all_steps_activity recognition

January 12, 2021

[1]:
```
from helpers import math_helper
from sensors.activpal import *
from utils import read_functions
from scipy import signal
from sklearn.model_selection import train_test_split
from sklearn import tree
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪confusion_matrix, classification_report
from sklearn.ensemble import RandomForestClassifier

import pandas as pd
import statistics
import os

    #NEW RFE
from numpy import mean
from numpy import std
from sklearn.datasets import make_classification
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.feature_selection import RFE
from sklearn.tree import DecisionTreeClassifier
from sklearn.pipeline import Pipeline
# END
```

1 Feature Extraction

[2]:
```
activpal = Activpal()

#features_columns = ['standard_deviation_x', 'mean_x', 'standard_deviation_y',␣
 ↪'mean_y','standard_deviation_z', 'mean_z', 'activiteit']
features_columns = ['standard_deviation_x', 'mean_x', 'standard_deviation_y',␣
 ↪'mean_y','standard_deviation_z', 'mean_z', 'peak_distance_x',␣
 ↪'peak_distance_y','peak_distance_z', 'activiteit']
```

```
activities = ['lopen', 'rennen', 'springen', 'staan', 'traplopen', 'zitten']
segment_size = 12.8
```

[3]:
```
def calculate_peak_distance(activpal_segment, key):
    accelerations = activpal_segment[key]

    # todo: Think about what kind peaks we are looking for and what we want to␣
↪with it
    peak_index, _ = signal.find_peaks(accelerations)

    if len(peak_index) < 2:
        return 0

    peak_values = [accelerations[i] for i in peak_index]

    peak_values.sort(reverse=True)

    # There is a change there are is peak that shows up at multiple index
    # For this reason i am taking the index with highest value.
    highest_peak_index = activpal_segment[activpal_segment[key] ==␣
↪peak_values[0]].index.max()
    second_highest_peak_index = activpal_segment[activpal_segment[key] ==␣
↪peak_values[1]].index.max()

    diff_time = max(highest_peak_index, second_highest_peak_index) -␣
↪min(highest_peak_index, second_highest_peak_index)

    # It's better to use microseconds diveded by 1000 to get milliseconds. This␣
↪way you won't lose information
    # return diff_time.seconds * 1000
    return diff_time.microseconds / 1000
```

[4]:
```
def extract_features_from_correspondent(correspondent):
    features_df = pd.DataFrame(columns=features_columns, index=pd.
↪to_datetime([]))

    # Getting dataset for a correspodent
    activities_df = read_functions.read_activities(correspondent)

    for activity_name in activities:
        activity = activities_df.loc[activity_name]
        if not activity.empty:
            start_time = activity.start
            stop_time = activity.stop
            activpal_df = activpal.read_data(correspondent, start_time,␣
↪stop_time)
```

```
            # denormalizing dataset
            activpal_df['x'] = math_helper.
↪convert_value_to_g(activpal_df['pal_accX'])
            activpal_df['y'] = math_helper.
↪convert_value_to_g(activpal_df['pal_accY'])
            activpal_df['z'] = math_helper.
↪convert_value_to_g(activpal_df['pal_accZ'])

            date_range = pd.date_range(start_time, stop_time,␣
↪freq=str(segment_size) + 'S')
            for time in date_range:
                segment_time = time + pd.DateOffset(seconds=segment_size)
                activpal_segment = activpal_df[(activpal_df.index >= time) &␣
↪(activpal_df.index <= segment_time)]

                # features
                peak_distance_x = calculate_peak_distance(activpal_segment, 'x')
                peak_distance_y = calculate_peak_distance(activpal_segment, 'y')
                peak_distance_z = calculate_peak_distance(activpal_segment, 'z')

                # stdev_x = lambda statistics.stdev(activpal_segment['x']) if␣
↪len(activpal_segment['x']) >= 2 else 0
                stdev_x =  statistics.stdev(activpal_segment['x']) if␣
↪len(activpal_segment['x']) >= 2 else 0
                mean_x = activpal_segment['x'].mean()

                stdev_y =  statistics.stdev(activpal_segment['y']) if␣
↪len(activpal_segment['y']) >= 2 else 0
                mean_y = activpal_segment['y'].mean()

                stdev_z =  statistics.stdev(activpal_segment['z']) if␣
↪len(activpal_segment['z']) >= 2 else 0
                mean_z = activpal_segment['z'].mean()


              #  features_df.loc[segment_time] = [stdev_x, mean_x, stdev_y,␣
↪mean_y, stdev_z, mean_z, activity_name]
                features_df.loc[segment_time] = [stdev_x, mean_x, stdev_y,␣
↪mean_y, stdev_z, mean_z, peak_distance_x, peak_distance_y, peak_distance_z, ␣
↪activity_name]

    return features_df
```

