

```
import os

import math

import numpy as np

import pandas as pd

from tqdm import tqdm

from pathlib import Path

from random import randrange

import matplotlib.pyplot as plt


from scipy.fft import fft

from scipy import signal, ndimage

from scipy.signal import argrextrema, hilbert

from scipy.stats import moment, zscore, mode, iqr


from scripts.data_handling import resample_axis

from scripts.preprocessing import preprocess_ecg, preprocess_gsr, preprocess_resp, preprocess_emg,
butter_filter
```

'''

This file implements several hand-crafted-feature approaches to analyze physiological sensors in the context of pain recognition.

For example the paper 'Automatic Pain Recognition from Video and Biomedical Signals' is used.

[https://www.researchgate.net/publication/268513442\\_Automatic\\_Pain\\_Recognition\\_from\\_Video\\_and\\_Biomedical\\_Signals](https://www.researchgate.net/publication/268513442_Automatic_Pain_Recognition_from_Video_and_Biomedical_Signals)

'''

```
#-----
```

```
# Supporting functions
```

```
#-----
```

```
def moving_average(x, w) :
```

```
    """
```

```
        Moving average for a one dimensional numpy vector.
```

```
        Each element in x is updated by calculating the mean of a window of elements with size 'w'
        centered around the element.
```

```
        Window is cropped to the start and end of 'x'.
```

```
    Parameters
```

```
    -----
```

```
    x: np. Vector which will be modified by the moving_average.
```

```
    w: int. Size of the window.
```

```
    Returns
```

```
    -----
```

```
    x: np. Vector.
```

```
    """
```

```
    assert x.ndim==1
```

```
    x = np.pad(x, (w//2, w//2 - 1), 'constant', constant_values=(x[0], x[-1]))
```

```
    x = np.convolve(x, np.ones(w)/w, mode='valid')
```

```
    return x
```

```
def RMS_envelope(x, w) :
```

```
    """
```

RMS envelope for a one dimensional numpy vector.

Each element in x is updated by calculating the RMS of a window of elements with size 'w' centered around the element.

Window is cropped to the start and end of 'x'.

Parameters

```
-----
```

x: np. Vector which will be modified by the moving\_average.

w: int. Size of the window.

Returns

```
-----
```

x: np. Vector.

```
    """
```

```
    assert x.ndim==1
```

```
    l = len(x)
```

```
    result = np.zeros(l)
```

```
    for i in np.arange(l):
```

```
        start = max(0, i - w//2)
```

```
        end = min(l, i + w//2)
```

```
        result[i] = math.sqrt(np.mean(x[start:end])**2)
```

```
    return result
```

```
def normalize(x):
```

'''

Function to normalize a dataframe.

Dataframe can be of type list, Pandas or Numpy.

If a Pandas Dataframe or list is given, it is converted to numpy.

Expects either 1 or 2 dimensional data. If a dataframe with two dimensions is given normalization is done along the first axis.

Parameters

-----

x: np, df or list. Data to normalize.

Returns

-----

Normalized data.

'''

if isinstance(x, pd.Series):

    x = x.to\_frame()

if isinstance(x, pd.DataFrame):

    result = x.copy()

    for feature\_name in result.columns:

        max\_value = result[feature\_name].max()

        min\_value = result[feature\_name].min()

        if max\_value != min\_value:

            result[feature\_name] = (result[feature\_name] - min\_value) /  
(max\_value - min\_value)

```

        else:
            result[feature_name] = 0
    return result

if isinstance(x, list):
    x = np.array(x)
if isinstance(x, np.ndarray):
    x = x.astype(float)
    if len(x.shape) == 1:
        x = x[np.newaxis, ...]
    if len(x.shape) == 2:
        for i, column in enumerate(x):
            max_value = np.max(column)
            min_value = np.min(column)
            if max_value != min_value:
                x[i, :] = (column - min_value) / (max_value - min_value)
            else:
                x[i, :] = 0
        if x.shape[0]==1:
            return x[0]
        return x
    print("Shape of len 1 or 2 was expected. Not implemented for shape: ", x.shape)
    return None

def best_fit_slope(xs,ys):
    """
    Simple solution to fit linear curve through data and return the slope of it.
    Found on https://pythonprogramming.net/how-to-program-best-fit-line-machine-learning-tutorial/.

```

## Parameters

-----

xs: np. x data

xy: np. y data.

## Returns

-----

int slope.

'''

```
m = (((np.mean(xs)*np.mean(ys)) - np.mean(xs*ys)) /
      ((np.mean(xs)*np.mean(xs)) - np.mean(xs*xs))) if (np.mean(xs)*np.mean(xs)) -
np.mean(xs*xs) != 0 else 0
return m
```

```
def calc_hr_peaks(x, sampling_rate, plot= False):
```

'''

ECG R-peak segmentation algorithm.

Follows the approach by Engelse and Zeelenberg [EnZe79]\_ with the  
modifications by Lourenco \*et al.\* [LSLL12]\_.

.. [EnZe79] W. Engelse and C. Zeelenberg, "A single scan algorithm for  
QRS detection and feature extraction", IEEE Comp. in Cardiology,  
vol. 6, pp. 37-42, 1979

.. [LSLL12] A. Lourenco, H. Silva, P. Leite, R. Lourenco and A. Fred,  
"Real Time Electrocardiogram Segmentation for Finger Based ECG  
Biometrics", BIOSIGNALS 2012, pp. 49-54, 2012

Further information:

# [https://biosignalsplux.com/learn/notebooks/Categories/Detect/r\\_peaks\\_rev.php](https://biosignalsplux.com/learn/notebooks/Categories/Detect/r_peaks_rev.php)

# <https://www.biorxiv.org/content/biorxiv/early/2019/08/06/722397.full.pdf>

Parameters

-----

x: np. 1D ecg signal.

plot: bool. Whether a plot should be shown.

Returns

-----

np peaks.

'''

```
assert x.ndim==1
```

```
df = pd.DataFrame()
```

```
df["input"]= x
```

```
# --- Differentiated - x[n]-x[n-4]
```

```
y1 = np.zeros(len(x))
```

```
y1[4:] = x.flat[4:] - x.flat[:-4]
```

```
df["Diff"]= y1
```

```
# Low pass filter - five tap FIR windowed smoothing filter with the coefficients= [1,4,6,4,1]
```

```
# https://github.com/PIA-Group/BioSPPy/blob/master/biosppy/signals/ecg.py
```

```

# y2[n]= sum ci*y1[n-1]

#c = [1, 4, 6, 4, 1, -1, -4, -6, -4, -1]

y2 = np.zeros(len(df["Diff"]))

y2[:-4] = np.convolve(df["Diff"].values,[1, 4, 6, 4, 1], 'valid')

df["fir"] = y2

```

# Other approach in NeuroKit:

```

#
https://github.com/neuropsychology/NeuroKit/blob/a04760bd83c544253ca919d214a46eb70cc06c39/neurokit2/ecg/ecg\_findpeaks.py#L653

```

```

'''

ci = [1, 4, 6, 4, 1]

low_pass = signal.lfilter(ci, 1, df["Diff"])

low_pass[: int(0.2 * sampling_rate)] = 0

df["fir"] = low_pass

'''

