FinalTraining

January 22, 2024

1 Yet to decide on Train-Val check or Inner-Outer Fold check

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
from latex import latexify, format_axes
import numpy as np
import tsfel
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import export_graphviz
from sklearn import tree
import graphviz
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪accuracy_score
import seaborn as sns
from MakeDataset import *
%matplotlib inline
# Retina
%config InlineBackend.figure_format = 'retina'
```

```
Training data shape:  (108, 500, 3)
Testing data shape:  (36, 500, 3)
Validation data shape:  (36, 500, 3)
```

[3]:
```
X_train, y_train
X_test, y_test
X_val, y_val
```

[3]:
```
(180, 500, 3)
```

1.0.1 $(a_x^2 + a_y^2 + a_z^2)$

[2]:
```
X_train_TS = np.sum(np.square(X_train), axis = -1)
X_test_TS = np.sum(np.square(X_test), axis = -1)
X_val_TS = np.sum(np.square(X_val), axis = -1)
print(X_train_TS.shape, X_test_TS.shape, X_val_TS.shape)
```

```
(108, 500) (36, 500) (36, 500)
```

[3]:
```
features_sel = ["0_Area under the curve", "0_Mean", "0_Variance", "0_Peak to␣
↪peak distance", "0_Mean absolute deviation"]
```

[4]:
```
classesN = {1 : 'WALKING', 2 : 'WALKING_UPSTAIRS', 3 : 'WALKING_DOWNSTAIRS', 4 :
↪ 'SITTING', 5 : 'STANDING', 6 : 'LAYING'}
namedLabel = [classesN[i] for i in y_train]
classesN
```

[4]:
```
{1: 'WALKING',
 2: 'WALKING_UPSTAIRS',
 3: 'WALKING_DOWNSTAIRS',
 4: 'SITTING',
 5: 'STANDING',
 6: 'LAYING'}
```

[5]:
```
def Featuriser(XTimeSeries, features):
    cfg = tsfel.get_features_by_domain()
    df = pd.DataFrame(XTimeSeries)
    dataFrames = []
    for i in df.index:
        dataFrames.append(tsfel.time_series_features_extractor(cfg, df.iloc[i,:
↪], fs = 50))
    dfN = pd.concat(dataFrames, axis = 0)
    dfNFeaturized = dfN[features]
    return dfNFeaturized
```

1.1 Featurising all the X_train_TS, X_test_TS, X_val_TS

[ ]:
```
dfTrain = Featuriser(X_train_TS, features_sel)
dfTest = Featuriser(X_test_TS, features_sel)
dfVal = Featuriser(X_val_TS, features_sel)
```

[7]:
```
dfTrain.shape
```

[7]:
```
(108, 5)
```

[8]:
```
dfTest.shape
```

[8]:
```
(36, 5)
```

[9]:
```
dfVal.shape
```

[9]:
```
(36, 5)
```

[10]:
```
dfTrain
```

[10]:
```
   0_Area under the curve    0_Mean  0_Variance  0_Peak to peak distance  \
0                10.560741  1.058182    0.000441                 0.276308
0                10.705240  1.072680    0.000439                 0.302652
0                11.378087  1.141142    0.281282                 2.951101
0                11.901536  1.193139    0.442850                 2.853736
0                10.038794  1.005901    0.000026                 0.042222
..                     …         …         …                      …
0                13.257830  1.328807    1.370835                 4.655614
0                11.855087  1.188371    0.436127                 3.625210
0                10.639416  1.066069    0.000026                 0.031092
0                11.149920  1.116685    0.245975                 2.492894
0                11.162236  1.118337    0.250313                 2.180257

   0_Mean absolute deviation
0                   0.010239
0                   0.011554
0                   0.382585
0                   0.537589
0                   0.004003
..                       …
0                   0.995502
0                   0.506932
0                   0.004027
0                   0.382408
0                   0.381846

[108 rows x 5 columns]
```

[11]:
```python
hyperparams = {"max_depth" : [2, 3, 4, 5, 6, 7, 8, 9, 10], "criterion" :␣
↪["gini", "entropy"], "min_samples" : [2, 3, 4, 5, 6, 7, 8]}
hyperparams
```

[11]:
```
{'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10],
 'criterion': ['gini', 'entropy'],
 'min_samples': [2, 3, 4, 5, 6, 7, 8]}
```

[12]:
```python
from itertools import product
final, counter = {}, 0
for max_depth, criteria, min_sample in product(hyperparams["max_depth"],␣
↪hyperparams["criterion"], hyperparams["min_samples"]):
    model = DecisionTreeClassifier(max_depth = max_depth, criterion = criteria,␣
↪min_samples_split = min_sample, random_state = 42)
    model.fit(dfTrain, y_train)
    val_score = model.score(dfVal, y_val)
    final[counter] = {"max_depth" : max_depth, "criterion" : criteria,␣
↪"min_samples" : min_sample, "val_score" : val_score}
    counter += 1
```

[13]:
```python
hparam_df = pd.DataFrame(final).T
hparam_df
```

[13]:
```
     max_depth criterion min_samples val_score
0            2      gini           2  0.638889
1            2      gini           3  0.638889
2            2      gini           4  0.638889
3            2      gini           5  0.638889
4            2      gini           6  0.638889
..         …        …          …        …
121         10   entropy           4  0.666667
122         10   entropy           5  0.694444
123         10   entropy           6  0.666667
124         10   entropy           7  0.638889
125         10   entropy           8  0.638889

[126 rows x 4 columns]
```

[14]:
```python
hparam_df.sort_values(by = "val_score", ascending = False).head(10)
```

[14]:
```
     max_depth criterion min_samples val_score
63           6   entropy           2      0.75
93           8   entropy           4      0.75
64           6   entropy           3      0.75
92           8   entropy           3  0.722222
120         10   entropy           3  0.722222
106          9   entropy           3  0.722222
94           8   entropy           5  0.722222
119         10   entropy           2  0.694444
107          9   entropy           4  0.694444
83           7   entropy           8  0.694444
```

[15]:
```python
dfTrain_Val_Test = pd.concat([dfTrain, dfVal, dfTest], axis = 0)
y_train_test_val = np.hstack([y_train, y_val, y_test])
dfTrain_Val_Test
```

[15]:
```
    0_Area under the curve    0_Mean  0_Variance  0_Peak to peak distance
0                10.560741  1.058182    0.000441                 0.276308  \
0                10.705240  1.072680    0.000439                 0.302652
0                11.378087  1.141142    0.281282                 2.951101
0                11.901536  1.193139    0.442850                 2.853736
0                10.038794  1.005901    0.000026                 0.042222
..                     …         …          …                        …
0                10.107278  1.012756    0.000036                 0.046293
0                10.275541  1.029612    0.000035                 0.055289
0                12.188508  1.221348    0.614296                 3.526818
0                11.667436  1.168859    0.455832                 3.239159
```

```
0                11.567573  1.159747    0.317845                 2.934196

    0_Mean absolute deviation
0                    0.010239
0                    0.011554
0                    0.382585
0                    0.537589
0                    0.004003
..                        …
0                    0.004625
0                    0.004476
0                    0.662692
0                    0.501238
0                    0.436656

[180 rows x 5 columns]
```

[16]:
```python
model = DecisionTreeClassifier(max_depth = 6, min_samples_split = 2, criterion␣
↪= "entropy", random_state = 42)
model.fit(dfTrain_Val_Test, y_train_test_val)
```

[16]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=6, random_state=42)
```

[17]:
```python
def getTimeSeries(filename):
    filePath = f"./Time Series Data/{filename}"
    df = pd.read_csv(filePath)
    return df
```

[18]:
```python
df = getTimeSeries('TS2Walking.csv')
df
```

[18]:
```
            time     gFx     gFy     gFz      0
0       0.004371 -0.9965  0.1796  0.2842  1.068
1       0.005229 -1.0007  0.1845  0.2910  1.075
2       0.005670 -1.0034  0.1886  0.2964  1.080
3       0.006074 -1.0026  0.1903  0.2984  1.080
4       0.006489 -0.9985  0.1920  0.2954  1.076
…            …       …       …       …      …
19310  38.514996 -0.9303 -0.0344  0.4249  1.032
19311  38.516256 -0.9301 -0.0349  0.4234  1.031
19312  38.518234 -0.9315 -0.0347  0.4222  1.032
19313  38.520242 -0.9335 -0.0354  0.4229  1.034
19314  38.522770 -0.9354 -0.0364  0.4251  1.037

[19315 rows x 5 columns]
```

[19]:
```
def fetchTotTS(dataFrame):
    return pd.DataFrame(dataFrame.iloc[:, 4]**2)
```

[20]:
```
def PlotTimeSeries(df, flag):
    latexify()
    if flag:
        plt.figure(figsize = (9, 3))
        plt.title(r"Time Series of Acceleration $(acc_x, acc_y, acc_z)$")
        colors = ["red", "green", "blue"]
        for k in range(1, 4):
            plt.plot(df.iloc[:, k], color = colors[k - 1], linewidth = 0.8)
        plt.xlabel("Time Samples")
        plt.ylabel(r"Acceleration in $m/s^2$")
        plt.legend([r"$a_x$", r"$a_y$", r"$a_z$"])
        plt.grid()
        plt.show()
    else:
        plt.figure(figsize = (9, 3))
        plt.title(r"Time Series of Total Acceleration $(acc_x^2 + acc_y^2 +␣
↪acc_z^2)$")
        plt.plot(df.iloc[:, 4]**2, color = "deeppink", linewidth = 0.8)
        plt.xlabel("Time Samples")
        plt.ylabel(r"Total Acceleration in $m/s^2$")
        plt.legend([r"$(acc_x^2 + acc_y^2 + acc_z^2)$"])
        plt.grid()
        plt.show()
```

1.1.1 Sampling Time $= \frac{\textbf{No. of Samples}}{f_s}$

1.1.2 $f_s = 500Hz$

[21]:
```
df.shape[0] / 500.0
```

[21]: 38.63

[31]:
```
def FeaturiserN(XTimeSeries, features):
    model1 = tsfel.get_features_by_domain()
    df = pd.DataFrame(XTimeSeries).T
    dfN = tsfel.time_series_features_extractor(model1, signal_windows = list(df.
↪iloc[0, :]), fs = 50)
    dfNFeaturized = dfN[features]
    return dfNFeaturized
```

[32]:
```
pd.DataFrame(fetchTotTS(df.iloc[2500:7500, :])).T
```

[32]:
```
       2500      2501      2502      2503      2504      2505      2506
0  0.751689  0.755161  0.758641  0.765625  0.776161  0.786769  0.799236  \
```

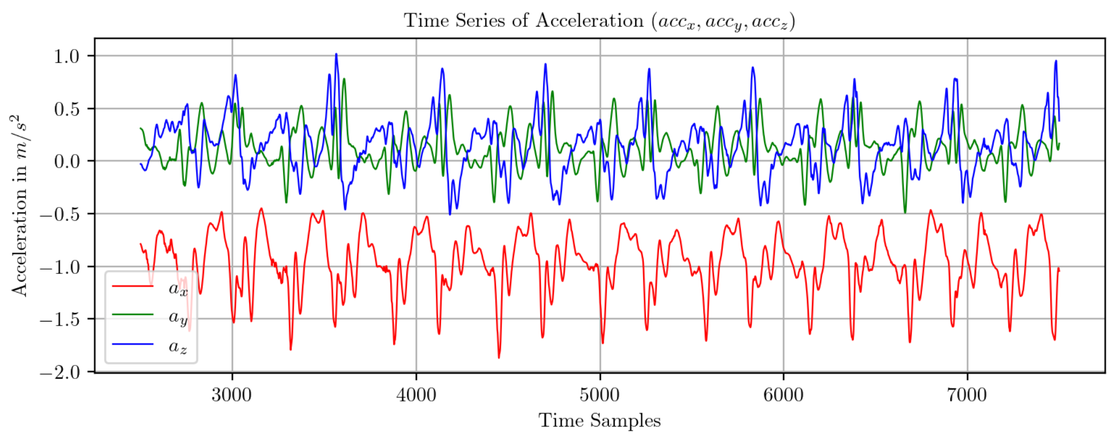
```
       2507      2508     2509  …      7490      7491      7492      7493  
0  0.808201  0.817216  0.8281  …  1.646089  1.565001  1.517824  1.485961  \

       7494      7495     7496      7497      7498      7499  
0  1.452025  1.420864  1.3924  1.364224  1.331716  1.301881  

[1 rows x 5000 columns]
```

