IEEE Signal Processing Cup 2020 - Qualifications

Team 2 : GMM

Report

Defining the problem

5 normal and 5 abnormal recordings are given as ROS .bag files.

(files can be found here: https://drive.google.com/drive/folders/1pBO4VxpCQf1Tta-efvQ6h2uh5gjwr9fF (folders 03 and 04))

The task is to implement models which will give a prediction wheter each sample in the recording is normal/abnormal based on measurements from .bag files.

Visualization:

Images were extracted from "/pylon_camera_node/image_raw" topic, rotated 180 degrees and saved as video files with 4fps framerate.

From extracted videos we see that the recordings come from some UAV, where the normal recordings were made during stable flight without fast movement while abnormal recordings were made during very unstable flight with sudden movements.

Preanalysis

Every recording has around hundred mesurements but we don't have class labels.

=> We can't use classic classification.

=> Possible solution: Gaussian Mixture Model

Measurement analysis

Based on extracted videos, the following measurements were chosen as relevant for analysis:

"/global_position/local", "/imu/data", "/imu/mag", "/global_position/compass_hdg"

Time plots and histograms show that the oscillations of some measurements are much larger on abnormal recordings than normal ones.

That means that the derivatives of those signals reach higher absolute values on abnormal recordings, which means that variances of those measurements are larger than on normal recordings so they are deemed as more informative.

Physical quantities that satisfy the above description are orientation, linear velocity, magnetic field and compass heading.

Compass heading was discarded because of correlation with magnetic field.

Their derivatives are angular velocity, linear acceleration (already available from IMU), and derivative of magnetic field.

All values are 3D, so the feature vector is 9D.

Feature engineering

We added "lookBack" features by adding k last samples to each sample, allowing the ML algorithm to "look back" in time.

Gaussian Mixture Model

Implemented GMM with 2 classes.

A sample is classified as abnormal if its posterior probability of abnormal GMM component is larger from the normal one.

Used regularization, and selected the best regularization parameter on CV set, via hold-out cross-validation.

Models are evaluated via BIC score, along with set constraints:

0 predicted abnromals from normal set,

"high" percentage of abnormals from abnormal set.

Overview of files:

```
%     addDerivative      - calculates derivatives of selected columns of the table and adds the
%     extractImages      - Extracts images from a bag object
%     files2bag          - Loads all .bag files from given directory into a cell array of bag o
%     gmm2dVisualisation - 2D visualization of a GMM. Draws a contour plot and a surf plot, for
%     gmmFit             - Fits GMM to data. Computes Gaussian mixture model on data Z with giv
%                           number of classes and regularization value Lambda.
%     lookBack           - For each row in the input matrix, append k last rows to the right.
%     mapFrames          - Matches IMU measurements with corresponding frames.
%                           Sorts IMU timestamps and measurements into table assigning each mea
%                           set a serial number of the frame that first comes after
%     splitData          - Split the given data into training, CV and test sets using given per

%     tables.mat         - saved data, extracted from the bag files
%     GMM.mat            - saved trained model with parameters for data preprocessing

%     main_GMM_en            - Main program.
```

Implementation

Work directories for normal and abnormal data.

```
clear;

% change if needed
workDirNormal = '03_normal';
workDirAbnormal = '04_abnormal';
```

Loading the data

Loading .bag files, selecting relevant measurements and converting into tables.

```
bagsNormal = files2bag(workDirNormal);
bagsAbnormal = files2bag(workDirAbnormal);
```

Extracting features

```
[frameIdxNormal, TimeNormal, TNormal] = mapFrames(bagsNormal);
[frameIdxAbnormal, TimeAbnormal, TAbnormal] = mapFrames(bagsAbnormal);
% save temp.mat TNormal TAbnormal -mat
```

Adding derivative features

```
% load temp.mat
tableNormalMagDer = addDerivative(TNormal, 'Mag', {'X', 'Y', 'Z'});
tableAbnormalMagDer = addDerivative(TAbnormal, 'Mag', {'X', 'Y', 'Z'});

tableNormal = removevars(tableNormalMagDer, {'MagX', 'MagY', 'MagZ'});
tableAbnormal = removevars(tableAbnormalMagDer, {'MagX', 'MagY', 'MagZ'});
```

```
save tables.mat tableNormal tableAbnormal frameIdxNormal frameIdxAbnormal TimeNormal TimeAbnorm
```

loading saved data

```
clear; close all; clc;
load('tables.mat')
```

Adding "lookBack" features - appending k previous samples to each sample

```
X_normal = tableNormal{:,:};
X_abnormal = tableAbnormal{:,:};

kLast = 3;      % keep in mind that there are around 3 data samples per frame
X_normal = lookBack(X_normal, kLast);
X_abnormal = lookBack(X_abnormal, kLast);
```

