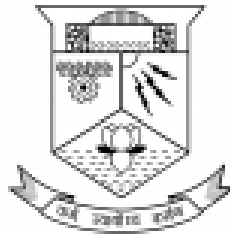


# **LABORATORY MANUAL**

**Subject code: 221LEC001**

**Subject Name: SIGNAL PROCESSING LAB 1**

**2022-2023**



**DEPARTMENT OF ELECTRONICS AND COMMUNICATION  
COLLEGE OF ENGINEERING TRIVANDRUM**

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## Course PO mapping

<b>221LEC001 Signal Processing Lab-1</b>		<b>PO1</b>	<b>PO2</b>	<b>PO3</b>	<b>PO4</b>	<b>PO5</b>	<b>PO6</b>
<b>CO1</b>	Apply the principles of linear algebra and random processes in signal processing applications, analyze observations of experiments/simulations and infer.	0	0	3	0	0	3
<b>CO2</b>	Implement algorithms in machine learning.	0	0	3	0	0	3
<b>CO3</b>	Design and implement a real world applications of signal processing.	0	3	0	0	0	3
	<b>Course PO mapping</b>	0	3	3	0	0	3

# Syllabus

No	Topics
1	<b>Linear Algebra</b>
1.1	Row Reduced Echelon Form: To reduce the given $m \times n$ matrix into Row reduced Echelon form
1.2	Gram-Schmidt Orthogonalization: To find orthogonal basis vectors for the given set of vectors. Also find orthonormal basis.
1.3	Least Squares Fit to a Sinusoidal function
1.4	Least Squares fit to a quadratic polynomial
1.5	Eigen Value Decomposition
1.6	Singular Value Decomposition
1.7	Karhunen- Loeve Transform
2	<b>Advanced DSP</b>
2.1	Sampling rate conversion: To implement Down sampler and Up sampler and study their characteristics
2.2	Two channel Quadrature Mirror Filterbank: Design and implement a two channel Quadrature Mirror Filterbank
3	<b>Random Processes</b>
3.1	To generate random variables having the following probability distributions (a) Bernoulli(b) Binomial(c) Geometric(d) Poisson(e)Uniform,(f) Gaussian(g)Exponential (h) Laplacian
3.2	Central Limit Theorem: To verify the sum of sufficiently large number of Uniformly distributed random variables is approximately Gaussian distributed and to estimate the probability density function of the random variable.
4	<b>Machine Learning</b>
4.1	Implementation of K Nearest Neighbours Algorithm with decision region plots
4.2	Implementation of K Means Algorithm with decision region plots
4.3	Implementation of Perceptron Learning Algorithms with decision region plots
4.4	Implementation of SVM algorithm for classification applications
5	<b>Implement a mini project pertaining to an application of Signal Processing in real life, make a presentation and submit a report</b>

## **Experiment 1:**

### **Reduction of a Matrix to Row Reduced Echelon Form**

**Objective:** The objective of this experiment is to familiarize students with the process of reducing a given  $m \times n$  matrix to its row reduced echelon form (RREF).

#### **Steps:**

1. Initialize Variables:
  - Set variables for the number of rows ( $m$ ) and columns ( $n$ ) in the matrix.
  - Set lead to 0.
2. Loop Over Rows:
  - For each row in the matrix:
    - Check if lead is greater than or equal to  $n$ . If true, break the loop.
    - Find the pivot index (first non-zero entry) in the current column.
    - If a pivot is found:
      - Swap the current row with the row containing the pivot.
      - Scale the pivot row so that the pivot element is 1.
      - Eliminate non-zero entries above and below the pivot in the current column.
  - Move to the next column by incrementing lead.
3. Scale Row:
  - Implement a function to scale a row by a constant factor.
4. Add Scaled Row:
  - Implement a function to add a scaled row to another row.
5. Swap Rows:
  - Implement a function to swap two rows.
6. End:
  - The algorithm ends when the loop is completed for all rows or when lead is greater than or equal to  $n$ .

**Result:** The row reduced Echelon form of the given  $m \times n$  matrix is determined.

## **Experiment 2:**

### **Gram-Schmidt Orthogonalization**

**Aim:** To find orthonormal basis vectors for a given set of vectors using the Gram-Schmidt orthogonalization process.

#### **Steps:**

1. Initialize:
  - Set the number of vectors in the set:  $n$
  - Initialize an array to store orthogonalized vectors: `orthogonal_set`
  - Initialize an array to store intermediate orthogonalized vectors: `temp_set`
2. Input Vectors:
  - Input the set of vectors:  $v_1, v_2, \dots, v_n$
3. Gram-Schmidt Process:
  - For each vector  $v_i$  in the set:
    - Set  $u_i$  equal to  $v_i$
    - For each previously orthogonalized vector  $u_j$  (where  $j < i$ ):
      - Calculate the projection of  $u_i$  onto  $u_j$  and subtract it from  $u_i$
    - Normalize  $u_i$  (divide by its magnitude)
    - Add  $u_i$  to the `orthogonal_set`
    - Store  $u_i$  in `temp_set`
4. Output Orthogonal Set:
  - The `orthogonal_set` now contains the orthogonalized vectors.
5. End:
  - The process ends.

**Result:** The orthonormal basis vectors for the given set of vectors is obtained.

## **Experiment 3:**

### **Least Squares Fit to a Sinusoidal Function**

#### **Aim:**

To determine the least squares fit to a sinusoidal function for a given set of data points.

