3. For continuous CMAC, performed the following steps.

I. The 1-D function selected is cos(x).
II. The number of weights is selected as 35 and generalization factor as 10
III. The data of 100 coordinates of x and corresponding cos(x) is selected.
IV. It is then divided into a ratio of 70:30 for training and testing.
V. M_matrix is created to map the input data to number of weights - generalization factor + 1
VI. Here the M_matrix contains a range consisting of upper and lower bounds in which the mapped data is associated.
VII. Corresponding Association map is created where the weights are initialized to 1 and then corrected based on the error of calculated and actual output.
VIII. Finally, the test data is predicted based on the test data points and accuracy is calculated.



The accuracy found for 30 test data points is

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Continuous Accuracy 0.9554255495925669
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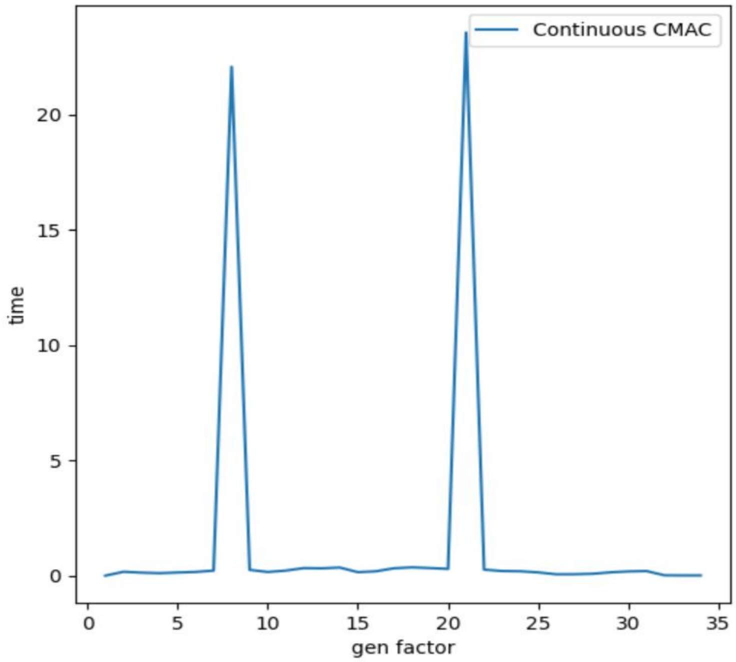
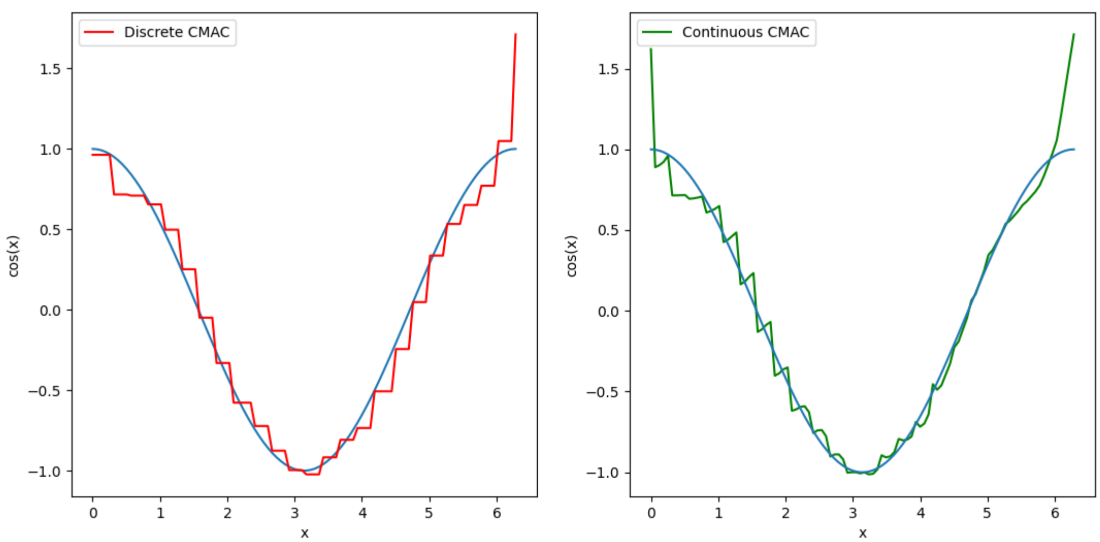
Time of Convergence

As the generalization factor increases, the overlap between the weights of the association increases, which results in slower convergence (the convergence time increases).



Comparison of Discrete CMAC and Continuous CMAC



Q4.

I. If the number of weights is increased, the overlap in the association will decrease.

II. This will result in increased accuracy as the number of overlapped parameters will be close to NULL.

III. As the number of weights are increased, it will be computationally economical to train the data as the time of convergence will be faster.

The disadvantages of CMAC are:

I. It is difficult to train complex data using CMAC.

II. The feedforward designs are static in nature.

III. It is relatively slow for complex networks.

Q5.

I. Recurrent Neural Network allows previous output used as the input for the next node.
II. It is different from the standard Feed Forward networks in the sense that it stores and learns from the previous inputs.
III. The main advantage of RNN is that it learns intermediate information. It possesses Long Short-Term Memory (LSTM) which is useful in series prediction.
IV. To train a CMAC using recurrent connections, a function must be added that depends on the output. This function is self-dependent, hence making the connection recurrent.