```

# peak detection:  $y2[n] > Th$ , with  $Th = 0.6 * \max(y2[n])$

# Changed this value from 0.6 to 0.4

$Th = 0.4 * \max(y2)$

i=0

peaks = []

nthi = None

nthf = None

while i < len(y2):

    if  $y2[i] > Th$  and nthi is None:

        nthi = i



```
if y2[i] < Th and nthi is not None:
```

```
    nthf = i
```

```
# found interval [nthi;nthf]
```

```
if nthf is not None and nthi is not None:
```

```
    # 160 ms window to the right of nthf
```

```
    start, end = nthf, int(nthf + (0.160 * sampling_rate))
```

```
    if plot:
```

```
        plt.axvline(x=start, color='slategrey', linestyle='dashed')
```

```
        plt.axvline(x=end, color='slategrey', linestyle='dashed')
```

```
    window = y2[start : end]
```

```
    # at least 10 ms of consecutive points with condition y2[n]< -Th
```

```
    # condition
```

```
    cond = window < - Th
```

```
    # consecutive
```

```
    if sum(cond) >= math.floor(0.010 * sampling_rate):
```

```
        peak = (start + np.argmax(x[start:end]), np.max(x[start:end]))
```

```
        peaks.append(peak)
```

```
    i= end
```

```
    nthi = None
```

```
    nthf = None
```

```
    i += 1
```

```
peaks_np = np.array(peaks)
```

```
p_list = []
```

```
q_list = []
```

```
s_list = []
```

```

t_list = []

# Return empty lists if there are no peaks
if peaks_np.size == 0:
    return p_list, q_list, peaks_np, s_list, t_list

# find p,q,s and t
qs_range = (0.100 * sampling_rate) # QRS complex is 100 ms for a healthy person
for r in peaks_np[:, 0]:
    half_qrs = int(qs_range//2)
    q_window_start = max(0, int(r - half_qrs))
    q = np.argmin(x[q_window_start : int(r)]) + q_window_start
    q_list.append([q, x[q]])

    s = np.argmin(x[int(r) : int(r + half_qrs)]) + int(r)
    s_list.append([s, x[s]])

    p_window_start = max(0, q - sampling_rate//4)
    p_window_end = max(1, q - sampling_rate//20)
    p = np.argmax(x[p_window_start : p_window_end]) + p_window_start
    p_list.append([p, x[p]])

    t_window_end = min(len(x), s + sampling_rate//3)
    t = np.argmax(x[s : t_window_end]) + s
    t_list.append([t, x[t]])

[p_list, q_list, s_list, t_list] = [np.array(i) for i in [p_list, q_list, s_list, t_list]]

# Plot peaks

```

```

if plot:
    #plt.axhline(y=Th, color='r', linestyle='-')
    if peaks_np.size > 0:
        plt.scatter(p_list[:, 0], p_list[:, 1], marker='o', c="black", zorder=10, label="P")
        plt.scatter(q_list[:, 0], q_list[:, 1], marker='o', c="green", zorder=10, label="Q")
        plt.scatter(peaks_np[:, 0], peaks_np[:, 1], marker='o', c="orange", zorder=10,
label="R-Peaks")
        plt.scatter(s_list[:, 0], s_list[:, 1], marker='o', c="purple", zorder=10, label="S")
        plt.scatter(t_list[:, 0], t_list[:, 1], marker='o', c="red", zorder=10, label="T")
    plt.legend()

if len(peaks) == 0:
    plt.plot(x)
    plt.title("No peaks could be found in the following ECG signal:")
    plt.show()
    print("'peaks' list is empty.\nIs the ECG signal fine? Is it upside down?")

return p_list, q_list, peaks_np, s_list, t_list

def power_spectrum(y, sampling_rate, show_plot = False):
    """
    Calculates a Single-Sided Amplitude Spectrum of y(t)
    From https://glowingpython.blogspot.com/2011/08/how-to-plot-frequency-spectrum-with.html

    Parameters
    -----

    x: np. 1D ecg signal.

```

sample\_rate: int. Sample rate.

secs: int. Seconds of the given time window.

show\_plot: bool. Whether a plot should be shown.

Returns

-----

np power spectrum.

'''

```
secs = len(y)/sampling_rate
```

```
t = np.arange(0, secs, 1.0/sampling_rate)
```

```
n = len(y) # length of the signal
```

```
k = np.arange(n)
```

```
T = n/sampling_rate
```

```
frq = k/T # two sides frequency range
```

```
frq = frq[range(int(n//2))] # one side frequency range
```

```
Y = fft(y)/n # fft computing and normalization
```

```
Y = Y[range(int(n//2))]
```

```
if show_plot:
```

```
    ax1 = plt.subplot(2,1,1)
```

```
    ax1.plot(t, y)
```

```
    ax1.set_xlabel('Time')
```

```
    ax1.set_ylabel('Amplitude')
```

```
    ax2 = plt.subplot(2,1,2)
```

```
    ax2.plot(frq, abs(Y), 'r')
```

```
    ax2.set_xlabel('Freq (Hz)')
```

```
ax2.set_ylabel('|Y(freq)|')
plt.show()
```

```
return abs(Y)
```

```
#-----
```

```
# Extraction methods for GSR, ECG, EDA
```

```
#-----
```

```
def gsr_feature_extraction(x, sampling_rate, name="", plot= False):
```

```
    """
```

```
    Function to calculate features for an EDA signal.
```

```
    Different features are calculated for the given signal 'x'.
```

```
    Parameters
```

```
    -----
```

```
    x: np. Sensor data.
```

```
    sampling_rate: Int. Sampling rate of the given sensor data.
```

```
    name: String. String to put a name in front of computed features. Default is "".
```

```
    plot: Bool. Boolean that describes whether to plot the outcome of the analysis or not. Default is
False.
```

```
    Returns
```

```
    -----
```

```
    result: df. Pandas Dataframe describing the computed features.
```

```
    """
```

```
    df = pd.DataFrame()
```

```
# Plot one example
```

```
if plot:
```

```
    example = x[randrange(x.shape[0])]
```

```
    example = preprocess_gsr(example, sampling_rate= sampling_rate, plot= True)
```

```
    plt.legend()
```

```
    plt.title("EDA preprocessing")
```

```
    plt.show()
```

```
analyze_EDA(example, sampling_rate= sampling_rate, plot= True)
```

```
plt.show()
```

```
# max
```

```
df[name + "_max"] = np.max(x, axis=1)
```

```
# min
```

```
df[name + "_min"] = np.min(x, axis=1)
```

```
# range
```

```
df[name + "_range"] = (np.max(x, axis=1)-np.min(x, axis=1))
```

```
# std
```

```
df[name + "_std"] = (np.std(x, axis=1))
```

```
# iqr
```

```
df[name + "_iqr"] = (iqr(x, axis=1))
```

```
# mean
```

```
df[name + "_mean"] = np.mean(x, axis=1)
```

```
print("Finished simple EDA metrics. Start computing more complex ones...")
```

```
# rms
```

```
df[name + "_rms"] = (np.sqrt(np.mean(x**2, axis=1)))
```

```

# local maxima

df[name + "_local_max"] = [np.mean(argrelextrema(i, np.greater)) if argrelextrema(i,
np.greater)[0].size>0 else 0 for i in x]

# local minima

df[name + "_local_min"] = [np.mean(argrelextrema(i, np.less)) if argrelextrema(i,
np.less)[0].size>0 else 0 for i in x]

# mean absolut value

df[name + "_mean_abs"] = (np.mean(np.abs(x), axis= 1))

# mean absolut values of the first differences

df[name + "_mean_abs_1_diff"] = np.mean(np.abs(x[:, 1:] - x[:, :-1]), axis= 1)

# mean absolut values of the second differences

df[name + "_mean_abs_2_diff"] = np.mean(np.abs(x[:, 2:] - x[:, :-2]), axis= 1)

# zscore (relative to the sample mean and standard deviation) as standardization method

standardized_gsr = zscore(x)

# mean absolut values of the first differences -standardized - z score

df[name + "_mean_abs_1_diff_std"] = np.mean(np.abs(standardized_gsr[:, 1:] -
standardized_gsr[:, :-1]), axis= 1)

# mean absolut values of the second differences -standardized - z score

df[name + "_mean_abs_2_diff_std"] = np.mean(np.abs(standardized_gsr[:, 2:] -
standardized_gsr[:, :-2]), axis= 1)

# Variation of the first and second moment of the signal over time

df[name + "_var_mom"] = np.apply_along_axis(lambda x: np.var([moment(x, 1), moment(x, 2)]),
arr=x, axis=1)

# ----- Selfmade

# Location max (selfmade)

df[name + "_argmax"] = np.argmax(x, axis= 1)

# Location min (selfmade)

df[name + "_argmin"] = np.argmin(x, axis= 1)

# Difference start, end (selfmade)