Modeling

Train, CV, Test data split

```
splitPcg = [70, 0];
[X_normal_train, X_normal_cv, X_normal_test, idx_normal_train, idx_normal_cv, idx_normal_test]
[X_abnormal_train, X_abnormal_cv, X_abnormal_test, idx_abnormal_train, idx_abnormal_cv, idx_abr

X_train = [X_normal_train; X_abnormal_train];
X_cv = [X_normal_cv; X_abnormal_cv];
X_test = [X_normal_test; X_abnormal_test];

M = size(X_train, 1);
M_normal = size(X_normal_train, 1);
M_abnormal = size(X_abnormal_train, 1);
```

Feature mapping (scaling and normalization)

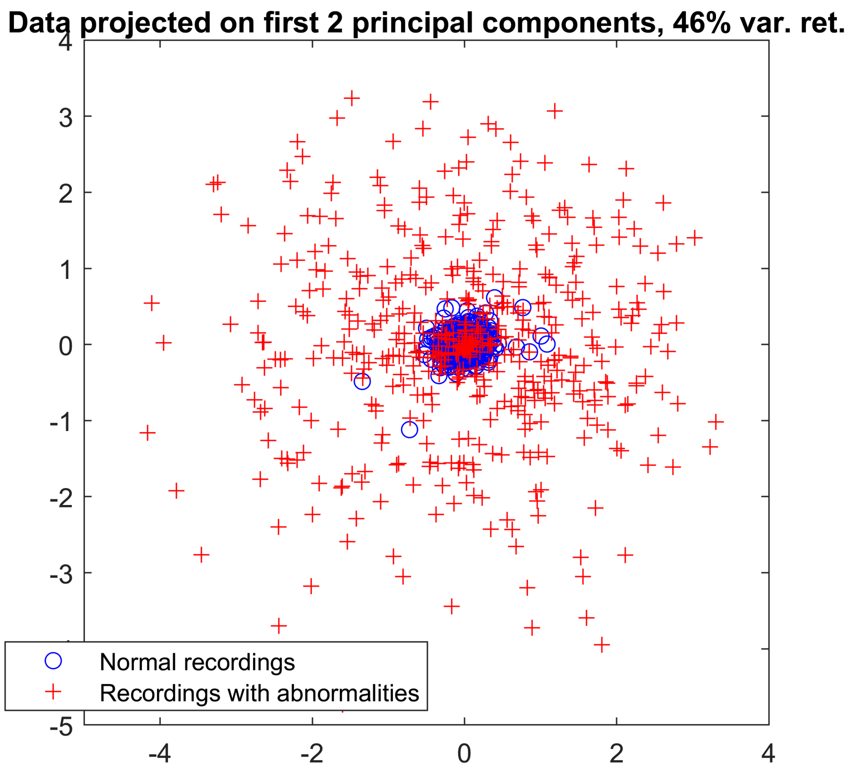
```
mu = 0;
scalingFactor = 10^(-5);

X_train_mapped = (X_train - mu) * scalingFactor;
```

PCA

```
[coeff,score,latent,tsquared,explained,mu_pca] = pca(X_train_mapped);

varianceRetained = 99;
numComponents = find(cumsum(explained) >= varianceRetained, 1);

U = coeff(:,1:numComponents);

Z = (X_train_mapped - mu_pca)* U;

save Z.mat Z -mat
```

Training data vizualization

```
y = [zeros(M_normal,1); ones(M_abnormal,1)];
figure
    gscatter(Z(:,1), Z(:,2), y, 'br', 'o+');
    legend('Normal recordings','Recordings with abnormalities');
    title(['Data projected on first 2 principal components, ' int2str(sum(explained(1:2))) '% v
    axis square
```




```
disp(['Number of principal components with ' int2str(varianceRetained) '% variance retained: '.
    int2str(numComponents) '/' int2str(size(X_train, 2))]);
```

```
Number of principal components with 99% variance retained: 11/36
```

Gaussian Mixture Model

```
load Z.mat
numClasses = 2;
% max_eval = 0;
min_AIC = inf;
Iterations = 1000;
Lambdas = 0.05 : 0.0005 : 0.1; % nice for kLast = 3;
% Lambdas = 0.02 : 0.0005 : 0.06; % nice for kLast = 5,6;

for Lambda = Lambdas
%     disp(['Lambda = ' num2str(Lambda)]);
    [GMM, labelName, normal, abnormal, middle] = gmmFit(Z, numClasses, Lambda, Iterations);
    eval = GMM.AIC;

    % prediction
    P_test = posterior(GMM, Z);
    [~, y_pred] = max(P_test, [], 2);

    n_an = nnz(y_pred(1:M_normal) == abnormal);
    n_aa = nnz(y_pred(M_normal+1 : end) == abnormal);

    % the percentage of predicted abnormals from normal set should be 0,
    % the percentage of predicted abnormals from abnormal set should be high,
    if (n_an/M_normal > 0) || (n_aa/M_abnormal < 0.66)
        eval = inf;
    end
%     disp(['Evaluation (smaller is better): ' num2str(eval)])

    if eval < min_AIC
        min_AIC = eval;
        GMM_opt = GMM;
        Lambda_opt = Lambda;
        normal_opt = normal;
        abnormal_opt = abnormal;
        labelName_opt = labelName;
    end

end

GMM = GMM_opt;
Lambda = Lambda_opt;
normal = normal_opt;
abnormal = abnormal_opt;
labelName = labelName_opt;
disp(['Optimal Lambda is:' num2str(Lambda_opt)]);
```

```
Optimal Lambda is:0.053
```