#### **Procedure:**

- Define a function that takes an array of data points  $(x, y)$  and a guess for the sinusoidal function parameters (amplitude, frequency, phase shift)

- Calculate the residuals (differences between the predicted y-values from the sinusoidal function and the actual y-values)
- Calculate the Jacobian matrix (matrix of partial derivatives of the residuals with respect to the sinusoidal function parameters)
- Use an optimization algorithm (e.g., gradient descent, Newton's method) to minimize the sum of squared residuals by iteratively updating the sinusoidal function parameters
- Return the updated sinusoidal function parameters as the least square fit to the data points

**Conclusion:** Least square fit to a sinusoidal function is obtained.

#### **Experiment 4:**

### **Least Squares Fit to a Quadratic Polynomial**

#### **Aim:**

To determine the least squares fit to a quadratic polynomial for a given set of data points.

#### **Procedure:**

- Create a matrix containing the x-values and squared x-values.
- Solve the least squares problem.
- Plot the fitted quadratic polynomial.

**Conclusion:** Least square fit to a quadratic polynomial is obtained.

#### **Experiment 5:**

### **Eigenvalue Decomposition**

#### **Aim:**

- Import the necessary libraries.
- Define a function to perform eigenvalue decomposition.
- Call the eigenvalue decomposition function.
- Print the eigenvalues and eigenvectors.

**Conclusion:** Eigen values of the given  $m \times n$  matrix is determined.

# RANDOM PROCESSES

## Experiment 1:

### Random Variables for Probability Distribution

**Aim:** To generate random variables following various probability distributions, including Bernoulli, Geometric, Poisson, Exponential, Uniform, and Binomial.

#### Steps:

- Set seed for reproducibility
- Number of random variables to generate
- Bernoulli Distribution ( $p=0.5$ , one trial)
- Binomial Distribution ( $n=5$ ,  $p=0.3$ , five trials)
- Geometric Distribution ( $p=0.2$ , probability of success)
- Poisson Distribution ( $\lambda=3$ , average rate)
- Uniform Distribution (low=0, high=1)
- Exponential Distribution ( $\beta=0.5$ , inverse of the rate parameter)
- Plotting histograms for each distribution

**Conclusion:** Generated random variables having the following probability distributions Bernoulli, Binomial, Geometric, Poisson, Uniform, Exponential.

## **Experiment 2:**

### **Central Limit Theorem**

**Aim:** To verify the Central Limit Theorem by demonstrating that the sum of a sufficiently large number of uniformly distributed random variables is approximately Gaussian distributed. Additionally, estimate the probability density function of the random variable.

#### **Procedure:**

- Parameters for the original distribution, size of each sample, number of samples to generate
- Generate samples from the original distribution (e.g., uniform, exponential, etc.)
- Calculate the means of each sample
- Plot the histogram of the sample means
- Plot the theoretical normal distribution based on the Central Limit Theorem

**Conclusion:** Verified that the sum of sufficiently large number of Uniformly distributed random variables is approximately Gaussian distributed and estimated the probability density function of the random variable.



# ADVANCED DSP

## **Experiment 1:**

### **Sampling Rate Conversion**

**Aim:** To implement a Down Sampler and Up Sampler and study their characteristics in the context of sampling rate conversion.

#### **Procedure:**

- Create a sample signal (e.g., a sine wave)
- Down Sample the signal
- Up Sample the down-sampled signal
- Plot the original, down-sampled, and up-sampled signals

**Conclusion:** Implemented Down sampler and Up sampler and studied their characteristics.

## **Experiment 2:**

### **Two-Channel Quadrature Mirror Filterbank**

**Aim:** To design and implement a two-channel Quadrature Mirror Filterbank (QMF).

#### **Procedure:**

- Design the analysis filters (e.g., simple half-band filters)
- Apply the analysis filters
- Design the synthesis filters (mirror of the analysis filters)
- Apply the synthesis filters
- Create a sample signal
- Apply the QMF analysis
- Apply the QMF synthesis
- Plot the original and reconstructed signals

**Conclusion:** Designed and implemented a two channel Quadrature Mirror Filterbank.

# MACHINE LEARNING

## EXPERIMENT NO:1

### K MEANS ALGORITHM

**AIM :** To Implement K Means Algorithm with decision region plots.

- Generate synthetic data
- Apply K-Means algorithm
- Get cluster centers and labels
- Plot the original data and cluster centers
- Plot original data points
- Plot cluster centers

**RESULT:** Implemented K Means Algorithm with decision region plots.

## EXPERIMENT NO:2

### PERCEPTRON LEARNING

**AIM:** To implement Perceptron Learning Algorithms with decision region plots.

#### **STEPS:**

- Generate synthetic data
- Apply Perceptron learning algorithm
- Make predictions on the same data for visualization
- Plot the decision region
- Plot data points
- Plot decision boundary
- Highlight misclassified points
- Evaluate accuracy on the training set

**RESULT:** Implemented perceptron learning algorithm with decision region plots.

### **EXPERIMENT NO:3**

#### **SUPPORT VECTOR MACHINE**

**AIM :** To implement SVM algorithm for classification applications.

#### **STEPS:**

- Generate synthetic data for binary classification
- Split the data into training and testing sets
- Apply SVM for classification
- Make predictions on the test set
- Plot the decision boundary
- Plot decision boundary on training set
- Evaluate accuracy on the test set

**RESULT:** Implemented SVM algorithm with decision region plots.

### **EXPERIMENT NO:4**

#### **K NEAREST NEIGHBOUR**

**AIM:** To implement K Nearest Neighbours Algorithm with decision region plots.

#### **STEPS:**

- Generate synthetic data for binary classification
- Split the data into training and testing sets
- Apply KNN for classification
- Make predictions on the test set
- Plot the decision boundary
- Plot decision boundary on training set

- Evaluate accuracy on the test set

**RESULT:** Implemented K Nearest Neighbours Algorithm with decision region plots.