```

```

df[name + "_diff_start_end"] = x[:, -1]-x[:, 0]

# Further analysis: For example compute Tonic and phasic components
print("Start EDA decomposition...")
features = [analyze_EDA(i, sampling_rate= sampling_rate) for i in tqdm(x)]
# Unpack results
phasic = [i[0] for i in features]
tonic = [i[1] for i in features]
peaks = [i[2] for i in features]
onsets = [i[3] for i in features]
offsets = [i[4] for i in features]
rise_times = [i[5] for i in features]
amplitudes = [i[6] for i in features]
recovery = [i[7] for i in features]
half_recovery = [i[8] for i in features]

# Mean phasic - tonic
df[name + "_mean_phasic"] = [np.mean(x) for x in phasic]
df[name + "_mean_tonic"] = [np.mean(x) for x in tonic]
# STD phasic - tonic
df[name + "_std_phasic"] = [np.std(x) for x in phasic]
df[name + "_std_tonic"] = [np.std(x) for x in tonic]
# Range tonic
df[name + "_range_tonic"] = [x[-1]-x[0] for x in tonic]
# Number of GSR-peaks
df[name + "_#GSR"] = [len(x) for x in peaks]
# Mean + STD amplitude
df[name + "_mean_amplitudes"] = [np.mean(x) if len(x)>0 else 0 for x in amplitudes]
df[name + "_std_amplitudes"] = [np.std(x) if len(x)>0 else 0 for x in amplitudes]

```



```

# Mean + STD rise_times
df[name + "_mean_rise_times"] = [np.mean(x) if len(x)>0 else 0 for x in rise_times]
df[name + "_std_rise_times"] = [np.std(x) if len(x)>0 else 0 for x in rise_times]

# Mean + STD half_recovery
df[name + "_mean_half_recovery"] = [np.mean(x) if len(x)>0 else 0 for x in half_recovery]
df[name + "_std_half_recovery"] = [np.std(x) if len(x)>0 else 0 for x in half_recovery]

# Mean + STD recovery
df[name + "_mean_recovery"] = [np.mean(x) if len(x)>0 else 0 for x in recovery]
df[name + "_std_recovery"] = [np.std(x) if len(x)>0 else 0 for x in recovery]

# Mean + STD onsets
df[name + "_mean_onsets"] = [np.mean(x) if len(x)>0 else 0 for x in onsets]
df[name + "_std_onsets"] = [np.std(x) if len(x)>0 else 0 for x in onsets]

# Mean + STD offsets
df[name + "_mean_offsets"] = [np.mean(x) if len(x)>0 else 0 for x in offsets]
df[name + "_std_offsets"] = [np.std(x) if len(x)>0 else 0 for x in offsets]

#-----

# Features from: Data Descriptor: Emotional ratings and skin conductance response to visual,
auditory and haptic stimuli

# sum of amplitude
df[name + "_sum_amp"] = [np.sum(x) if len(x)>0 else 0 for x in amplitudes]

# first amp
df[name + "_first_amp"] = [x[0] if len(x)>0 else 0 for x in amplitudes]

#phasic max
df[name + "_phasic_max"] = [np.max(x) for x in phasic]

#-----

#-----

# Features on normalized data

```

```

normalized_x = normalize(x)

df[name + "_norm_mean"] = [np.mean(x) for x in normalized_x]

df[name + "_norm_std"] = [np.std(x) for x in normalized_x]

df[name + "_norm_var"] = [np.var(x) for x in normalized_x]

#-----

# Features for review

def get_cvxEDA(y, delta, tau0=2., tau1=0.7, delta_knot=10., alpha=8e-4, gamma=1e-2,
               solver=None, options={'reltol':1e-9, 'show_progress': False, 'gp':
dict(msg_lev='GLP_MSG_OFF'))):
    """CVXEDA Convex optimization approach to electrodermal activity processing
    This function implements the cvxEDA algorithm described in "cvxEDA: a
    Convex Optimization Approach to Electrodermal Activity Processing"
    (http://dx.doi.org/10.1109/TBME.2015.2474131, also available from the
    authors' homepages).

    Arguments:

    y: observed EDA signal (we recommend normalizing it:  $y = \text{zscore}(y)$ )

    delta: sampling interval (in seconds) of y

    tau0: slow time constant of the Bateman function

    tau1: fast time constant of the Bateman function

    delta_knot: time between knots of the tonic spline function

    alpha: penalization for the sparse SMNA driver

    gamma: penalization for the tonic spline coefficients

    solver: sparse QP solver to be used, see cvxopt.solvers.qp

    options: solver options, see:
        http://cvxopt.org/userguide/coneprog.html#algorithm-parameters

    Returns (see paper for details):

    r: phasic component

```

p: sparse SMNA driver of phasic component

t: tonic component

l: coefficients of tonic spline

d: offset and slope of the linear drift term

e: model residuals

obj: value of objective function being minimized (eq 15 of paper)

''''''

```
import cvxopt as cv
```

```
n = len(y)
```

```
y = cv.matrix(y)
```

```
# bateman ARMA model
```

```
a1 = 1./min(tau1, tau0) # a1 > a0
```

```
a0 = 1./max(tau1, tau0)
```

```
ar = np.array([(a1*delta + 2.) * (a0*delta + 2.), 2.*a1*a0*delta**2 - 8.,  
               (a1*delta - 2.) * (a0*delta - 2.)]) / ((a1 - a0) * delta**2)
```

```
ma = np.array([1., 2., 1.])
```

```
# matrices for ARMA model
```

```
i = np.arange(2, n)
```

```
A = cv.spmatrix(np.tile(ar, (n-2,1)), np.c_[i,i], np.c_[i,i-1,i-2], (n,n))
```

```
M = cv.spmatrix(np.tile(ma, (n-2,1)), np.c_[i,i,i], np.c_[i,i-1,i-2], (n,n))
```

```
# spline
```

```
delta_knot_s = int(round(delta_knot / delta))
```

```
spl = np.r_[np.arange(1.,delta_knot_s), np.arange(delta_knot_s, 0., -1.)] # order 1
```

```
spl = np.convolve(spl, spl, 'full')
```

```
spl /= max(spl)
```

```
# matrix of spline regressors
```

```
i = np.c_[np.arange(-(len(spl)//2), (len(spl)+1)//2)] + np.r_[np.arange(0, n, delta_knot_s)]
```

```
nB = i.shape[1]
```

```
j = np.tile(np.arange(nB), (len(spl),1))
```

```
p = np.tile(spl, (nB,1)).T
```

```
valid = (i >= 0) & (i < n)
```

```
B = cv.spmatrix(p[valid], i[valid], j[valid])
```

```
# trend
```

```
C = cv.matrix(np.c_[np.ones(n), np.arange(1., n+1.)/n])
```

```
nC = C.size[1]
```

```
# Solve the problem:
```

```
# .5*(M*q + B*I + C*d - y)^2 + alpha*sum(A,1)*p + .5*gamma*I'*I
```

```
# s.t. A*q >= 0
```

```
old_options = cv.solvers.options.copy()
```

```
cv.solvers.options.clear()
```

```
cv.solvers.options.update(options)
```

```
if solver == 'conelp':
```

```
    # Use conelp
```

```
    z = lambda m,n: cv.spmatrix([],[],[],(m,n))
```

```
    G = cv.sparse([[ -A,z(2,n),M,z(nB+2,n)],[z(n+2,nC),C,z(nB+2,nC)],
```

```
                  [z(n,1),-1,1,z(n+nB+2,1)],[z(2*n+2,1),-1,1,z(nB,1)],
```

```
                  [z(n+2,nB),B,z(2,nB),cv.spmatrix(1.0, range(nB),
```

```
range(nB))]]])
```

```
    h = cv.matrix([z(n,1),.5,.5,y,.5,.5,z(nB,1)])
```

```
    c = cv.matrix([(cv.matrix(alpha, (1,n)) * A).T,z(nC,1),1,gamma,z(nB,1)])
```

```

        res = cv.solvers.conelp(c, G, h, dims={'l':n,'q':[n+2,nB+2],'s':[]})
        obj = res['primal objective']
    else:
        # Use qp
        Mt, Ct, Bt = M.T, C.T, B.T
        H = cv.sparse([[Mt*M, Ct*M, Bt*M], [Mt*C, Ct*C, Bt*C],
range(nB))]])

        f = cv.matrix([(cv.matrix(alpha, (1,n)) * A).T - Mt*y, -(Ct*y), -(Bt*y)])
        res = cv.solvers.qp(H, f, cv.spmatrix(-A.V, A.I, A.J, (n,len(f))),
                                cv.matrix(0., (n,1)), solver=solver)

        obj = res['primal objective'] + .5 * (y.T * y)

    cv.solvers.options.clear()
    cv.solvers.options.update(old_options)

    l = res['x'][-nB:]
    d = res['x'][n:n+nC]
    t = B*l + C*d
    q = res['x'][:n]
    p = A * q
    r = M * q
    e = y - r - t

    return (np.array(a).ravel() for a in (r, p, t, l, d, e, obj))