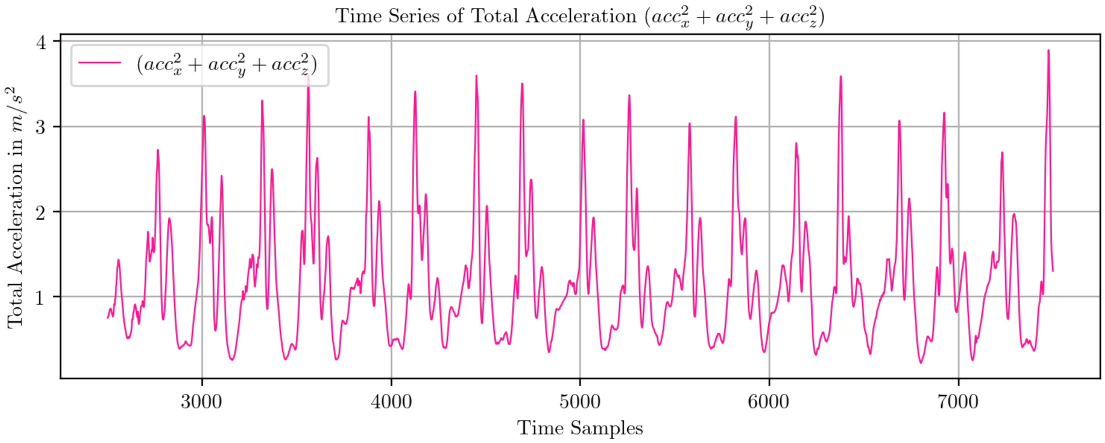
[33]:
```python
dfN1 = FeaturiserN(fetchTotTS(df.iloc[2500:7500, :]), features_sel)
dfN1
```

```
*** Feature extraction started ***

<IPython.core.display.HTML object>


*** Feature extraction finished ***
```

[33]:
```
   0_Area under the curve   0_Mean  0_Variance  0_Peak to peak distance  \
0              118.015507  1.18036     0.49156                 3.675776   

   0_Mean absolute deviation  
0                   0.540058  
```

[34]:
```python
PlotTimeSeries(df.iloc[2500:7500,:], 1)
PlotTimeSeries(df.iloc[2500:7500,:], 0)
```





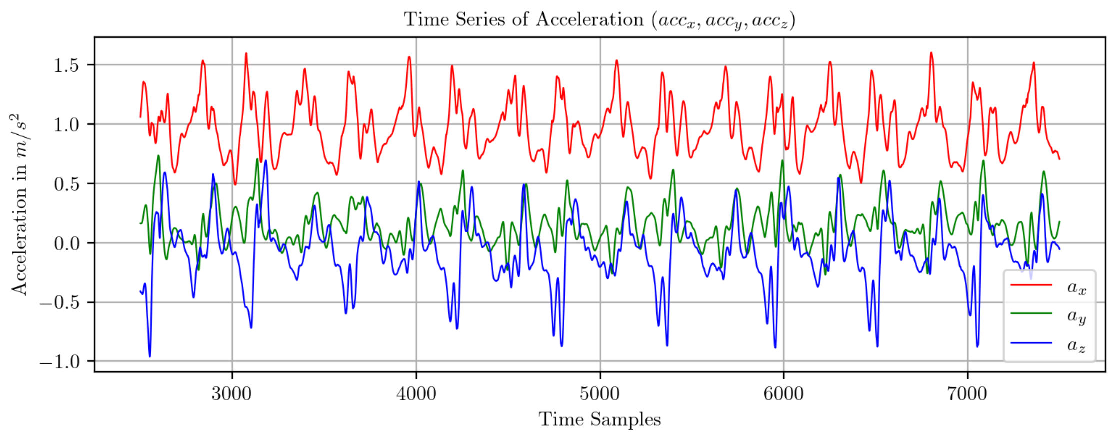
[35]:
```
y_pred = model.predict(dfN1)
y_pred
```

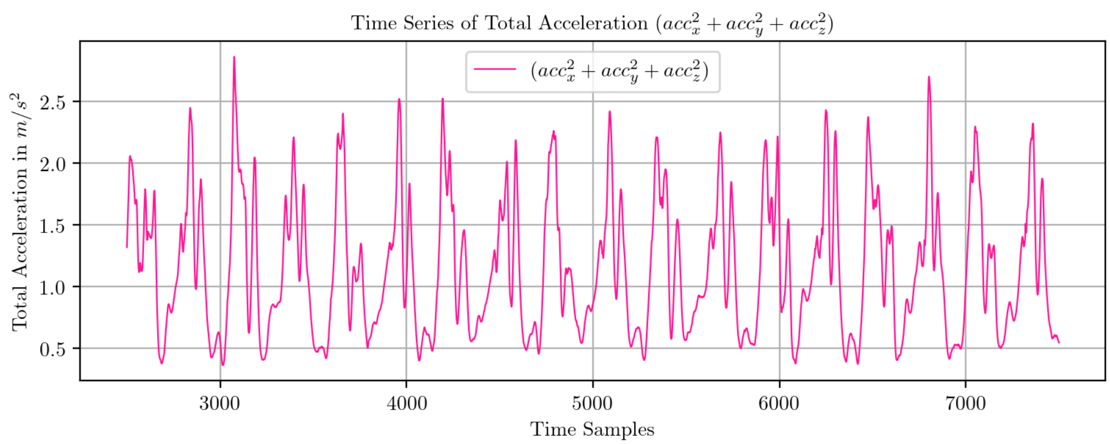
[35]: array([2])

[36]:
```
classesN
```

[36]:
```
{1: 'WALKING',
 2: 'WALKING_UPSTAIRS',
 3: 'WALKING_DOWNSTAIRS',
 4: 'SITTING',
 5: 'STANDING',
 6: 'LAYING'}
```

[37]:
```
df1 = getTimeSeries('TS4Walking.csv')
DF = df1.iloc[2500:7500, :]
PlotTimeSeries(DF, 1)
PlotTimeSeries(DF, 0)
dfN2 = FeaturiserN(fetchTotTS(DF), features_sel)
y_pred = model.predict(dfN2)
classesN[y_pred[0]]
```

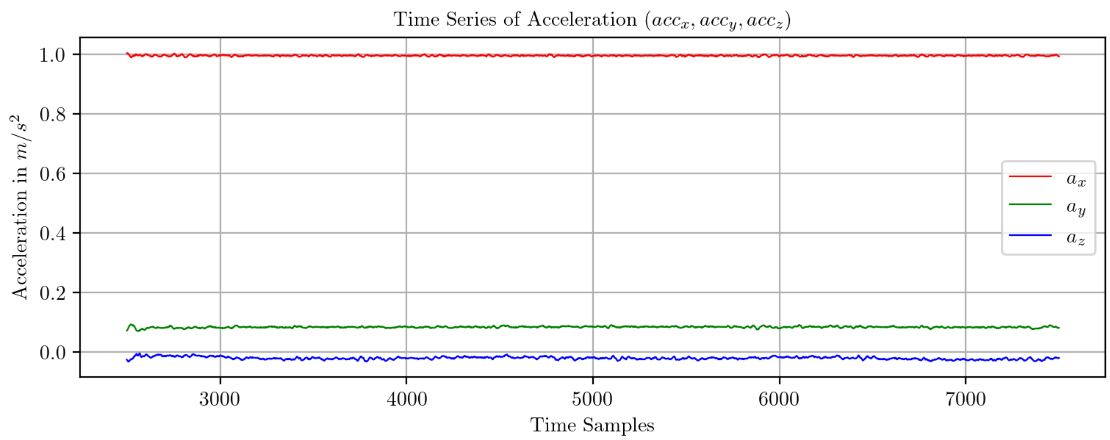


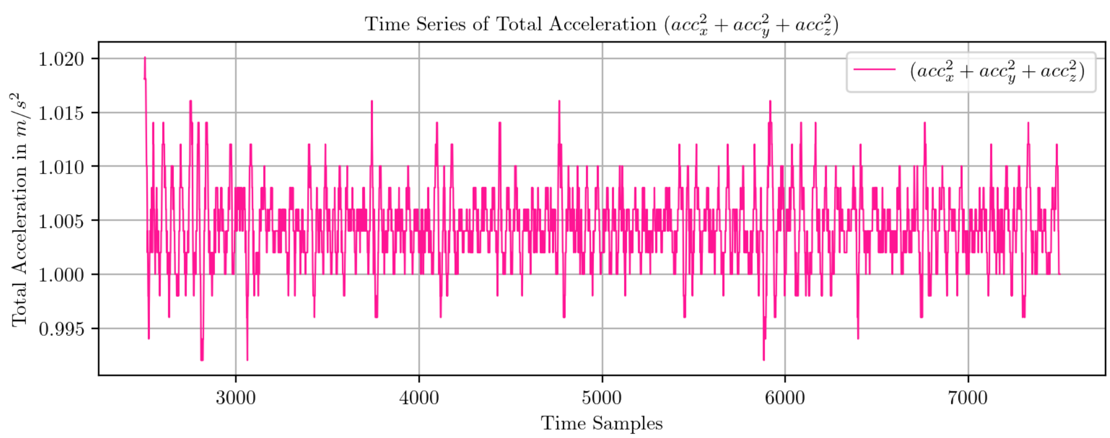



```
*** Feature extraction started ***
<IPython.core.display.HTML object>


*** Feature extraction finished ***
```

[37]: 'WALKING_UPSTAIRS'

[38]:
```
df2 = getTimeSeries('TS10Sitting.csv')
DF = df2.iloc[2500:7500, :]
PlotTimeSeries(DF, 1)
PlotTimeSeries(DF, 0)
dfN3 = FeaturiserN(fetchTotTS(DF), features_sel)
y_pred = model.predict(dfN3)
classesN[y_pred[0]]
```






```
*** Feature extraction started ***
```

```
&lt;IPython.core.display.HTML object&gt;
```

```
*** Feature extraction finished ***
```

[38]: 'SITTING'

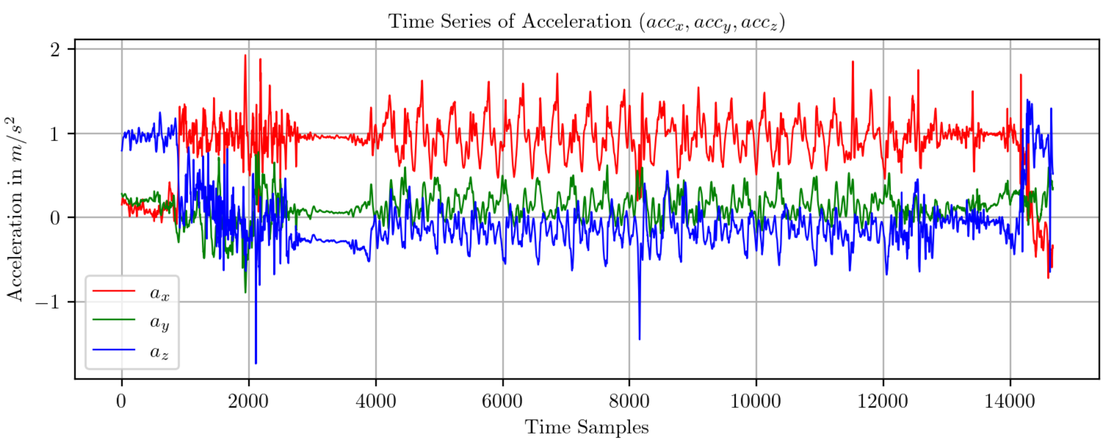
[39]:
```
# flag = 1 -> Only display the orginal untrimmed TS and trim-prediction on flag␣
↪!= 1
def PredictPlot(filename,  flag = 1, start = None, end = None):
    df = getTimeSeries(filename)
    if flag:
        print("Original Time Series")
        PlotTimeSeries(df, 1)
        PlotTimeSeries(df, 0)
```