[5]:
```
def extract_features_from_all_correspondents():
    all_features_df = pd.DataFrame(index=pd.to_datetime([]))
```

```
    for directory in os.walk('../../data'):
        if directory[0] == '../../data':
            for respDirect in directory[1]:
                if respDirect not in ['output', 'throughput', 'Test data','.
↪ipynb_checkpoints', 'BMR035', 'BMR100', 'BMR051', 'BMR027']:
                    print("Extracting " + respDirect)
                    features_df =␣
↪extract_features_from_correspondent(respDirect)
                    all_features_df = pd.concat([all_features_df, features_df])

    print("Done extracting features")

    return all_features_df
```

[6]:
```
features_dataset = extract_features_from_all_correspondents()
```

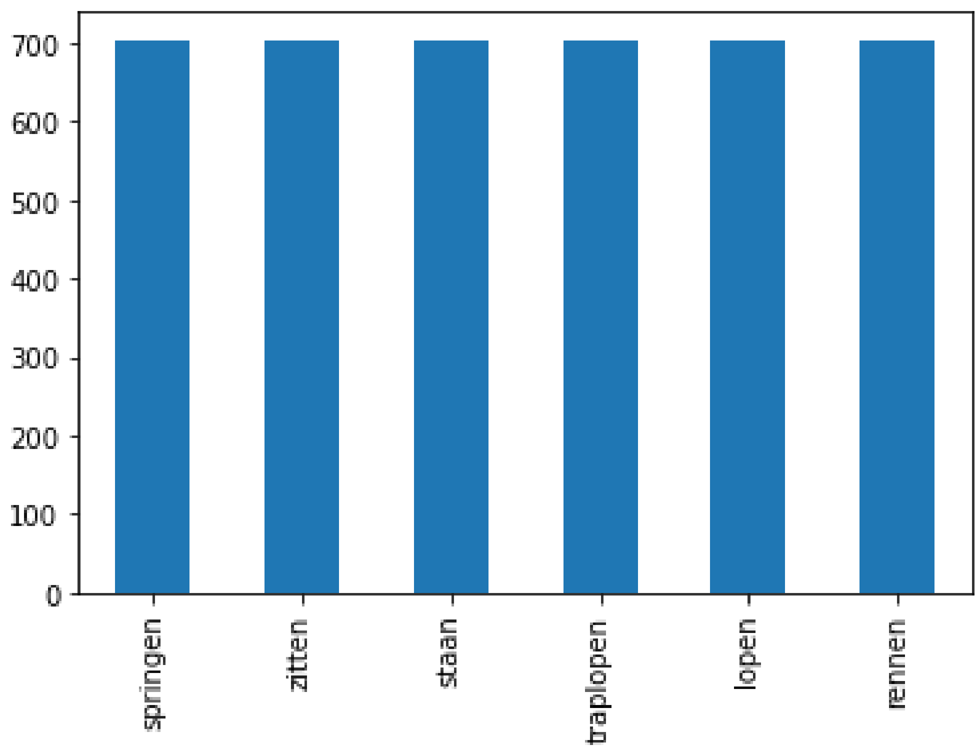
```
Extracting BMR099
Extracting BMR025
Extracting BMR060
Extracting BMR012
Extracting BMR030
Extracting BMR044
Extracting BMR043
Extracting BMR004
Extracting BMR011
Extracting BMR098
Extracting BMR034
Extracting BMR014
Extracting BMR036
Extracting BMR052
Extracting BMR002
Extracting BMR031
Extracting BMR097
Extracting BMR008
Extracting BMR015
Extracting BMR033
Extracting BMR064
Extracting BMR055
Extracting BMR041
Extracting BMR053
Extracting BMR042
Extracting BMR018
Extracting BMR058
Extracting BMR040
Extracting BMR032
Done extracting features
```