```

```

def get_dPhEDA(x):
    length = len(x)
    new = np.zeros(length)
    for i, value in enumerate(x):

```

```
if (i - 2) < 0 or (i + 2) > (length - 1):
```

```
    new[i]= value
```

```
    continue
```

```
new[i] = (x[i-2] - 8*x[i-1] + 8*x[i+1] - x[i+2]) / (12 * (1/2))
```

```
return new
```

```
# --- Preprocess
```

```
# resample to 4 Hz
```

```
sec = x.shape[1]/sampling_rate
```

```
resampled_first = resample_axis(x, input_fs= sampling_rate, output_fs= 4)
```

```
# median filter
```

```
median_filtered = [ndimage.median_filter(i, size= 4) for i in resampled_first]
```

```
# resample to 2 Hz
```

```
resampled_second = resample_axis(median_filtered, input_fs= 4, output_fs= 2)
```

```
# highpass filter #
```

```
highpass_filtered = [butter_filter(data= i, cutoff_freq= 0.01, fs= sampling_rate, btype=  
"highpass", order= 8) for i in resampled_second]
```

```
# --- dPhEDA route
```

```
# cvxEDA
```

```
print("Extract cvxEDA EDA...")
```

```
cvxEDA = [get_cvxEDA(i, 1./2) for i in tqdm(highpass_filtered)]
```

```
# get the pasic part
```

```

phasic = [list(i)[0] for i in cvxEDA]

# five point stencil

dPhEDA = [get_dPhEDA(i) for i in phasic]

if plot:

    plt.plot(resample_axis(x[0], sample_size= 250, axis= 0), label = "raw")

    plt.plot(resample_axis(resampled_first[0], sample_size= 250, axis= 0), label =
"resampled_first")

    plt.plot(resample_axis(median_filtered[0], sample_size= 250, axis= 0), label =
"median_filtered")

    plt.plot(resample_axis(resampled_second[0], sample_size= 250, axis= 0), label =
"resampled_second")

    plt.plot(resample_axis(highpass_filtered[0], sample_size= 250, axis= 0), label =
"highpass_filtered")

    plt.plot(resample_axis(phasic[0], sample_size= 250, axis= 0), label = "phasic")

    plt.plot(resample_axis(dPhEDA[0], sample_size= 250, axis= 0), label = "dPhEDA")

    plt.legend()

    plt.show()


# add dPhEDA to the feature list

dPhEDA = np.array(dPhEDA)

for i in range(len(dPhEDA[0])):

    df[name + "_dPhEDA_{}".format(i)] = dPhEDA[:, i]


# --- Time-Varying Index of Sympathetic Activity (TVSymp) and Modified TVSymp (MTVSymp)

# (time-frequency spectral analysis)


def get_MTVSymp(x, k_sec = 5, fs = 2):

    MTVSymp = np.zeros(len(x))

    for i in range(len(x)):

        start = max(i - (fs * k_sec), 0)

```

```

        end = max(i - 1, 0)

        if end == 0:
            MTVSymp[i] = x[i]
            continue

        ut = np.mean(x[start:end])

        if ut > x[i]:
            MTVSymp[i] = 0
        else:
            MTVSymp[i] = x[i] - ut

    return MTVSymp

```

# - VFCDM: variable frequency complex demodulation

# parameters

```
data_length = x[0].shape[0]
```

```
center_frequencies = [0.04, 0.12, 0.2, 0.28, 0.36, 0.44, 0.52, 0.6, 0.68, 0.76, 0.84, 0.92]
```

```
bandwidth = 0.04 #  $F\omega$ 
```

```
length = data_length//2 #  $N\omega$  is chosen to be approximately half the data length [16].
```

```
components = []
```

```
for center in center_frequencies[1:3]:
```

```
    # finite-impulse response (FIR)
```

```
    fir = signal.firwin(numtaps = length, cutoff= center, width= bandwidth)
```

```
    #adaptive lowpass filter (LPF)
```



```

component = [signal.lfilter(fir, 1, i) for i in highpass_filtered]

components.append(component)

# We summed the second and third components to include the sympathetic dynamics,
# which range between 0.045–0.25 Hz, followed by normalization to unit variance.
# The summed value is denoted by X'.

# sum of the second and third components
sum = np.sum(np.array(components), axis= 0)
# followed by normalization to unit variance
normed = [(i - i.mean(axis=0)) / i.std(axis=0) if i.std(axis=0) != 0 else i for i in sum]

# Hilbert transform
analytic_signal = [hilbert(i) for i in normed]

#TVSymp, a(t), is obtained by calculating the instantaneous amplitude of Z(t) ->
amplitude_envelope
TVSymp = [np.abs(i) for i in analytic_signal]

# --- Calculation of MTVSymp
MTVSymp = [get_MTVSymp(i) for i in TVSymp]

# add TVSymp to the feature list
TVSymp = np.array(TVSymp)
for i in range(len(TVSymp[0])):
    df[name + "_TVSymp_{}".format(i)] = TVSymp[:, i]

```

```

# defragment the DataFrame
df = df.copy()

# add MTVSymp to the feature list
MTVSymp = np.array(MTVSymp)
for i in range(len(MTVSymp[0])):
    df[name + "_MTVSymp_{}".format(i)] = MTVSymp[:, i]

if plot:
    plt.plot(resample_axis(x[0], sample_size= 250, axis= 0), label = "raw")
    plt.plot(resample_axis(normed[0], sample_size= 250, axis= 0), label = "normed")
    plt.plot(resample_axis(TVSymp[0], sample_size= 250, axis= 0), label = "TVSymp")
    plt.plot(resample_axis(MTVSymp[0], sample_size= 250, axis= 0), label = "MTVSymp")
    plt.legend()
    plt.show()

return df

```

```

def analyze_EDA(x, sampling_rate, plot= False, onset_threshold = 0.01, offset_threshold = 0,
peak_amplification_threshold = 0.04, method = "highpass"):

```

```

    """

```

Function to analyze a given EDA signal.

Filters the given signal with a lowpass filter and decomposes its into tonic + phasic component.

Furthermore, GSR are localized and returned.

Decomposition information: "<https://imotions.com/blog/skin-conductance-response/>"

+ "<https://www.biopac.com/knowledge-base/phasic-eda-issue/>"

Parameters

-----

x: np. Eda signal to analyze.

show\_plot: Bool. Whether to plot a graph with results or not. Default= False.

onset\_threshold = 0.01, offset\_threshold = 0, peak\_amplification\_threshold = 0.05 -> Default parameters to detect GSRs.

method: String. Method to decompose tonic/phasic signal. Can be either "highpass" or "median". Default: "highpass".

Returns

-----

Lists: phasic, tonic, peaks, onsets, offsets, rise\_times, amplitudes, recovery, half\_recovery.

"""

```
df = pd.DataFrame()
```

```
df["Filtered"] = x
```

```
# phasic/tonic decomposition
```

```
if method == "highpass":
```

```
    import scipy
```

```
    sos = scipy.signal.butter(2, 0.05, btype="lowpass", output="sos", fs=sampling_rate)
```

```
    df["Tonic"] = scipy.signal.sosfiltfilt(sos, x)
```

```
    sos = scipy.signal.butter(2, 0.05, btype="highpass", output="sos", fs=sampling_rate)
```

```
    df["Phasic"] = scipy.signal.sosfiltfilt(sos, x)
```

```
elif method == "median":
```

```

# Calculate Tonic
df["Tonic"] = moving_average(df["Filtered"].values, 4 * sampling_rate)

# Calculate Phasic
df["Phasic"] = df["Filtered"].values - df["Tonic"].values

else:

    print("Method '{}' not known to decompose EDA.".format(method))

    raise NotImplementedError

```

```

# --- GSR detection

possible_peaks = []

# find possible peaks: onset > 0.01 | | offset < 0

phasic = df["Phasic"].values

i = 0

while i < len(phasic):

    if phasic[i] > onset_threshold:

        for j in range(i + 1, len(phasic)):

            if phasic[j] < offset_threshold:

                possible_peaks.append([i, j])

                i = j + 1

                break

        i += 1