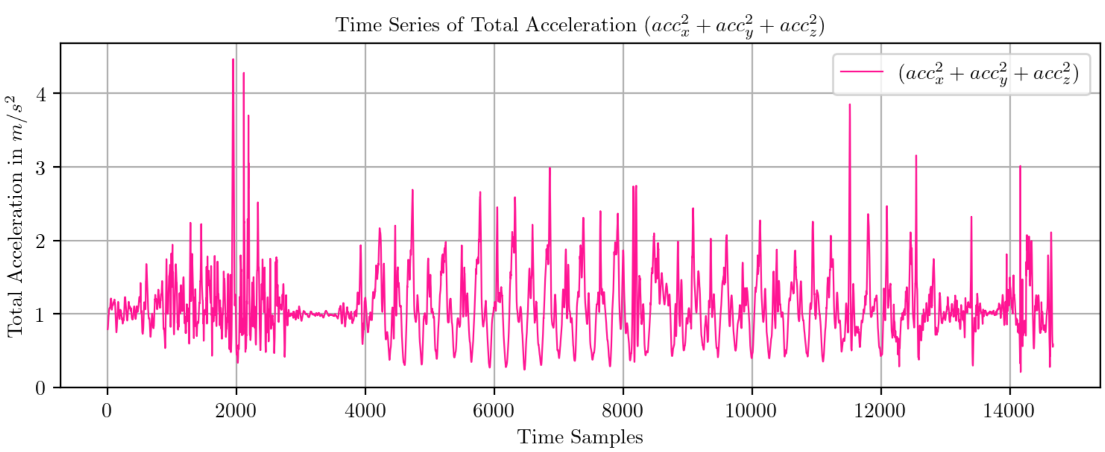
```python
    else:
        DF = df.iloc[start : end, :]
        print("Trimmed Time Series")
        PlotTimeSeries(DF, 1)
        PlotTimeSeries(DF, 0)
        dfN = FeaturiserN(fetchTotTS(DF), features_sel)
        y_pred = model.predict(dfN)
        print(classesN[y_pred[0]])
```

[40]:

```python
PredictPlot("TS5WalkingUpstairs.csv", 1)
```

```
Original Time Series
```

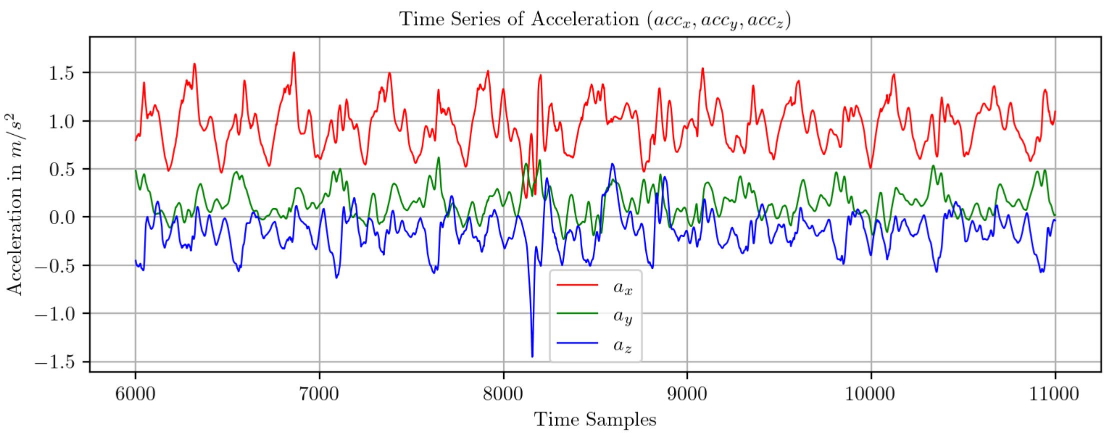


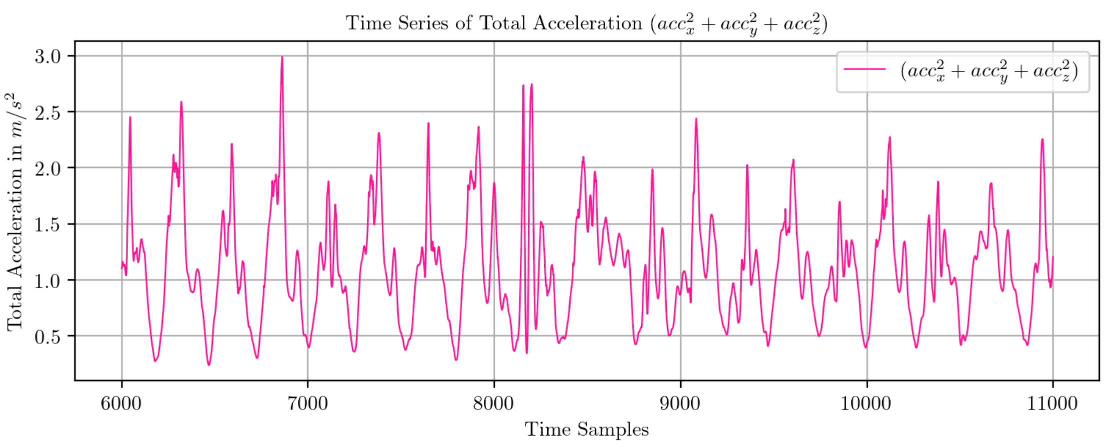


[41]:

```python
PredictPlot("TS5WalkingUpstairs.csv", 0, 6000, 11000)
```

```
Trimmed Time Series
```

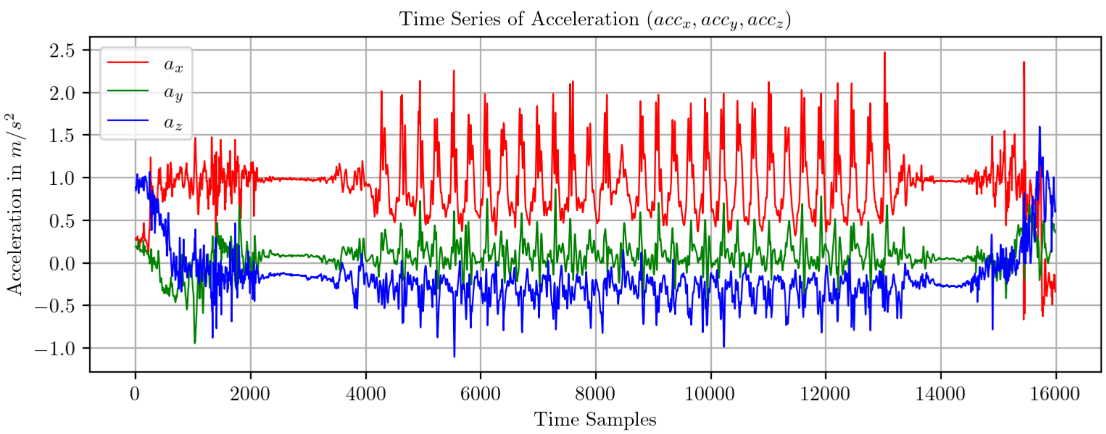


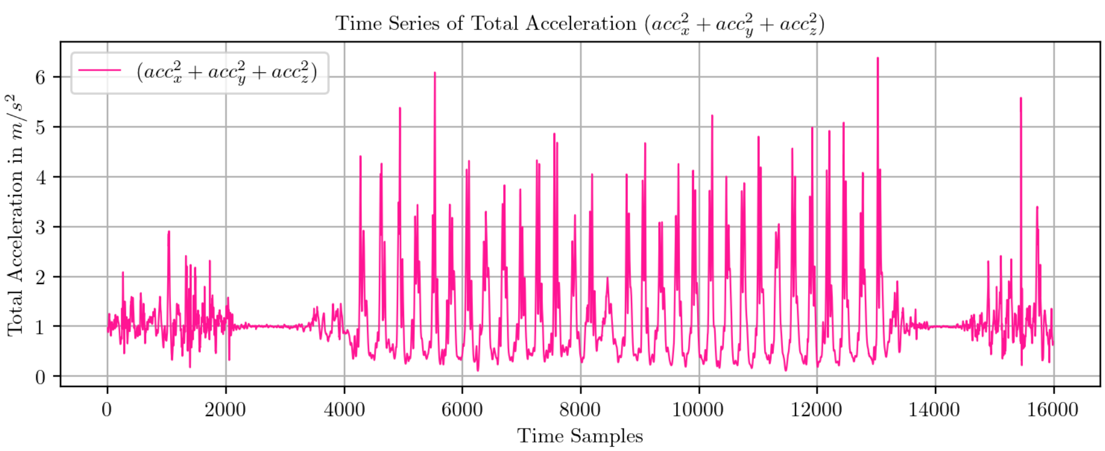



```
*** Feature extraction started ***
<IPython.core.display.HTML object>


*** Feature extraction finished ***
WALKING
```

[42]:
```
PredictPlot("TS6WalkingDownstairs.csv", 1)
```

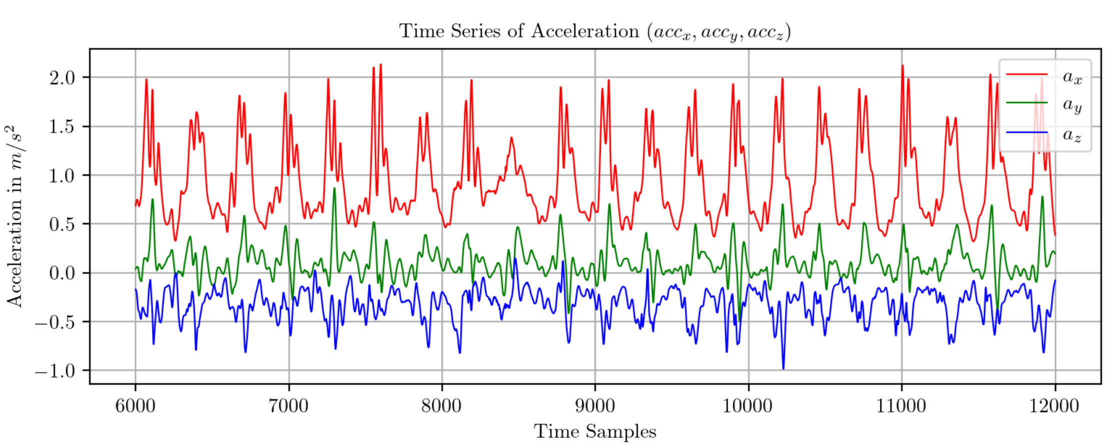
```
Original Time Series
```

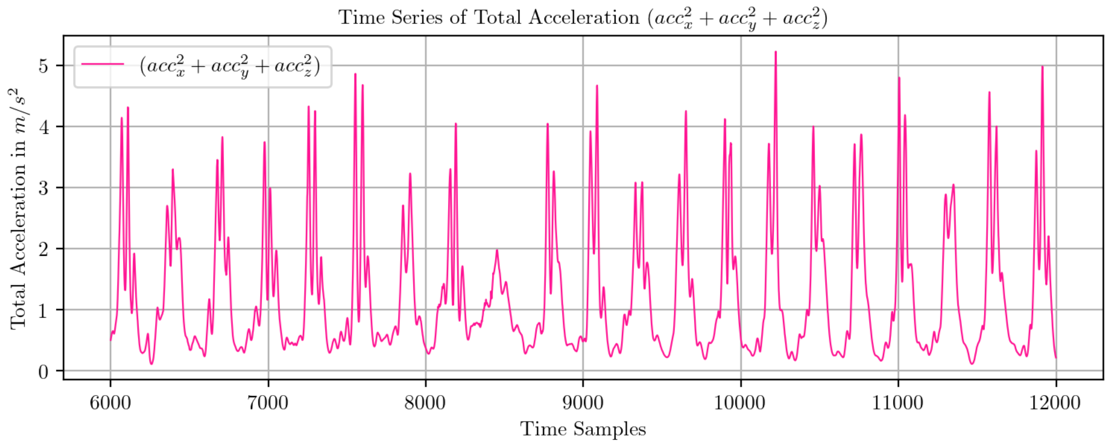




[43]:
```
PredictPlot("TS6WalkingDownstairs.csv", 0, 6000, 12000)
```

```
Trimmed Time Series
```