2 Balancing dataset

[7]:
```
def balance_dataset_by_activity(dataset):
    highest_frequency  = dataset.groupby('activiteit').
 ↪count()['standard_deviation_x'].max()
    unbalanced_dataset = dataset.copy()

    for activity_name in unbalanced_dataset.activiteit.unique():
        activity_data = unbalanced_dataset[unbalanced_dataset['activiteit'] ==␣
 ↪activity_name]

        multiplier =  int(highest_frequency / len(activity_data)) - 1
        unbalanced_dataset = unbalanced_dataset.append([activity_data] *␣
 ↪multiplier, ignore_index=True)

        activity_amount = len(unbalanced_dataset[␣
 ↪unbalanced_dataset['activiteit'] == activity_name])
        missing_amount = highest_frequency - activity_amount
        unbalanced_dataset = unbalanced_dataset.append(activity_data[:
 ↪missing_amount], ignore_index=True)

    return unbalanced_dataset

features_dataset = balance_dataset_by_activity(features_dataset)
```

[8]:
```
features_dataset['activiteit'].value_counts().plot.bar()
```

[8]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9c8b8a6fd0>



3 model preperation

[9]:
```
activities = ['lopen', 'rennen', 'springen', 'staan', 'traplopen', 'zitten']

features_dataset[['activity_walking', 'activity_running', 'activity_jumping',␣
↪'activity_standing', 'activity_traplopen',
                  'activity_sitten']] = 0
```

[10]:
```
features_dataset.loc[(features_dataset['activiteit'] == 'lopen'),␣
↪'activity_walking'] = 1
features_dataset.loc[(features_dataset['activiteit'] == 'rennen'),␣
↪'activity_running'] = 1
features_dataset.loc[(features_dataset['activiteit'] == 'springen'),␣
↪'activity_jumping'] = 1
features_dataset.loc[(features_dataset['activiteit'] == 'staan'),␣
↪'activity_standing'] = 1
features_dataset.loc[(features_dataset['activiteit'] == 'traplopen'),␣
↪'activity_traplopen'] = 1
features_dataset.loc[(features_dataset['activiteit'] == 'zitten'),␣
↪'activity_sitten'] = 1
```

```
features_dataset.drop('activiteit', axis=1, inplace=True)
```

[11]:
```
for column in features_columns[:-1]:
    features_dataset[column].fillna(0, inplace=True)
```

[12]:
```
features_dataset.head()
```

[12]:
```
   standard_deviation_x    mean_x  standard_deviation_y    mean_y  \
0              0.400827 -1.048051              0.313266  0.028658
1              0.478785 -1.029443              0.330056  0.038406
2              0.508147 -1.046631              0.352266  0.036316
3              0.528202 -1.011204              0.396568  0.022533
4              0.526253 -1.026743              0.383155  0.023408

   standard_deviation_z    mean_z  peak_distance_x  peak_distance_y  \
0              0.493007  0.184609          399.993            0.003
1              0.565512  0.154373          999.996          599.995
2              0.536173  0.160027          349.993          100.001
3              0.599671  0.150638          450.000          249.996
4              0.561279  0.148107          199.997          450.003

   peak_distance_z  activity_walking  activity_running  activity_jumping  \
0              0.0                 1                 0                 0
1              0.0                 1                 0                 0
2              0.0                 1                 0                 0
3              0.0                 1                 0                 0
4              0.0                 1                 0                 0

   activity_standing  activity_traplopen  activity_sitten
0                  0                   0                0
1                  0                   0                0
2                  0                   0                0
3                  0                   0                0
4                  0                   0                0
```

3.1 Preparing feature dataset for learning

3.1.1 Splitting in x and y

[13]:
```
x = features_dataset[features_columns[:-1]]
y = features_dataset[['activity_walking', 'activity_running',␣
↪'activity_jumping', 'activity_standing', 'activity_traplopen',␣
↪'activity_sitten']]
train_x, valid_x, train_y, valid_y = train_test_split(x,y, test_size=0.2,␣
↪random_state=23, stratify=y)
```