```

```

# features to be saved

peaks_x = [] # x-values of peak

onsets_x = [] # x-values of onset

offsets_x = [] # x-values of offset

rise_times = [] # Number of samples between onset and peak

amplitudes = [] # Y difference between peak and offsets

recovery_times = [] # Number of samples between peak and offset

```

```

half_recovery_times = [] # Number of samples between peak and half recovery

# remove from possible peaks where peak is not exceeding 0.05
for p in possible_peaks:
    data = df["Filtered"].values[p[0]:p[1]]
    rise = np.max(data) - data[0]
    if rise >= peak_amplification_threshold:
        index = int(np.argmax(data) + p[0])
        peaks_x.append(index)
        onsets_x.append(p[0])
        offsets_x.append(p[1])
        rise_times.append(index - p[0])
        amplitudes.append(rise)
        recovery_times.append(p[1] - index)
        peak_offset_difference = abs(x[index] - x[p[1]])
        half_recovery_y = (peak_offset_difference/2) + min(x[index : p[1]])
        half_recovery_times.append(np.argmin(abs(x[index:p[1]] - half_recovery_y)))

    assert len(peaks_x) == len(onsets_x) == len(offsets_x) == len(rise_times) == len(amplitudes) ==
len(recovery_times) == len(half_recovery_times)

if plot:
    fig = plt.figure()

    linewidth= 3
    fontsize= 18
    marker_size= 130

    # --- First plot

```

```

ax = fig.add_subplot(311)

ax.plot(df["Filtered"].values, color="royalblue", label= "Filtered", linewidth=linewidth)

ax.plot(df["Tonic"].values, color="lightgreen", label= "Tonic", linewidth=linewidth)

ax.legend(loc='upper left', fontsize= fontsize)

ax.tick_params(left=False,

               bottom=False,

               labelleft=False,

               labelbottom=False)

```

# --- Second plot

```

ax = fig.add_subplot(312)

ax.plot(df["Phasic"].values, color="orange", label= "Phasic", linewidth=linewidth)

ax.axhline(0, color="gainsboro", linestyle= "dashed", linewidth=linewidth)

ax.axhline(onset_threshold, color="mediumseagreen", linestyle= "dashed", label=
"Onset threshold", linewidth=linewidth)

possible_onsets = [x[0] for x in possible_peaks]

possible_offsets = [x[1] for x in possible_peaks]

ax.scatter(possible_onsets, [df["Phasic"][x] for x in possible_onsets], s= marker_size,
marker='>', c="dimgrey", zorder=10, label="Possible Onset", edgecolors='b')

ax.scatter(possible_offsets, [df["Phasic"][x] for x in possible_offsets], s= marker_size,
marker='<', c="darkgrey", zorder=10, label="Possible Offset", edgecolors='b')

ax.legend(loc='upper left', fontsize= fontsize)

ax.tick_params(left=False,

               bottom=False,

               labelleft=False,

               labelbottom=False)

```

# --- Third plot

```

ax = fig.add_subplot(313)

```

```

half_recovs_x = [i + j for i, j in zip(half_recovery_times, peaks_x)]

def get_y(x):
    return df["Filtered"][x]

ax.plot(df["Filtered"].values, color= "#E91E63", label= "Raw", linewidth=linewidth)

for peak_x, onset_x, half_recovery_x in zip(peaks_x, onsets_x, half_recovs_x):
    peak_y, onset_y, half_recovery_y = get_y(peak_x), get_y(onset_x),
    get_y(half_recovery_x)

    # color peak "royalblue"
    # plot risetime
    plt.plot([peak_x, onset_x], [onset_y, onset_y], c="#FFA726", linestyle="dashed",
linewidth=linewidth)

    # plot amplitude
    plt.plot([peak_x, peak_x], [onset_y, peak_y], c="#1976D2", linestyle="solid",
linewidth=linewidth)

    # plot half recovery
    plt.plot([half_recovery_x, peak_x], [half_recovery_y, half_recovery_y],
c="#FDD835", linestyle="dashed", linewidth=linewidth)

ax.scatter(peaks_x, [df["Filtered"][x] for x in peaks_x], s= marker_size, marker='v',
c="orange", zorder=10, label="Peaks", edgecolors='b')

ax.scatter(onsets_x, [df["Filtered"][x] for x in onsets_x], s= marker_size, marker='>',
c="dimgrey", zorder=10, label="Onset", edgecolors='b')

ax.scatter(offsets_x, [df["Filtered"][x] for x in offsets_x], s= marker_size, marker='<',
c="darkgrey", zorder=10, label="Offset", edgecolors='b')

ax.scatter(half_recovs_x, [df["Filtered"][x] for x in half_recovs_x], s= marker_size,
marker='o', c="skyblue", zorder=10, label="Half recovery", edgecolors='b')

ax.legend(loc= 'upper left', fontsize= fontsize)

ax.tick_params(left=False,
bottom=False,

```

```
        labelleft=False,  
        labelbottom=False)
```

```
    return df["Phasic"].values, df["Tonic"].values, peaks_x, onsets_x, offsets_x, rise_times,  
    amplitudes, recovery_times, half_recovery_times
```

```
def ecg_feature_extraction(x, sampling_rate, name="", plot= False):
```

```
    '''
```

```
    Function to calculate features for an ECG signal.
```

```
    Different features are calculated for the given signal 'x'.
```

```
    Parameters
```

```
    -----
```

```
    x: np. Sensor data.
```

```
    sampling_rate: Int. Sampling rate of the given sensor data.
```

```
    name: String. String to put a name in front of computed features. Default is "".
```

```
    plot: Bool. Boolean that describes whether to plot the outcome of the analysis or not. Default is  
False.
```

```
    Returns
```

```
    -----
```

```
    result: df. Pandas Dataframe describing the computed features.
```

```
    '''
```

```
    df = pd.DataFrame()
```

```
    # preprocess
```

```
    #x = np.apply_along_axis(preprocess_ecg, axis=1, arr= x, plot= False, sampling_rate=  
sampling_rate)
```

```
    # Plot one example
```



if plot:

```
example = x[0]

# Plot preprocessing
preprocess_ecg(example, sampling_rate= sampling_rate, plot= True)

plt.title("Ecg preprocessing")

plt.show()
```

```
# Plot the QRS complex points
calc_hr_peaks(example, sampling_rate= sampling_rate, plot= True)

plt.plot(example)

plt.legend()

plt.title("ECG analysis")

plt.show()
```

```
# Plot Biosppy analysis

from biosppy.signals import ecg

out = ecg.ecg(signal=example, sampling_rate=250, show=True)

plt.show()
```

```
# Retrieve peaks - Format List with "DataSamples" entries of type Array(RPeak, XY-Axis)
print("Calculate HR peaks...")

features = [calc_hr_peaks(i, sampling_rate= sampling_rate, plot= False) for i in tqdm(x)]

# Unpack results
p_list = [i[0] for i in features]
q_list = [i[1] for i in features]
peaks = [i[2] for i in features]
s_list = [i[3] for i in features]
t_list = [i[4] for i in features]
```

```

# Retrieve RR interval - Difference of x component ("[:, 0]") of the peaks
rr = [np.diff(i[:, 0]) if len(i) > 0 else [] for i in peaks]

# remove empty slides
rr = [x if len(x)>0 else [0] for x in rr]

# mean RR
df[name + "_meanRR"] = [np.mean(x) for x in rr]

# RMSSD: take the square root of the mean square of the differences
df[name + "_RMSSD"] = [np.sqrt(np.mean(np.square(np.diff(x)))) if len(x)>1 else 0 for x in rr]

# mean of the std of the RR-intervals
df[name + "_stdRR"] = [np.std(x) if len(x)>1 else 0 for x in rr]

# slope of the linear regression of RR
df[name + "_slope"] = [best_fit_slope(xs=np.arange(len(x)), ys=x) for x in rr]

# Own: number of found R-peaks
df[name + "_#_r_peaks"] = [len(x) for x in peaks]

# --- additional features

# max
df[name + "_max"] = np.max(x, axis=1)

# min
df[name + "_min"] = np.min(x, axis=1)

# range
df[name + "_range"] = (np.max(x, axis=1)-np.min(x, axis=1))

# std
df[name + "_std"] = (np.std(x, axis=1))

# iqr
df[name + "_iqr"] = (iqr(x, axis=1))

# mean