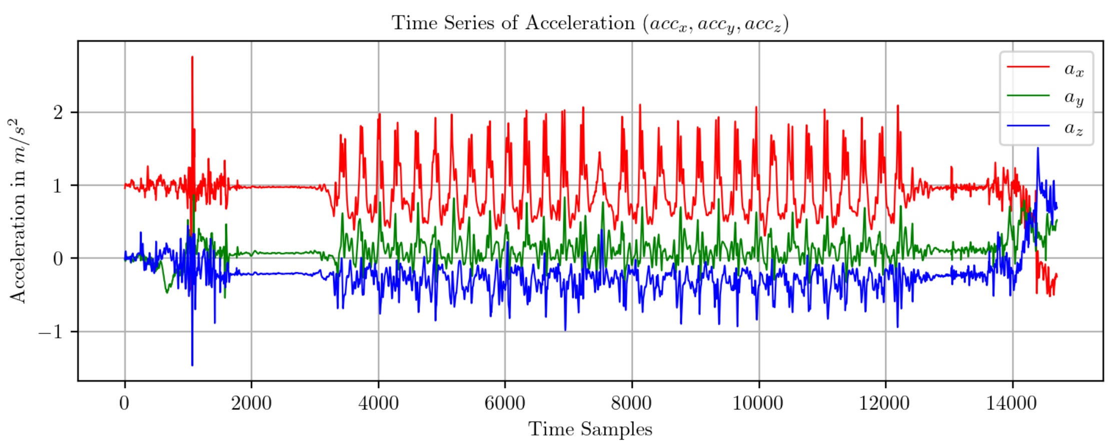


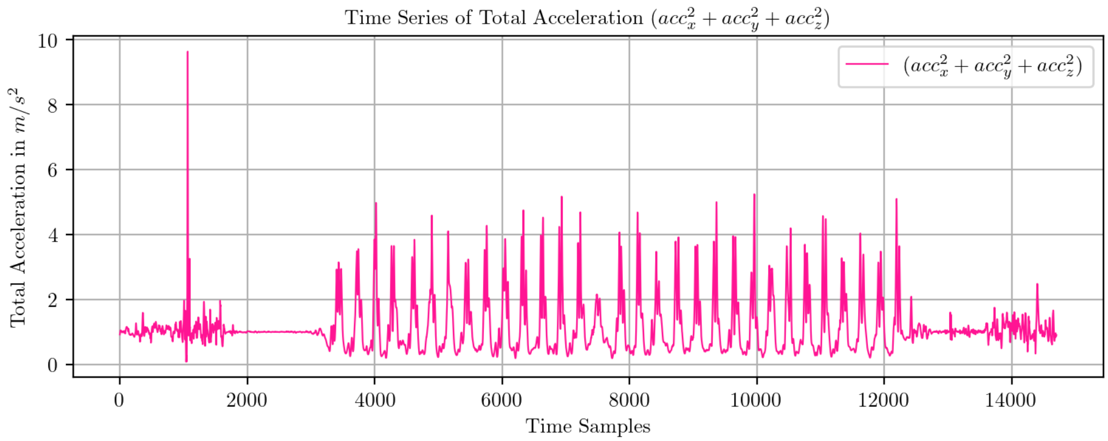



```
*** Feature extraction started ***
<IPython.core.display.HTML object>

*** Feature extraction finished ***
WALKING_DOWNSTAIRS
```

[44]:
```python
PredictPlot("TS7WalkingDownstairs.csv", 1)
```

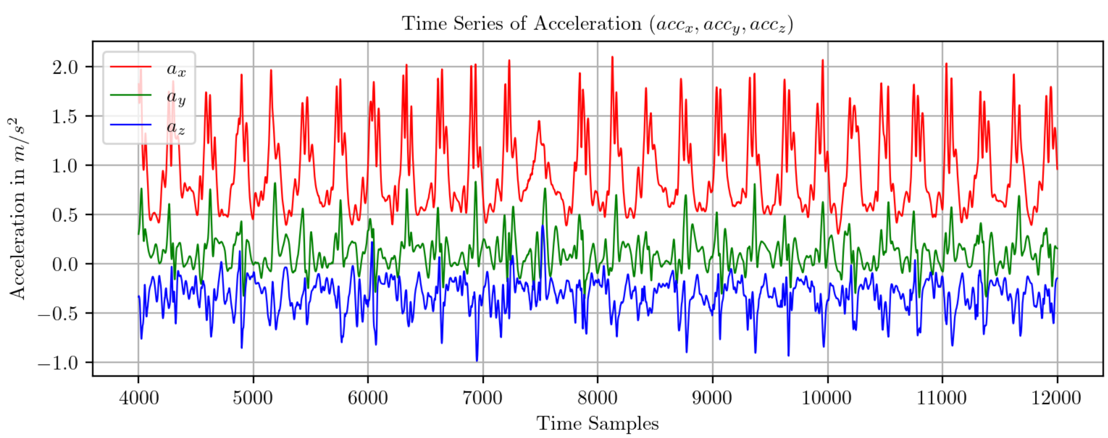
```
Original Time Series
```

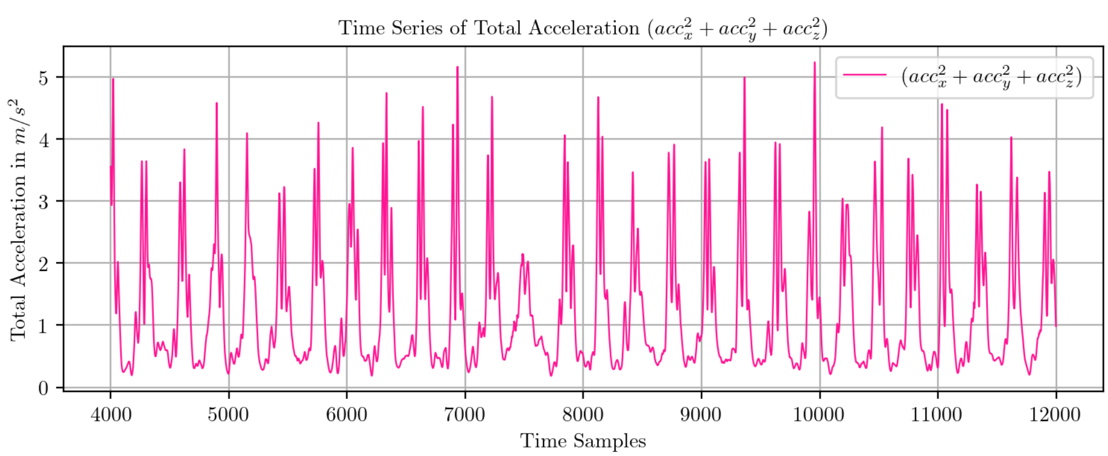





```
[45]: PredictPlot("TS7WalkingDownstairs.csv", 0, 4000, 12000)
```

```
Trimmed Time Series
```

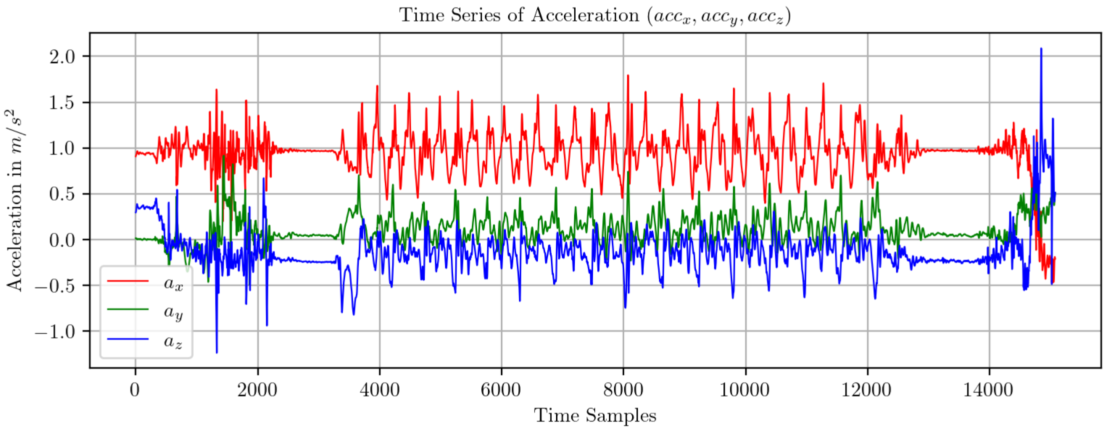


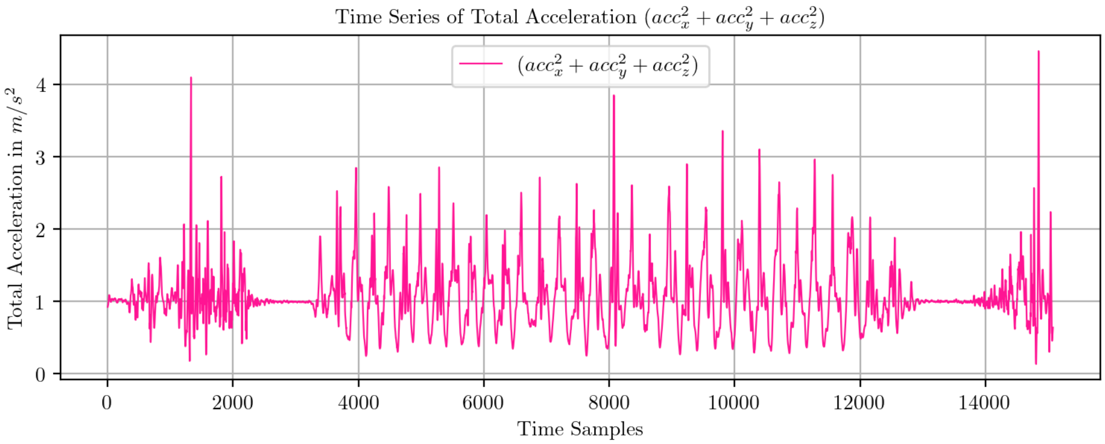


```
*** Feature extraction started ***

<IPython.core.display.HTML object>


*** Feature extraction finished ***
WALKING_DOWNSTAIRS
```