[14]:
```
# ## WORK IN PROGRESS
# x, y = make_classification(n_samples=1600, n_features=9, n_informative=9,␣
↪n_redundant=0, random_state=1)
# rfe = RFE(estimator=DecisionTreeClassifier(), n_features_to_select=5)
# model = DecisionTreeClassifier()
# pipeline = Pipeline(steps=[('s',rfe),('m',model)])


# cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
# n_scores = cross_val_score(pipeline, x, y, scoring='accuracy', cv=cv,␣
↪n_jobs=-1, error_score='raise')
# # report performance
# print('Accuracy: %.3f (%.3f)' % (mean(n_scores), std(n_scores)))
```

[15]:
```
train_x.head()
```

[15]:
```
      standard_deviation_x    mean_x  standard_deviation_y    mean_y  \
3678              0.201742 -1.092971              0.202561  0.048073
4142              0.516105 -1.096234              0.309056  0.239153
3183              0.334857 -0.953740              0.205250 -0.113829
3382              0.236063 -0.990352              0.145241  0.035792
3566              0.272816 -1.019297              0.189206 -0.036539

      standard_deviation_z    mean_z  peak_distance_x  peak_distance_y  \
3678              0.208261  0.222676           50.000          300.007
4142              0.394643  0.211702          600.004          899.992
3183              0.362671  0.061886          100.000          899.995
3382              0.228462  0.034174          149.999          299.997
3566              0.385552  0.153066          199.999          450.006

      peak_distance_z
3678          249.999
4142          150.001
3183          649.997
3382          549.996
3566          100.000
```

4 Decision Tree model

[16]:
```
dtc = tree.DecisionTreeClassifier()
dtc.fit(train_x, train_y)
```

[16]:
```
DecisionTreeClassifier()
```

4.1 results

Random seed: 23

Features	
standard_deviation_x	mean_x
standard_deviation_y	mean_y
standard_deviation_z	mean_z
peak_distance_x	peak_distance_y
peak_distance_z	activiteit

Time range	Accuracy	Precision	Recall
0.4S	80%	86%	80%
0.8S	82%	90%	82%
1.0S	83%	90%	83%
1.6S	83%	90%	83%
2.0S	83%	90%	83%
3.2S	83%	89.5%	83%
4.0S	83%	90.5%	82%
6.4S	84%	90%	85%
8.0S	85%	91%	85%
12.8S	87%	92%	87%

12.8S gives the best result

[17]:
```
prediction_y = dtc.predict(valid_x)
```

Accuracy

[18]:
```
accuracy_score(valid_y, prediction_y)
```

[18]: 0.9633136094674556

Precision

[19]:
```
precision_score(valid_y, prediction_y, average='micro')
```

[19]: 0.9633136094674556

Recall

[20]:
```
recall_score(valid_y, prediction_y , average='micro')
```

[20]: 0.9633136094674556

5 Random tree forest

[21]:
```
#from sklearn.preprocessing import StandardScaler

#sc = StandardScaler()
#train_x = sc.fit_transform(train_x)
#valid_x = sc.transform(valid_x)
```

[22]:
```
rfc = RandomForestClassifier(n_estimators=20, random_state=0)
rfc.fit(train_x, train_y)
```

[22]: RandomForestClassifier(n_estimators=20, random_state=0)

5.1 Result

[23]:
```
prediction_y = rfc.predict(valid_x)
```

5.1.1 classification_report

Accuracy

[24]:
```
accuracy_score(valid_y, prediction_y, normalize=True)
```

[24]: 0.9656804733727811

[25]:
```
print(classification_report(valid_y, prediction_y,␣
↪target_names=['activity_walking', 'activity_running', 'activity_jumping',␣
↪'activity_standing', 'activity_traplopen',
                    'activity_sitten'], zero_division=0))
```

```
                   precision    recall  f1-score   support

  activity_walking       0.98      0.90      0.94       140
  activity_running       0.99      0.94      0.96       141
  activity_jumping       0.97      1.00      0.98       141
 activity_standing       0.95      0.98      0.97       141
activity_traplopen       0.99      1.00      0.99       141
   activity_sitten       1.00      0.97      0.99       141

         micro avg       0.98      0.97      0.97       845
         macro avg       0.98      0.97      0.97       845
      weighted avg       0.98      0.97      0.97       845
       samples avg       0.97      0.97      0.97       845
```

```python
[ ]:
```

```python
[ ]:
```