```

```

df[name + "_mean"] = np.mean(x, axis=1)

# rms
df[name + "_rms"] = (np.sqrt(np.mean(x**2, axis=1)))

# local maxima
df[name + "_local_max"] = np.apply_along_axis(lambda x: np.mean(argrelextrema(x,
np.greater)), arr=x, axis=1)

# local minima
df[name + "_local_min"] = np.apply_along_axis(lambda x: np.mean(argrelextrema(x, np.less)),
arr=x, axis=1)

# mean absolut value
df[name + "_mean_abs"] = (np.mean(np.abs(x), axis= 1))

# --- PQRST features

# Electrocardiogram Feature Extraction and Pattern Recognition Using a Novel Windowing
Algorithm

names = [name + "_pr_interval", name + "_qt_interval", name + "_pt_interval", name +
"_qrs_duration"]

zips = [[p_list, q_list], [q_list, t_list], [p_list, t_list], [q_list, s_list]]

for name, to_zip in zip(names, zips):

    df[name + "_mean"] = [np.mean(j[:,0] - i[:,0]) if len(i)>0 else 0 for i, j in zip(*to_zip)]
    df[name + "_std"] = [np.std(j[:,0] - i[:,0]) if len(i)>0 else 0 for i, j in zip(*to_zip)]
    df[name + "_range"] = [max(j[:,0] - i[:,0]) - min(j[:,0] - i[:,0]) if len(i)>0 else 0 for i, j in
zip(*to_zip)]
    df[name + "_diff"] = [(j[-1,0]-i[-1,0]) - (j[0,0]-i[0,0]) if len(i)>0 else 0 for i, j in zip(*to_zip)]

return df

def emg_feature_extraction(x, sampling_rate, name="", plot= False):
    """
    Function to calculate features for an EMG signal.

```

Different features are calculated for the given signal 'x'.

#### Parameters

-----

x: np. Sensor data.

sampling\_rate: Int. Sampling rate of the given sensor data.

name: String. String to put a name in front of computed features. Default is "".

plot: Bool. Boolean that describes whether to plot the outcome of the analysis or not. Default is False.

#### Returns

-----

result: df. Pandas Dataframe describing the computed features.

'''

```
df = pd.DataFrame()
```

```
# Plot one example
```

```
if plot:
```

```
    example = x[randrange(x.shape[0])]
```

```
    example = preprocess_emg(example, sampling_rate= sampling_rate, plot= True)
```

```
    analyze_emg(example, sampling_rate= sampling_rate, plot= True)
```

```
    plt.legend()
```

```
    plt.title("EMG analysis")
```

```
    plt.show()
```

```
# preprocess
```

```
#x = np.apply_along_axis(preprocess_emg, axis=1, arr= x, plot= False, sampling_rate=
sampling_rate)
```

```

# max
df[name + "_max"] = np.max(x, axis=1)

# min
df[name + "_min"] = np.min(x, axis=1)

# range
df[name + "_range"] = (np.max(x, axis=1)-np.min(x, axis=1))

# std
df[name + "_std"] = (np.std(x, axis=1))

# iqr
df[name + "_iqr"] = (iqr(x, axis=1))

# mean
df[name + "_mean"] = np.mean(x, axis=1)

# rms
df[name + "_rms"] = (np.sqrt(np.mean(x**2, axis=1)))

# mean absolut value
df[name + "_mean_abs"] = (np.mean(np.abs(x), axis= 1))

# mean absolut values of the first differences
df[name + "_mean_abs_1_diff"] = np.mean(np.abs(x[:, 1:] - x[:, :-1]), axis= 1)

# mean absolut values of the second differences
df[name + "_mean_abs_2_diff"] = np.mean(np.abs(x[:, 2:] - x[:, :-2]), axis= 1)

# zscore (relative to the sample mean and standard deviation) as standardization method
standardized_emg = zscore(x)

# mean absolut values of the first differences -standardized - z score
df[name + "_mean_abs_1_diff_std"] = np.mean(np.abs(standardized_emg[:, 1:] -
standardized_emg[:, :-1]), axis= 1)

# mean absolut values of the second differences -standardized - z score
df[name + "_mean_abs_2_diff_std"] = np.mean(np.abs(standardized_emg[:, 2:] -
standardized_emg[:, :-2]), axis= 1)

# Variation of the first and second moment of the signal over time

```

```
df[name + "_var_mom"] = np.apply_along_axis(lambda i: np.var([moment(i, 1), moment(i, 2)]),
arr=x, axis=1)
```

```
# Note: Empirical Mode Decomposition and time windows of activity are not implemented by
now.
```

```
# Note: Could be implemented: Degree of stationarity in the spectrum domain
```

```
# -- Additional EMG features
```

```
# signals power spectrum
```

```
print("Calc power spectrum for EMG...")
```

```
spec = [power_spectrum(i, sampling_rate= sampling_rate) for i in tqdm(x)]
```

```
# mode frequency of the signals power spectrum
```

```
df[name + "_freq_ps"] = [mode(i, keepdims=False)[0] for i in spec]
```

```
# mean frequency of the signals power spectrum
```

```
df[name + "_mean_freq"] = [np.mean(i) for i in spec]
```

```
# zero crossing of the time-domain signal
```

```
df[name + "_zero_crossing"] = np.apply_along_axis(lambda i: ((i[:-1] * i[1:]) < 0).sum()), arr=x,
axis=1)
```

```
# --- Further power sprectrum analysis
```

```
# Source: https://www.intechopen.com/books/computational-intelligence-in-electromyography-analysis-a-perspective-on-current-applications-and-future-challenges/the-usefulness-of-mean-and-median-frequencies-in-electromyography-analysis
```

```
# Power sprectrum using periodogram
```

```
print("Calc periodogram for EMG...")
```

```
PSD = [signal.periodogram(i) for i in tqdm(x)]
```

```
#PSD= f: Array of sample frequencies.; Pxx: Power spectral density or power spectrum of x.
```

```
if plot:
```

```
    example = PSD[randrange(x.shape[0])]
```

```

plt.plot(example[0], example[1])

plt.title("Periodogram: PSD estimator on EMG signal")

plt.show()

```

# MNF is an average frequency

```
df[name + "_MNF"] = [sum(i[0]*i[1])/sum(i[1]) if sum(i[1]) != 0 else 0 for i in PSD]
```

# MDF - frequency at which the EMG power spectrum is divided into two regions with equal amplitude or TTP (dividing the total power area into two equal parts)

```
def get_median_index(x):
```

```
    i = 1
```

```
    total_sum = sum(x)
```

```
    while (sum(x[:i]) < total_sum / 2):
```

```
        i += 1
```

```
    return i
```

```
df[name + "_MDF"] = [get_median_index(i[1]) for i in PSD]
```

# TTP - aggregate of EMG power spectrum

```
df[name + "_TTP"] = [sum(i[1]) for i in PSD]
```

# MNP - average power of EMG power spectrum

```
df[name + "_MNP"] = [np.mean(i[1]) for i in PSD]
```

# PKF is a frequency at which the maximum EMG power occurs

```
df[name + "_PKF"] = [i[0][np.argmax(i[1])] for i in PSD]
```

# SM1

```
df[name + "_SM1"] = [sum(i[1] * i[0]) for i in PSD]
```

# SM2

```
df[name + "_SM2"] = [sum(i[1] * (i[0] ** 2)) for i in PSD]
```

# SM3

```
df[name + "_SM3"] = [sum(i[1] * (i[0] ** 3)) for i in PSD]
```

# --- FR - FR is used to discriminate between relaxation and contraction of the muscle

# cutoff frequency between low- and high-frequencies

```

cutoffs = [np.argmin(abs(f - mnf)) for f, mnf in zip([i[0] for i in PSD], df[name + "_MNF"].values)]

df[name + "_FR"] = [sum(P[:c]) / sum(P[c:]) if sum(P[c:]) != 0 else 0 for P, c in zip([i[1] for i in
PSD], cutoffs)]

# PSR - extension version of PKF and FR features - ratio between the energy P0 which is nearby
the maximum value of the EMG power spectrum and the energy P which is the whole energy of the
EMG power spectrum

def psr(x, n= 20):

    f0 = np.argmax(x)

    start= max(f0-n, 0)

    end= min(len(x), f0+n)

    return sum(x[start:end]) - sum(x)

df[name + "_PKF"] = [psr(i[1]) for i in PSD]

# VCF - Variance of central frequency

df[name + "_VCF"] = [ (SM2/SM0) - (SM1/SM0) **2 if SM0 != 0 else 0 for SM0, SM1, SM2 in
zip(df[name + "_TTP"].values, df[name + "_SM1"].values, df[name + "_SM2"].values)]

# --- Selfmade

# PKF is a frequency at which the maximum EMG power occurs

df[name + "_max_power_spec"] = [np.max(i[1]) for i in PSD]

# RMS envelope analysis

print("Analyze EMG...")

RMS = [analyze_emg(i, sampling_rate= sampling_rate) for i in tqdm(x)]

df[name + "_mean_RMS"] = [np.mean(i) for i in RMS]

df[name + "_max_RMS"] = [np.max(i) for i in RMS]

df[name + "_std_RMS"] = [np.std(i) for i in RMS]

return df

def analyze_emg(x, sampling_rate, plot= False):

```



```
'''
```

Function to analyze an EMG signal.