[46]:
```python
PredictPlot("TS8WalkingUpstairs.csv", 1)
```

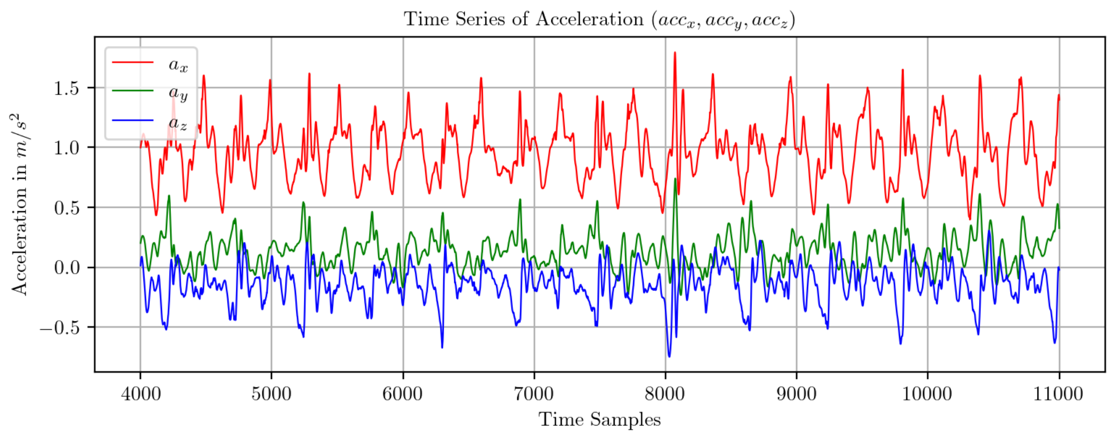
```
Original Time Series
```

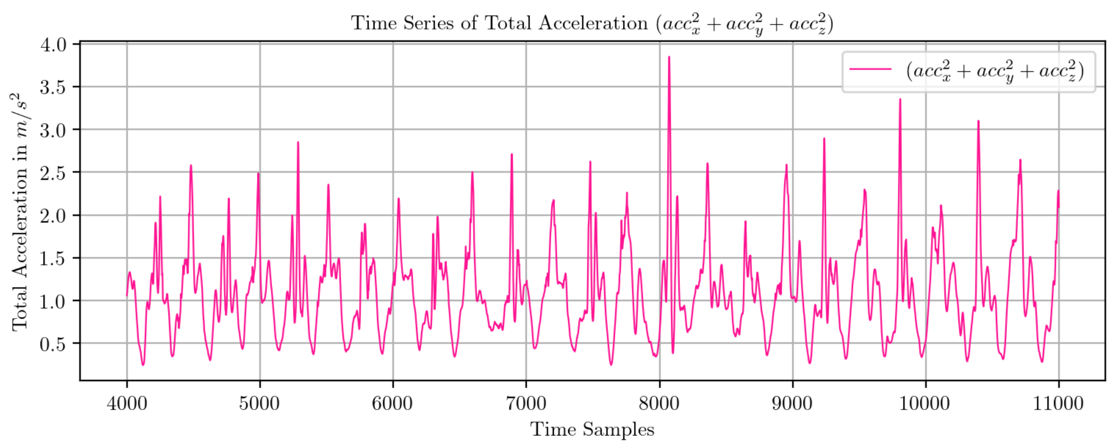




[47]:
```python
PredictPlot("TS8WalkingUpstairs.csv", 0, 4000, 11000)
```

```
Trimmed Time Series
```





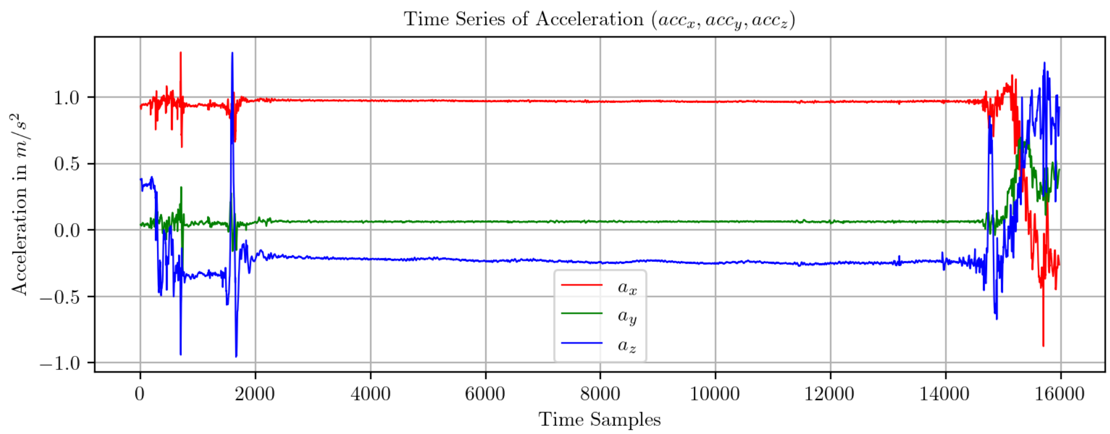

```
*** Feature extraction started ***
```

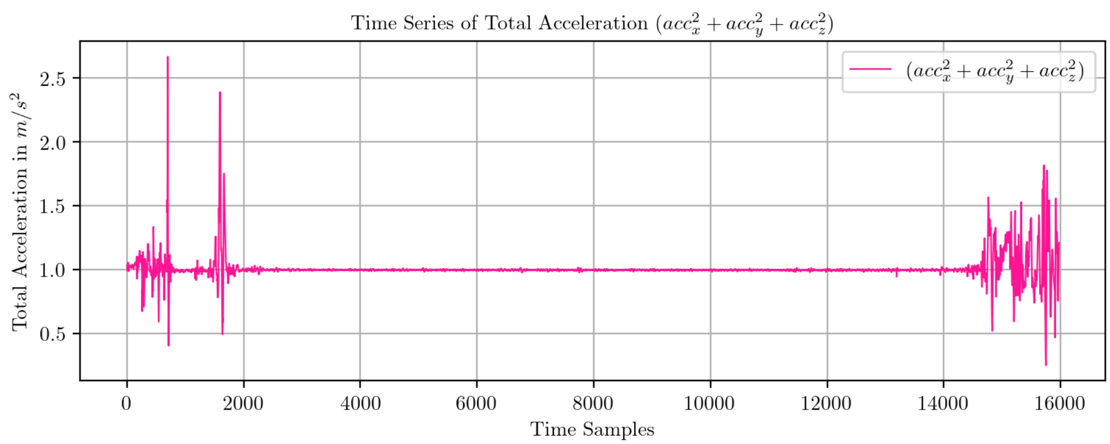
```
<IPython.core.display.HTML object>
```

```
*** Feature extraction finished ***
WALKING
```

[48]:
```
PredictPlot("TS9Sitting.csv", 1)
```

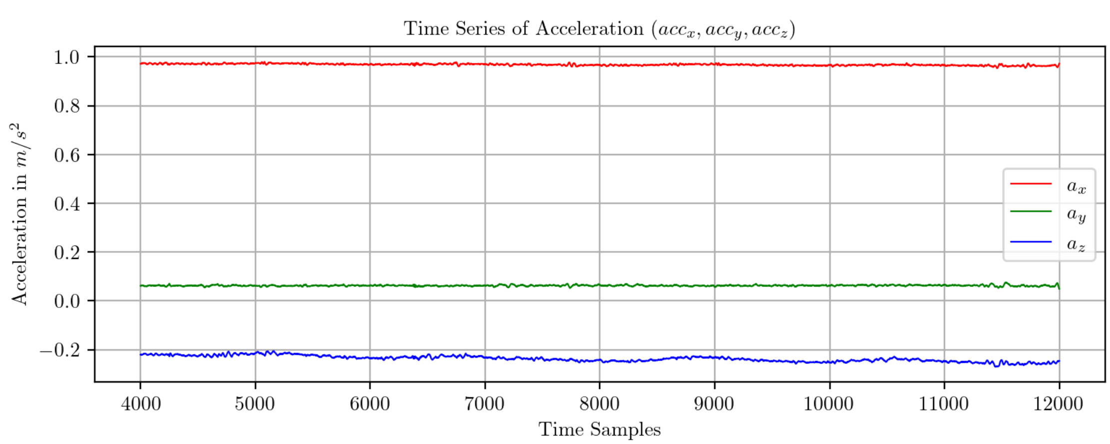
```
Original Time Series
```

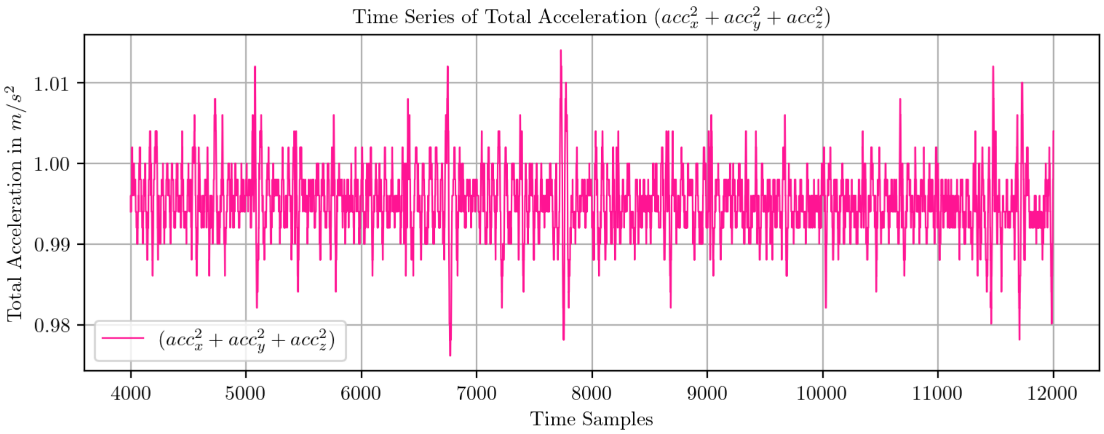




[49]:
```
PredictPlot("TS9Sitting.csv", 0, 4000, 12000)
```

```
Trimmed Time Series
```

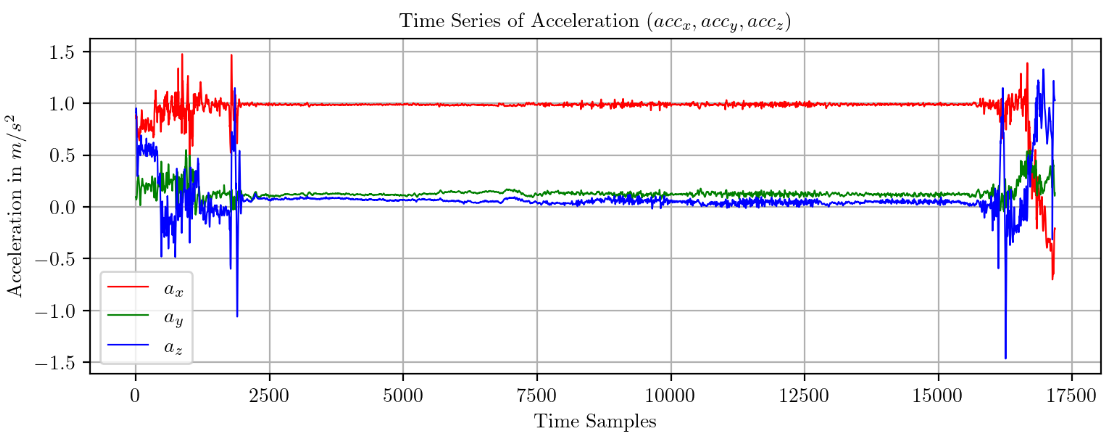


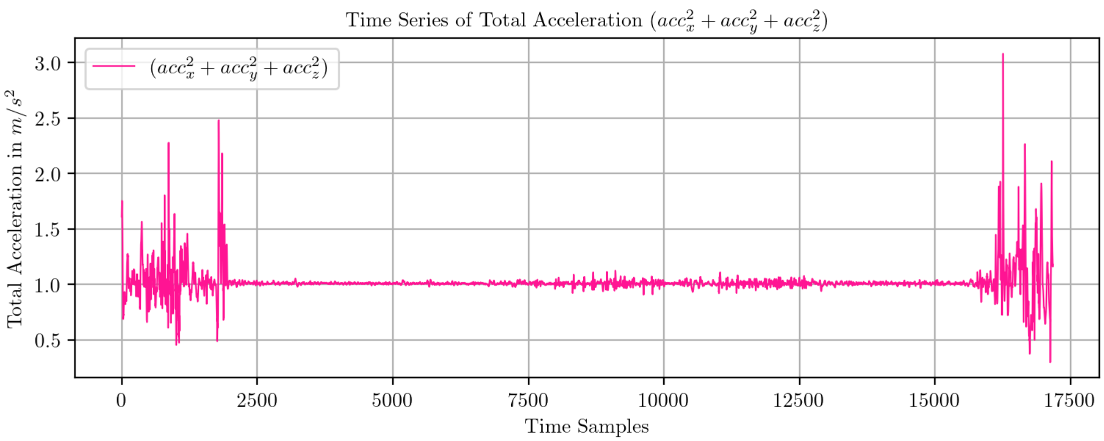



```
*** Feature extraction started ***

<IPython.core.display.HTML object>


*** Feature extraction finished ***
SITTING
```