Saving the model

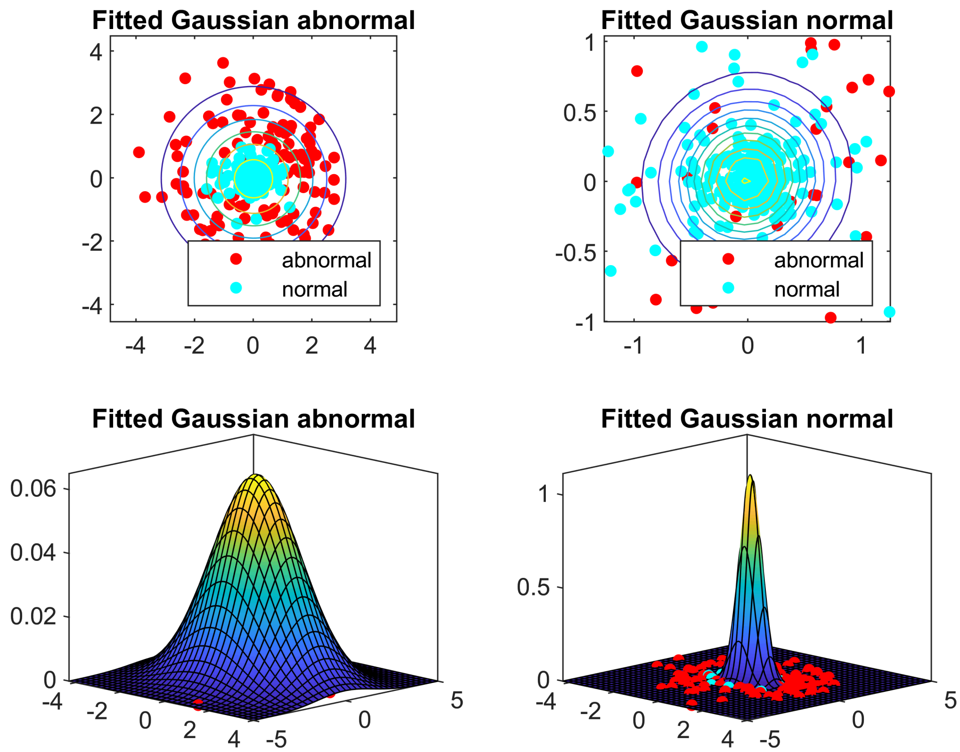
```
save GMM.mat GMM mu scalingFactor mu_pca U -mat
```

Evaluate on test set

```
% feature maping and dim. reduction
Z_test = ((X_test - mu)*scalingFactor - mu_pca) * U;

% prediction
P_test = posterior(GMM, Z_test);
[~, y_test] = max(P_test, [], 2);
```

Visualize predicitons

```
gmm2dVisualization(GMM, Z_test, y_test, labelName, Lambda);
```