Source: <https://www.mdpi.com/1424-8220/20/17/4892/htm>

#### Parameters

```
-----
```

x: np. Sensor data.

sampling\_rate: Int. Sampling rate of the given sensor data.

plot: Bool. Boolean that describes whether to plot the outcome of the analysis or not.

#### Returns

```
-----
```

result: DF. Filtered envelope of the EMG signal.

```
'''
```

```
# RMS is calculated over 100 ms windows
```

```
RMS = RMS_envelope(x, w= int(sampling_rate//10))
```

```
# 1st order Butterworth lowpass filter with cut-off frequency at 1 Hz is applied to the RMS
```

```
filtered = butter_filter(RMS, cutoff_freq= 2, fs= sampling_rate, order= 1, btype= "lowpass")
```

```
if plot:
```

```
    plt.plot(RMS, color="mediumseagreen", label= "RMS")
```

```
    plt.plot(filtered, color="orange", label= "Final filter")
```

```
return filtered
```

```
def generic_features(x, name= ""):
```

```
'''
```

Function to calculate generich features for any signal.

Different features are calculated for the given signal 'x'.

#### Parameters

-----

x: np. Sensor data.

name: String. String to put a name in front of computed features. Default is "".

#### Returns

-----

result: df. Pandas Dataframe describing the computed features.

'''

```
df = pd.DataFrame()
```

```
# max
```

```
df[name + "_" + "max"] = np.max(x, axis=1)
```

```
# min
```

```
df[name + "_" + "min"] = np.min(x, axis=1)
```

```
# range
```

```
df[name + "_" + "range"] = (np.max(x, axis=1)-np.min(x, axis=1))
```

```
# std
```

```
df[name + "_" + "std"] = (np.std(x, axis=1))
```

```
# iqr
```

```
df[name + "_" + "iqr"] = (iqr(x, axis=1))
```

```
# mean
```

```
df[name + "_" + "mean"] = np.mean(x, axis=1)
```

```
# diff mean first/second half
```

```
half = len(x)//2
```

```
df[name + "_" + "diff_1.2.half_mean"] = np.mean(x[:half], axis=1)-np.mean(x[half:], axis=1)
```

```
return df
```

```
def respiration_feature_extraction(x, sampling_rate, name="", plot= False):
```

```
    """
```

```
    Function to calculate features for a respiration signal.
```

```
    Different features are calculated for the given signal 'x'.
```

```
    Parameters
```

```
    -----
```

```
    x: np. Sensor data.
```

```
    sampling_rate: Int. Sampling rate of the given sensor data.
```

```
    name: String. String to put a name in front of computed features. Default is "".
```

```
    plot: Bool. Boolean that describes whether to plot the outcome of the analysis or not. Default is
False.
```

```
    Returns
```

```
    -----
```

```
    result: df. Pandas Dataframe describing the computed features.
```

```
    """
```

```
    df = pd.DataFrame()
```

```
    # Plot one example
```

```
    if plot:
```

```
        example = x[randrange(x.shape[0])]
```

```
        example = preprocess_resp(example, sampling_rate= sampling_rate, plot= plot)
```

```
        plt.title("Respiration preprocessing")
```

```
        plt.legend()
```

```
plt.show()
```

```
analyze_resp(example, plot= plot)
```

```
plt.legend()
```

```
plt.title("Respiration analysis")
```

```
plt.show()
```

```
# preprocess
```

```
#x = np.apply_along_axis(preprocess_resp, axis=1, arr= x, plot= False, sampling_rate=
sampling_rate)
```

```
# --- Generic statistical approaches
```

```
# max
```

```
df[name + "_max"] = np.max(x, axis=1)
```

```
# min
```

```
df[name + "_min"] = np.min(x, axis=1)
```

```
# range
```

```
df[name + "_range"] = (np.max(x, axis=1)-np.min(x, axis=1))
```

```
# std
```

```
df[name + "_std"] = (np.std(x, axis=1))
```

```
# iqr
```

```
df[name + "_iqr"] = (iqr(x, axis=1))
```

```
# mean
```

```
df[name + "_mean"] = np.mean(x, axis=1)
```

```
# --- Paper: Respiratory Feature Extraction for Radar-Based Continuous Identity Authentication
```

```
# breathing rate - FFT (standard: 12 to 20 beats per minute (0.2-0.33 Hz)
```

```
# Analyse the respiration signal
```

```
print("Analyze respiration...")
```

```

features = [analyze_resp(i) for i in tqdm(x)]

# Unpack results

peaks_x = [i[0] for i in features]

peaks_y = [i[1] for i in features]

lows_x = [i[2] for i in features]

lows_y = [i[3] for i in features]

inhale_areas = [i[4] for i in features]

exhale_areas = [i[5] for i in features]


# Number of peaks

df[name + "_#_peaks"] = [len(x) for x in peaks_x]

# Number of peaks

df[name + "_#_lows"] = [len(x) for x in lows_x]

# Mean Amplitude

df[name + "_mean_ampl_x"] = [np.mean([abs(x-y) for x,y in zip(i, j)]) for i, j in zip(peaks_x,
lows_x)]

df[name + "_mean_ampl_y"] = [np.mean([abs(x-y) for x,y in zip(i, j)]) for i, j in zip(peaks_y,
lows_y)]

# Std Amplitude

df[name + "_mean_ampl_x"] = [np.std([abs(x-y) for x,y in zip(i, j)]) for i, j in zip(peaks_x, lows_x)]

df[name + "_mean_ampl_y"] = [np.std([abs(x-y) for x,y in zip(i, j)]) for i, j in zip(peaks_y, lows_y)]

# Mean volume of in/exhalation

df[name + "_mean_in"] = [np.mean(i) if len(i)>0 else 0 for i in inhale_areas]

df[name + "_mean_ex"] = [np.mean(i) if len(i)>0 else 0 for i in exhale_areas]

# STD volume of in/exhalation

df[name + "_std_in"] = [np.std(i) if len(i)>0 else 0 for i in inhale_areas]

df[name + "_std_ex"] = [np.std(i) if len(i)>0 else 0 for i in exhale_areas]


return df

```

```

def analyze_resp(x, plot= False):
    """
    Function to analyze a respiration signal.

    Trapezius detection from paper: "Respiratory Feature Extraction for Radar-Based Continuous
    Identity Authentication"

    Parameters
    -----
    x: np. Sensor data.
    plot: Bool. Boolean that describes whether to plot the outcome of the analysis or not.

    Returns
    -----
    result: peaks, df["Filtered"][peaks], lows, df["Filtered"][lows], inhale_area, exhale_area
    """

    df = pd.DataFrame()
    df["Filtered"] = x

    # --- Peak detection
    # Difference of two consecutive y-values
    diff = np.diff(df["Filtered"])
    # Sign difference of "diff"
    sdiff = np.diff(np.sign(diff))
    # Rising edge
    zero_crossings_rising = (sdiff == 2)
    # Falling edge
    zero_crossings_falling = (sdiff == -2)