[52]:
```
PredictPlot("TS11Standing.csv", 1)
```

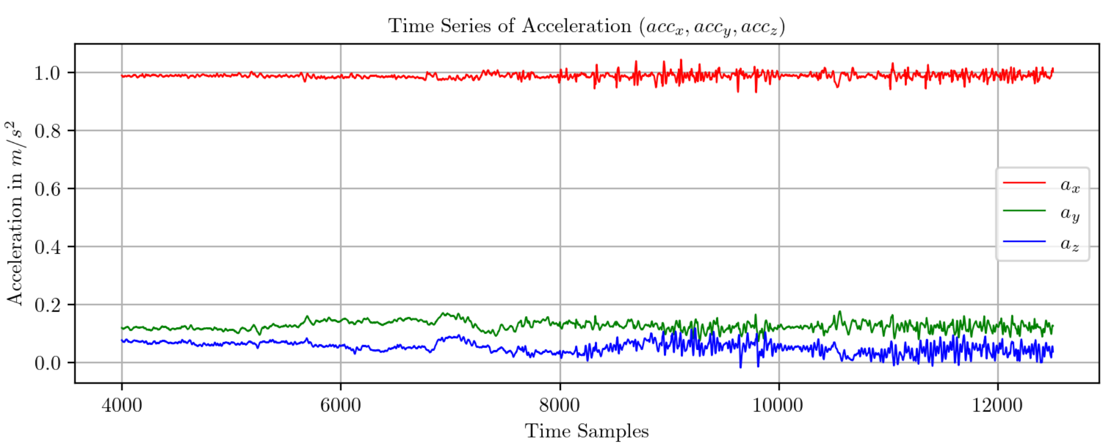
```
Original Time Series
```

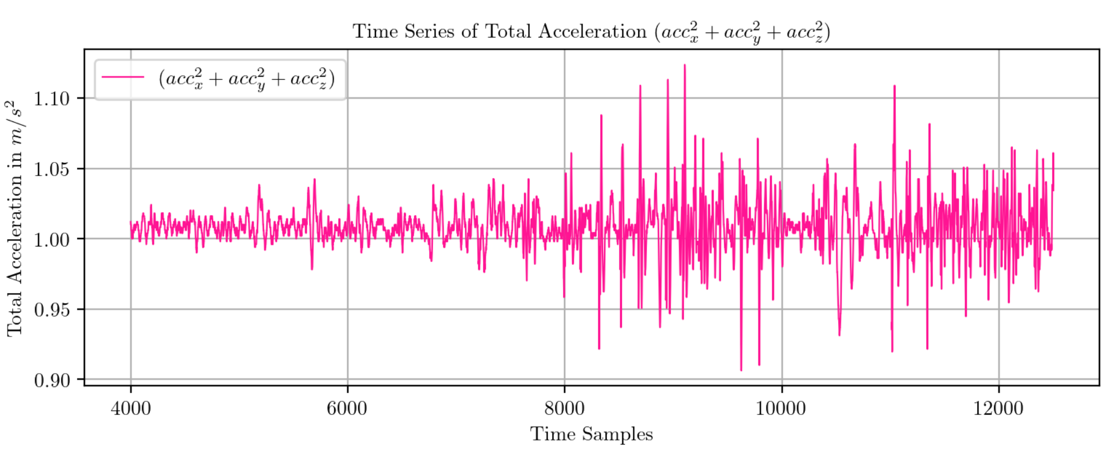





```
[53]: PredictPlot("TS11Standing.csv", 0, 4000, 12500)
```

```
Trimmed Time Series
```





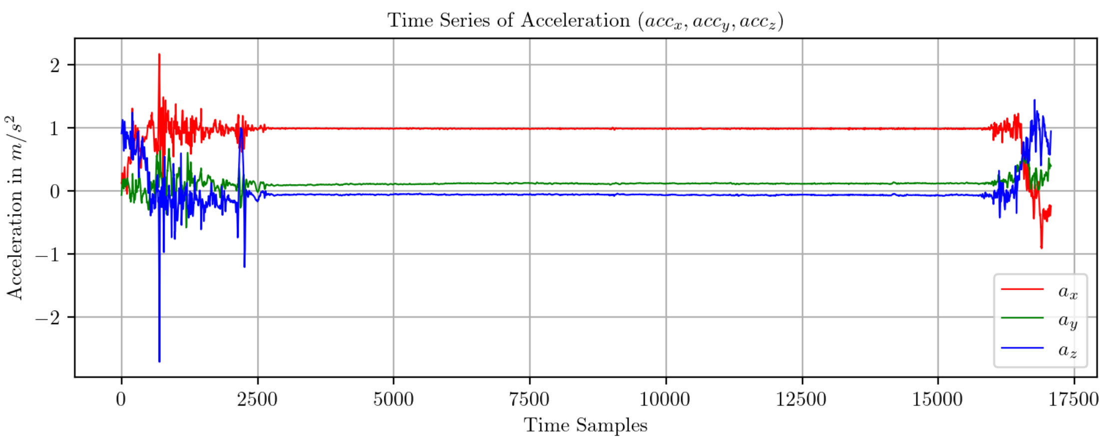
```
*** Feature extraction started ***
```

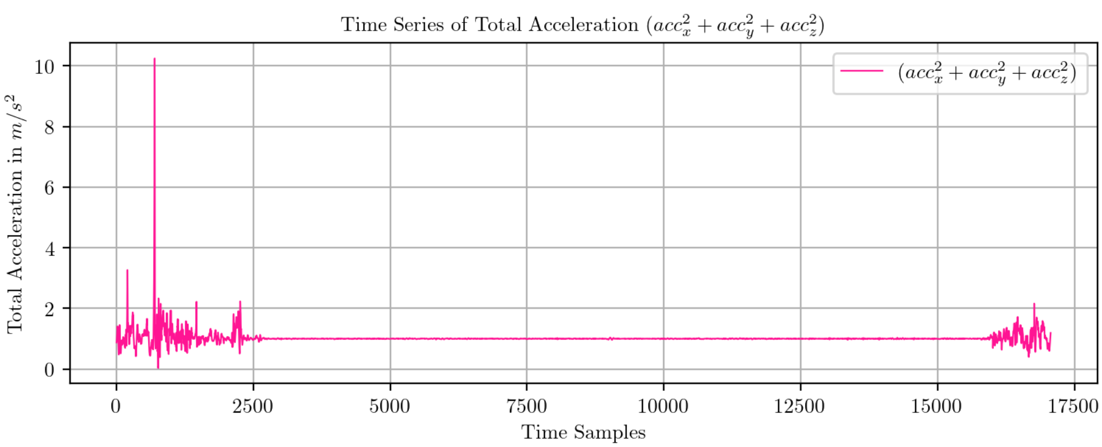
```
&lt;IPython.core.display.HTML object&gt;
```

```
*** Feature extraction finished ***
SITTING
```

[54]:
```
PredictPlot("TS12Standing.csv", 1)
```

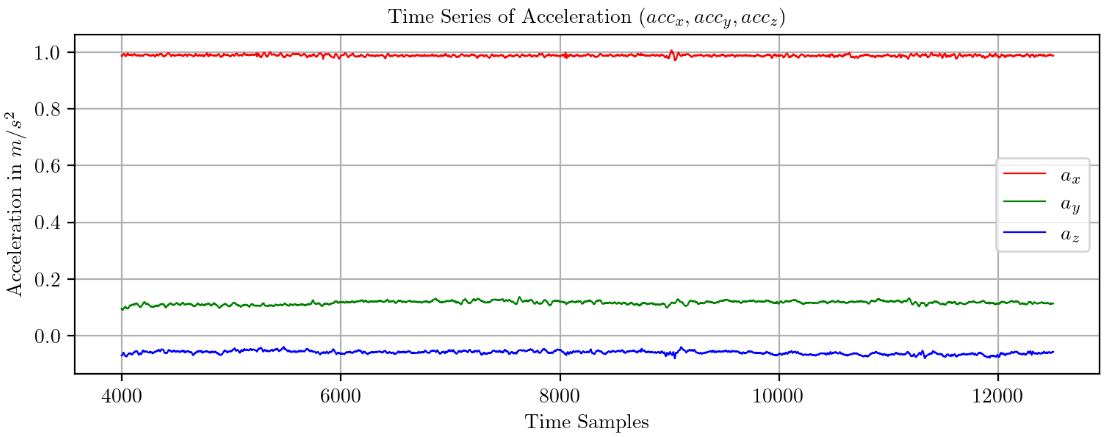
```
Original Time Series
```

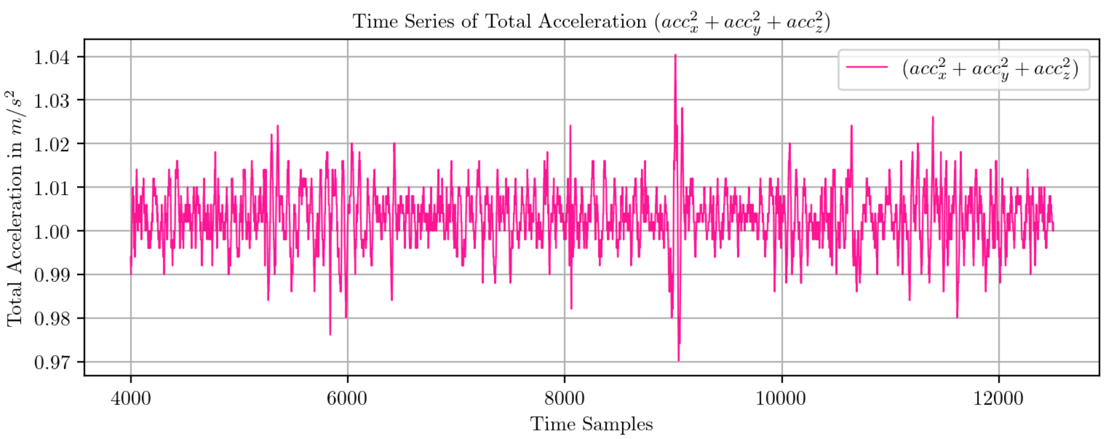




[55]:
```
PredictPlot("TS12Standing.csv", 0, 4000, 12500)
```

```
Trimmed Time Series
```