Some statistics

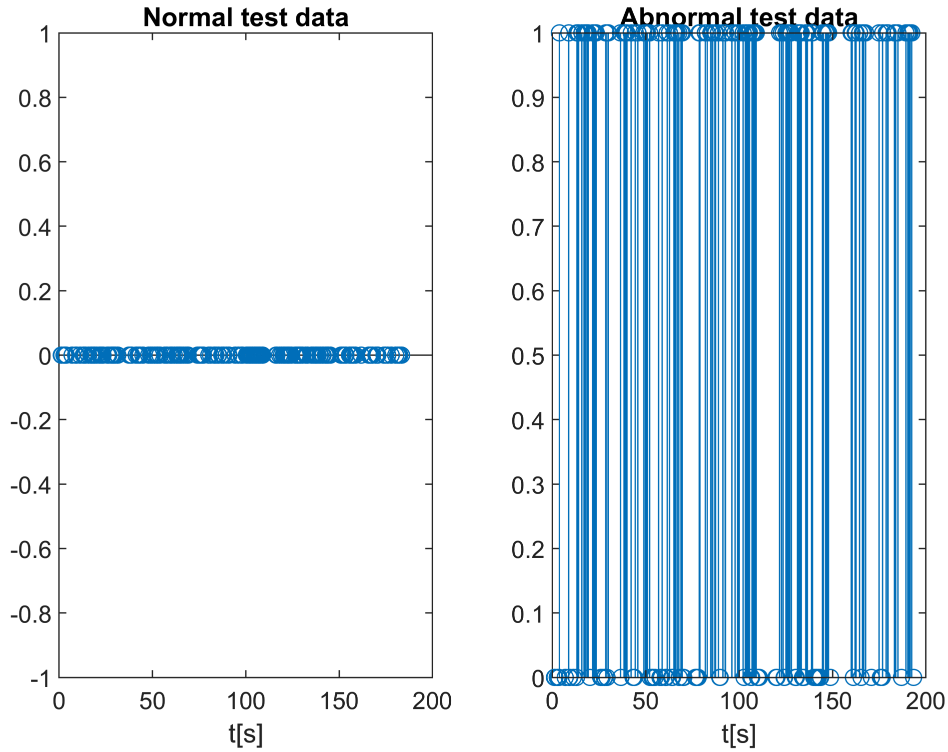
```
M_pred = [nnz(y_test == normal), nnz(y_test == abnormal)];
M_test = [length(X_normal_test), length(X_abnormal_test)];
M_pred_conf = [nnz(y_test(1:M_test(1)) == normal), nnz(y_test(1:M_test(1)) == abnormal);...
               nnz(y_test(M_test(1)+1:end) == normal), nnz(y_test(M_test(1)+1:end) == abnormal)
disp({  ['Num samples normal: ' int2str(M_test(1))];
        ['Num samples abnormal: ' int2str(M_test(2))];
        ['Num predicted normal: ' int2str(M_pred(normal))];
        ['Num predicted abnormal: ' int2str(M_pred(abnormal))];
        ['Num predicted normal from normal set: ' int2str(M_pred_conf(1,1))];
        ['Num predicted abnormal from normal set: ' int2str(M_pred_conf(1,2))];
        ['Num predicted normal from abnormal set: ' int2str(M_pred_conf(2,1))];
        ['Num predicted abnormal from abnormal set: ' int2str(M_pred_conf(2,2))]})
```

```
'Num samples normal: 207'
'Num samples abnormal: 212'
'Num predicted normal: 136'
'Num predicted abnormal: 283'
'Num predicted normal from normal set: 207'
'Num predicted abnormal from normal set: 0'
'Num predicted normal from abnormal set: 76'
'Num predicted abnormal from abnormal set: 136'
```

Time visualization

```
n_normal_normal = kLast + idx_normal_test(y_test(1:M_test(1)) == normal);
n_normal_abnormal = kLast + idx_normal_test(y_test(1:M_test(1)) == abnormal);
n_abnormal_normal = kLast + idx_abnormal_test(y_test(M_test(1)+1:end) == normal);
n_abnormal_abnormal = kLast + idx_abnormal_test(y_test(M_test(1)+1:end) == abnormal);

n_normal = [n_normal_normal n_normal_abnormal];
n_abnormal = [n_abnormal_normal n_abnormal_abnormal];

t_normal = TimeNormal{n_normal,1};
t_abnormal = TimeAbnormal{n_abnormal,1};

y_normal = [zeros(M_pred_conf(1,1), 1); ones(M_pred_conf(1,2), 1)];
y_abnormal = [zeros(M_pred_conf(2,1), 1); ones(M_pred_conf(2,2), 1)];

figure
    subplot(1,2,1)
        stem(t_normal, y_normal);
        title('Normal test data');
        xlabel('t[s]')

    subplot(1,2,2)
        stem(t_abnormal, y_abnormal);
        title('Abnormal test data');
        xlabel('t[s]')

    sgtitle('Abnormalities in time. 0 - normal, 1 - abnormality detected.');
```

Abnormalities in time. 0 - normal, 1 - abnormality detected.



Displaying detected frames

```
% this can be converted to display actual images:

% disp("Detected abnormal frames from abnormal datraset (there shouldn't be any):")
unique(frameIdxNormal{sort(n_normal_abnormal), 1});

% disp("Detected abnormal frames from abnormal dataset (there should be a lot):")
unique(frameIdxAbnormal{sort(n_abnormal_abnormal), 1});
```

Detecting most abnormal features (experimental)

```
f_names = mostAbnormalFeatures(Z_test(y_test == abnormal), GMM, normal, U, mu_pca,...
    scalingFactor, mu, kLast, tableNormal.Properties.VariableNames);
most_abnormal_features = unique(f_names);
disp(most_abnormal_features)
```

```
'MagDerivativeX'
'MagDerivativeY'
'MagDerivativeZ'
```