```

```

# X values of the lows
lows = np.where(zero_crossings_rising)[0]

# X values of the peaks
peaks = np.where(zero_crossings_falling)[0]

# All x values
indices_both = np.where(zero_crossings_rising | zero_crossings_falling)[0]
assert len(lows) + len(peaks) == len(indices_both)

# --- Breath ratio -> trapezium detection
upper_trap_points = []
lower_trap_points = []

for first, second in zip(indices_both[:-1], indices_both[1:]):
    amplitude = abs(df["Filtered"][first] - df["Filtered"][second])
    lowest_point = min(df["Filtered"][first], df["Filtered"][second])
    lower_border = amplitude * 0.3 + lowest_point
    higher_border = amplitude * 0.7 + lowest_point

    # Find closest point to "higher_border"
    diff_upper = np.abs(df["Filtered"].values[first:second] - higher_border)
    upper_trap_points.append(first + np.argmin(diff_upper))

    # Find closest point to "lower_border"
    diff_lower = np.abs(df["Filtered"].values[first:second] - lower_border)
    lower_trap_points.append(first + np.argmin(diff_lower))

# --- Form trapezium
inhale_x = []
exhale_x = []

for a, b, c, d in zip(upper_trap_points[:-1], lower_trap_points[:-1], upper_trap_points[1:],
lower_trap_points[1:]):

```

```

# check inhalte or exhale

if a > b:

    inhale_x.append((a,b,d,c))

else:

    exhale_x.append((a,b,d,c))


if plot:

    import matplotlib.patches as patches

    ax = plt.gca()

    ax.plot(df["Filtered"].values, color="royalblue", label= "Post filter")

    ax.scatter(peaks, [df["Filtered"][x] for x in peaks], marker='o', c="orange", zorder=10,
label="Positive Peaks")

    ax.scatter(lows, [df["Filtered"][x] for x in lows], marker='o', c="pink", zorder=10,
label="Negative Peaks")

    ax.scatter(upper_trap_points, [df["Filtered"][x] for x in upper_trap_points], marker='o',
color="green", zorder=10, label= "70% Border")

    ax.scatter(lower_trap_points, [df["Filtered"][x] for x in lower_trap_points], marker='o',
color="red", zorder=10, label= "30% Border")

    for x, y in zip(inhale_x, [[df["Filtered"][x] for x in b] for b in inhale_x]):

        ax.add_patch(patches.Polygon(xy=list(zip(x, y)), fill=True, label= "Inhale",
alpha=0.3))

    for x, y in zip(exhale_x, [[df["Filtered"][x] for x in b] for b in exhale_x]):

        ax.add_patch(patches.Polygon(xy=list(zip(x, y)), fill=True, label= "Exhale",
alpha=0.3, color="orange"))

    ax.plot(lower_trap_points, [df["Filtered"][x] for x in lower_trap_points], color="red",
linestyle='dashed', alpha=0.5)

    ax.plot(upper_trap_points, [df["Filtered"][x] for x in upper_trap_points], color="green",
linestyle='dashed', alpha=0.5)


# --- Calculate the are of in/exhale

inhale_area, exhale_area = [], []

```



```

for x in exhale_x:
    y = [df["Filtered"][i] for i in x]
    exhale_area.append(0.5*np.abs(np.dot(x,np.roll(y,1))-np.dot(y,np.roll(x,1))))

for x in inhale_x:
    y = [df["Filtered"][i] for i in x]
    inhale_area.append(0.5*np.abs(np.dot(x,np.roll(y,1))-np.dot(y,np.roll(x,1))))

return peaks, df["Filtered"][peaks], lows, df["Filtered"][lows], inhale_area, exhale_area

```

```

def feature_extraction(X, sensor_list, sampling_rate):

```

```

    """

```

Function to calculate hand-crafted-features for a given dataframe 'X'.

Dependen on the given 'sensor\_list' different features are computed for each sensor channel.

Parameters

```

    -----

```

X: np. Data to extract features from. Expect dataframe to be in shape [samples, time, sensors, 0].

sensor\_list: list. List of names of the sensors in 'X'. Should be in the same order as sensors in 'X'.

sampling\_rate: int. Integer defining the sampling rate of the given data.

Returns

```

    -----

```

result: DF. Pandas Dataframe in shape (samples, features).

```

    """

```

```

    result = pd.DataFrame()

```

```

    for i, sensor in enumerate(sensor_list):

```

```

        print("\n\n_____")

```

```

print(f"Start extracting features for sensor '{sensor}'...")

if sensor in ["time"]:

    continue

if sensor in ["gsr", "Eda_RB", "Eda_E4"]:

    result = pd.concat([result, gsr_feature_extraction(X[:, :, i, 0], name= sensor,
sampling_rate= sampling_rate)], axis=1, sort=False)

    continue

if sensor == "Resp":

    result = pd.concat([result, respiration_feature_extraction(X[:, :, i, 0], name=
sensor, sampling_rate= sampling_rate)], axis=1, sort=False)

    continue

if sensor in ["Ecg", "ecg"]:

    result = pd.concat([result, ecg_feature_extraction(X[:, :, i, 0], name= sensor,
sampling_rate= sampling_rate)], axis=1, sort=False)

    continue

if sensor in ["emg_trapezius", "Emg"]:

    result = pd.concat([result, emg_feature_extraction(X[:, :, i, 0], name= sensor,
sampling_rate= sampling_rate)], axis=1, sort=False)

    continue

result = pd.concat([result, generic_features(X[:, :, i, 0], name= sensor)], axis=1,
sort=False)

result = result.fillna(0)

return result

```

```
def get_hcf(dataset):
```

```
'''
```

Function to return hand-crafted-features for a given dataset.

Parameters

-----

dataset: String. String describing the used dataset. Should be either "painmonit" or "biovid".

Returns

-----

features: DF. Pandas Dataframe in shape (samples, features).

'''

```
np_dir = Path("datasets", dataset, "hcf")
```

```
feature_file = Path(np_dir, "features.csv")
```

```
if not feature_file.exists():
```

```
    raise FileExistsError(f"File '{feature_file.resolve()}' does not exists. Did you create hand-crafted features (run `hcf.py`)?")
```

```
return pd.read_csv(feature_file, sep=";", decimal=",")
```

```
def create_hcf(X, sensor_list, dataset, sampling_rate, overwrite= False):
```

```
    '''
```

```
    Features are just recomputed when there is no existing "features.csv" file containing already computed metrics.
```

Parameters

-----

X: np. Data to extract features from. Expect dataframe to be in shape [samples, time, sensors, 0].

sensor\_list: list. List of names of the sensors in 'X'. Should be in the same order as sensors in 'X'.

dataset: String. String describing the used dataset. Should be either "painmonit" or "biovid".

sampling\_rate: int. Integer defining the sampling rate of the given data.

'''

```

np_dir = Path("datasets", dataset, "hcf")
feature_file = str(Path(np_dir, "features.csv"))

if not overwrite and Path(feature_file).exists():
    print("HCF have been created before and will not be overwritten.")
    return

# create directory
if not Path(np_dir).exists():
    os.makedirs(np_dir)

# create numpy hcf
features = feature_extraction(X, sensor_list= sensor_list, sampling_rate= sampling_rate)

if features.isnull().values.any():
    print("Created features contain NaN. Try to remove columns containing NaN...")

    columns_with_nan = features.columns[features.isna().any()].tolist()
    print("Columns with NaN: {}".format(columns_with_nan))

    features = features.drop(columns_with_nan, axis=1)

# save the hcf
features.to_csv(feature_file, sep=";", decimal=".", index=False)
print(f"Features have been saved under '{feature_file}'.")

if __name__ == "__main__":
    """Main function.

```

```

"""

from config import painmonit_sensors, biovid_sensors, sampling_rate_painmonit,
sampling_rate_biovid

from scripts.data_handling import read_biovid_np, read_painmonit_np

print("Create HCF for Biovid...")

X_biovid, y_biovid, subjects_biovid = read_biovid_np()

create_hcf(X_biovid, sensor_list= biovid_sensors, dataset= "biovid", sampling_rate=
sampling_rate_biovid, overwrite= False)

print("HCF for Biovid created.")


print("Create HCF for UzL...")

X_uzl, y_uzl, subjects_uzl = read_painmonit_np(label= "heater")

create_hcf(X_uzl, sensor_list= painmonit_sensors, dataset= "painmonit", sampling_rate=
sampling_rate_painmonit, overwrite= False)

print("HCF for UzL created.")

```