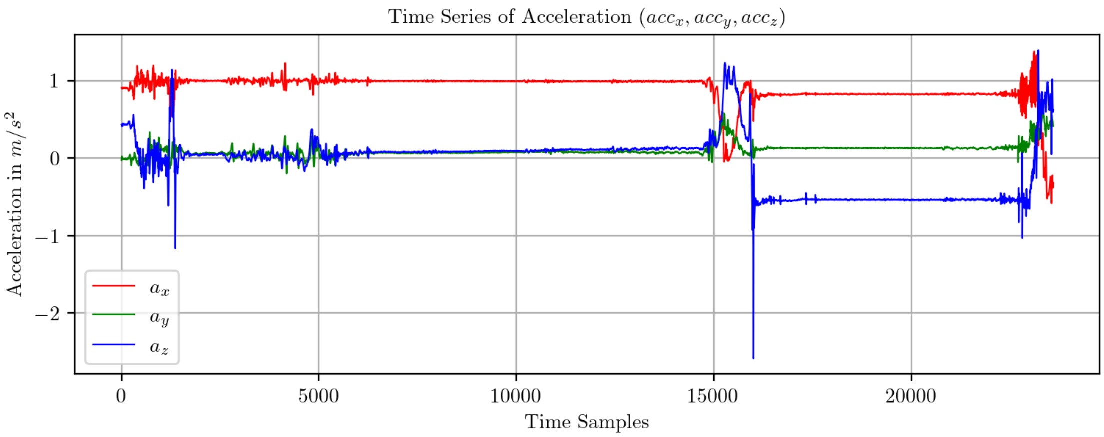


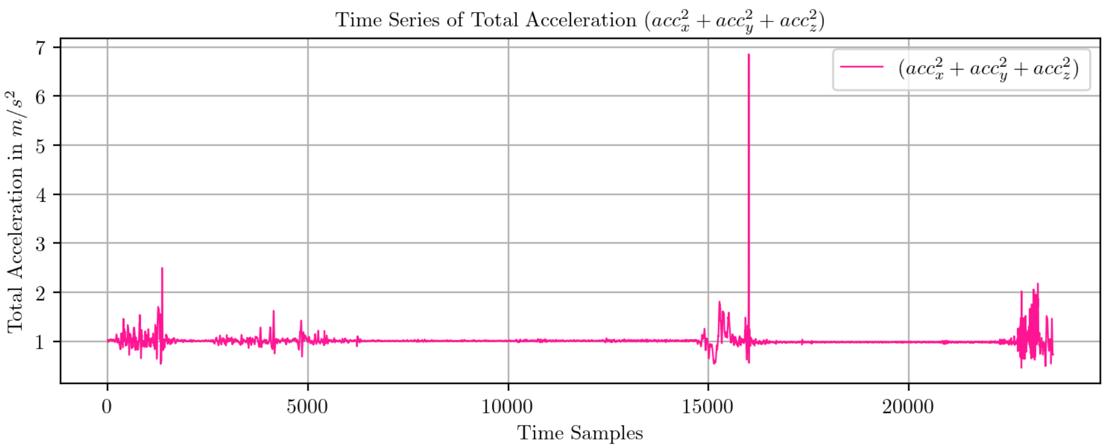



```
*** Feature extraction started ***

<IPython.core.display.HTML object>


*** Feature extraction finished ***
SITTING
```

[57]:
```
PredictPlot("TS13SittingStanding.csv", 1)
```

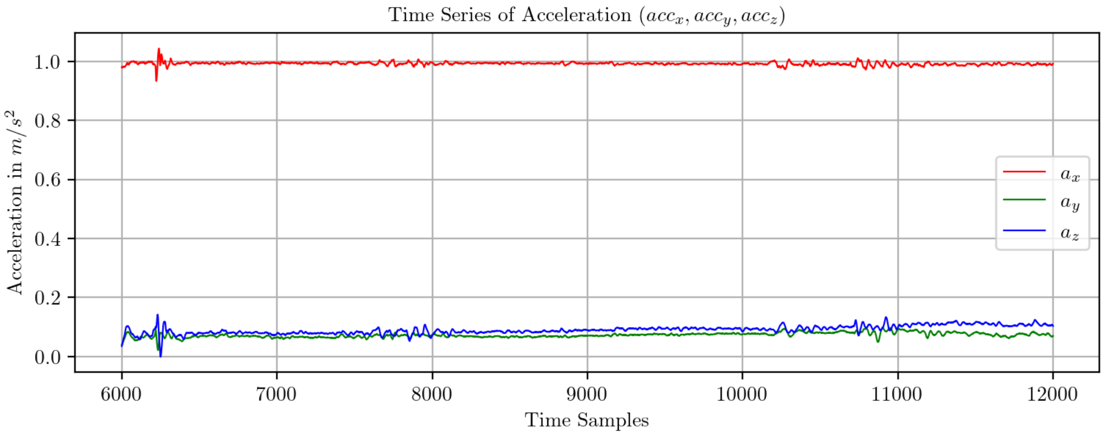
```
Original Time Series
```

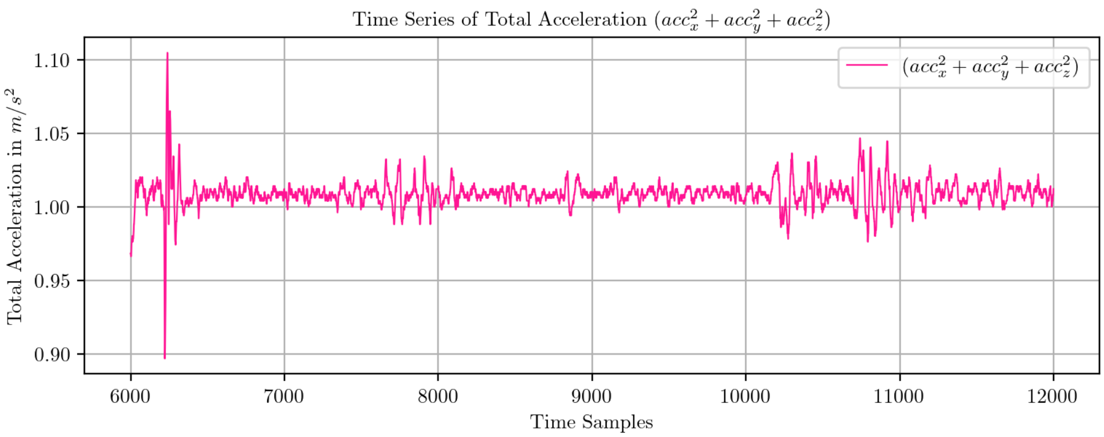




[58]:
```
PredictPlot("TS13SittingStanding.csv", 0, 6000, 12000)
```

```
Trimmed Time Series
```





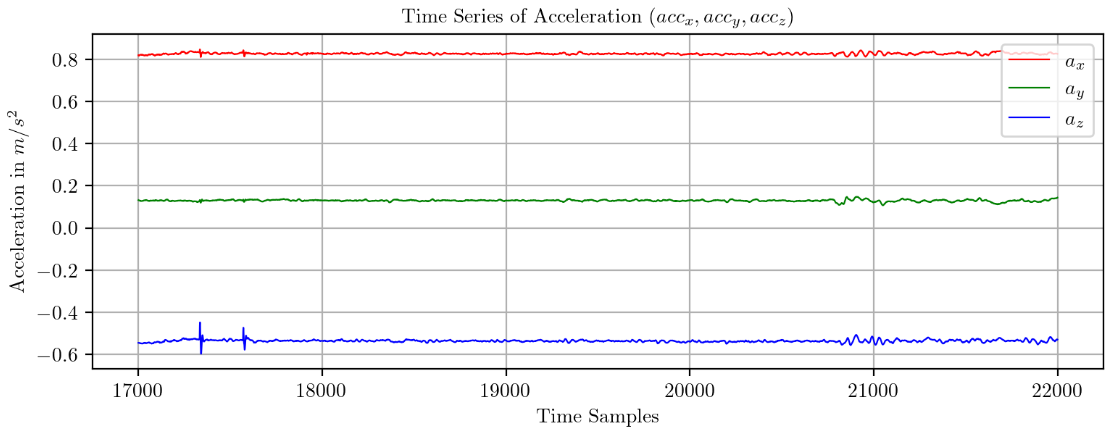

```
*** Feature extraction started ***
```

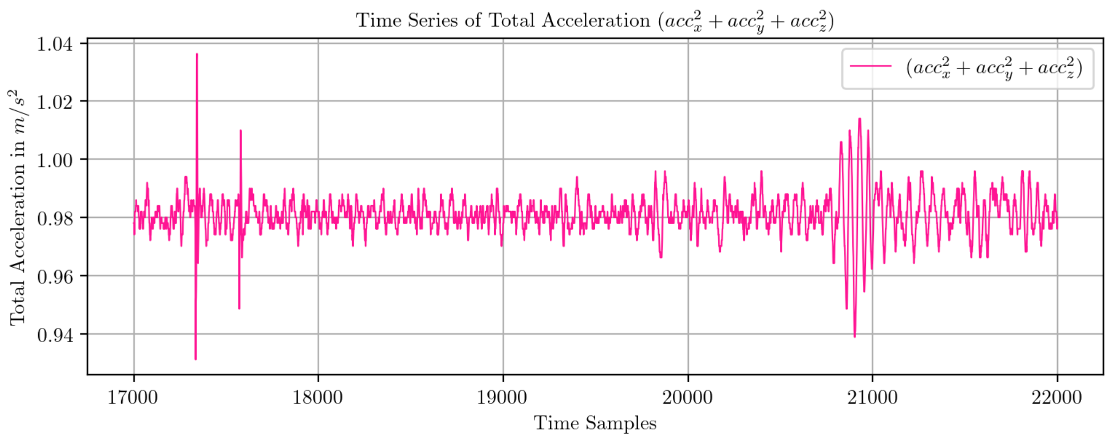
```
<IPython.core.display.HTML object>
```

```
*** Feature extraction finished ***
SITTING
```

[59]:
```
PredictPlot("TS13SittingStanding.csv", 0, 17000, 22000)
```

```
Trimmed Time Series
```

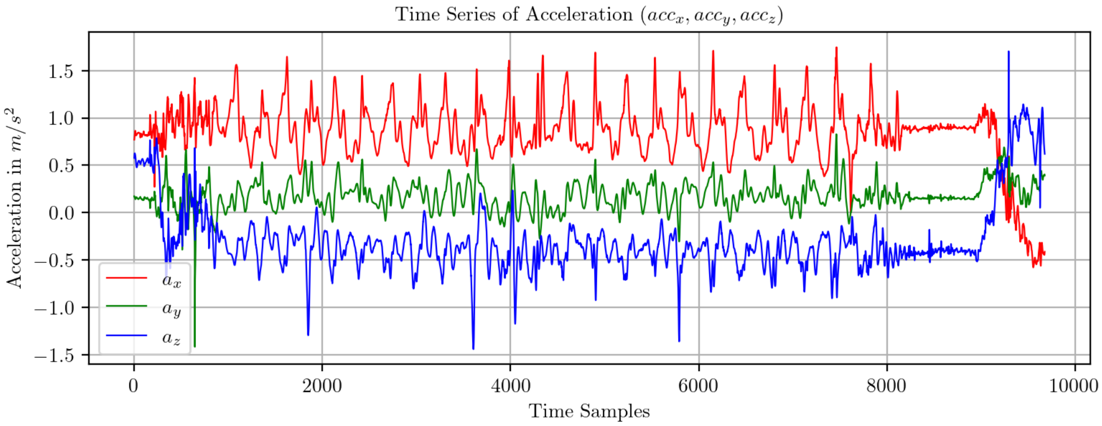


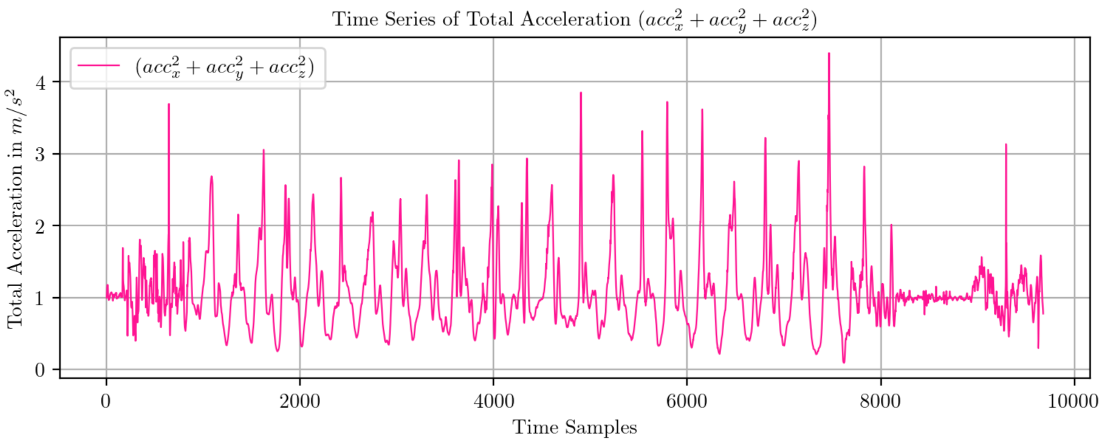



```
*** Feature extraction started ***
<IPython.core.display.HTML object>


*** Feature extraction finished ***
SITTING
```

[60]:
```
PredictPlot("TS14WalkingUpstairs.csv", 1)
```

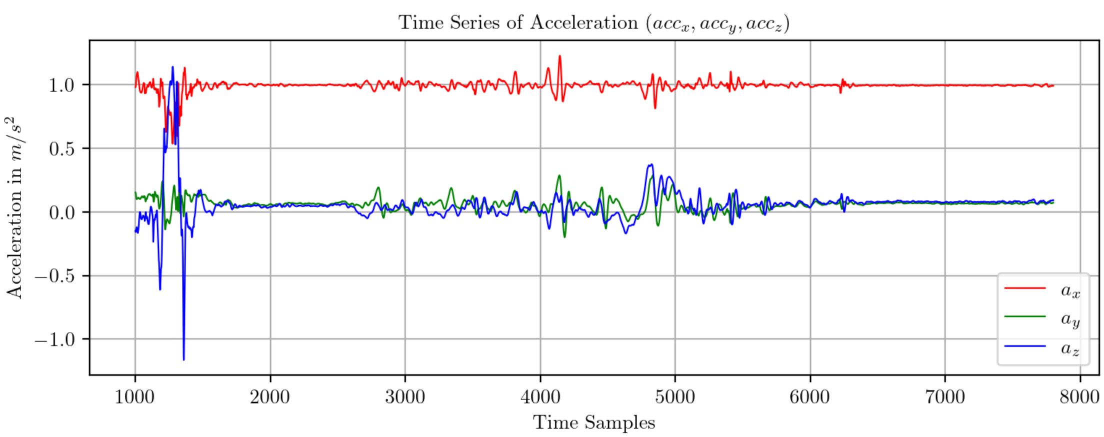
```
Original Time Series
```

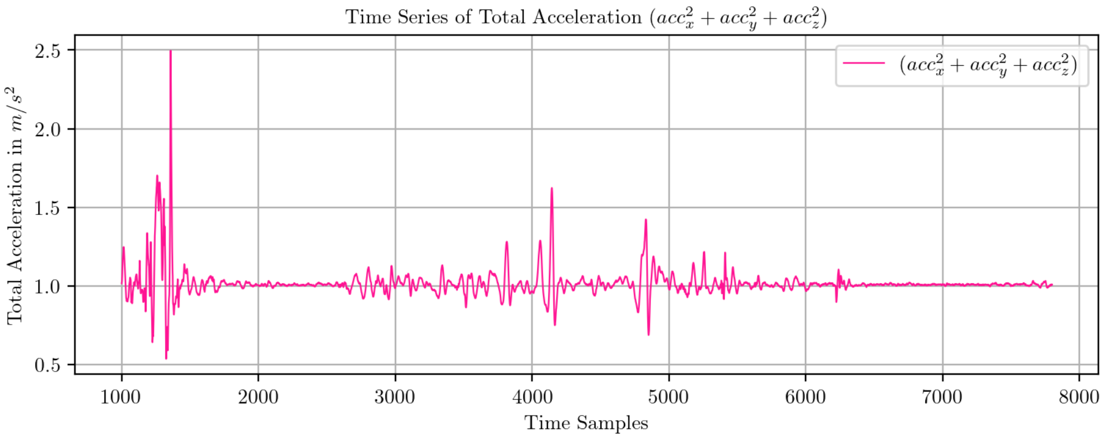




[61]:
```
PredictPlot("TS13SittingStanding.csv", 0, 1000, 7800)
```

```
Trimmed Time Series
```

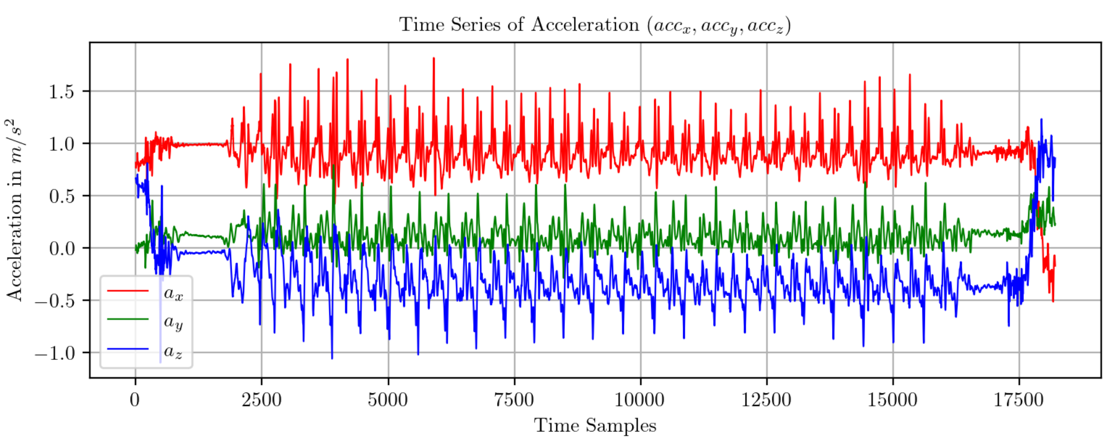


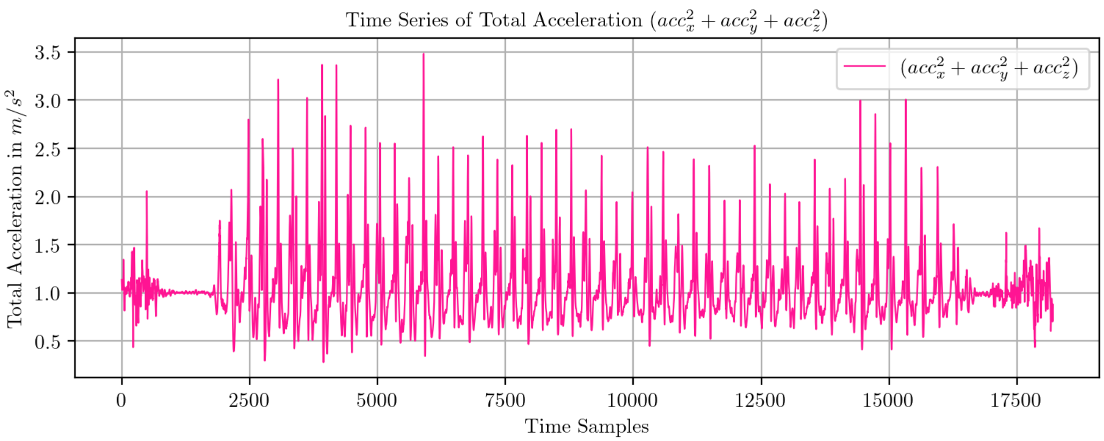



```
*** Feature extraction started ***
<IPython.core.display.HTML object>

*** Feature extraction finished ***
WALKING
```

[62]:
```
PredictPlot("TS15Walking.csv", 1)
```

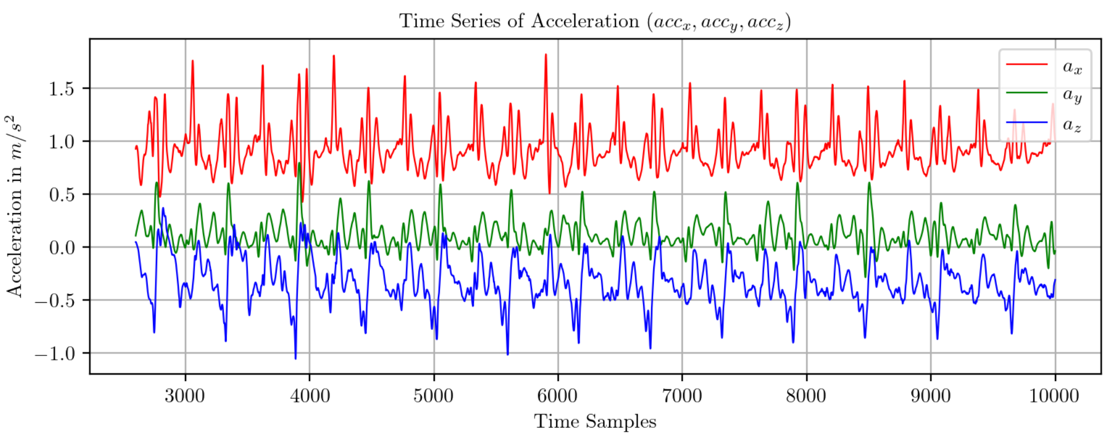
```
Original Time Series
```

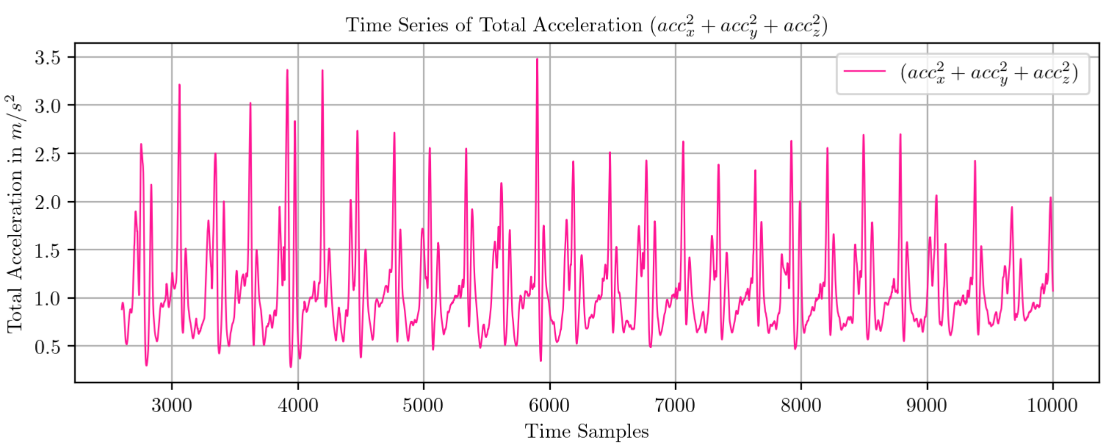





```
[64]: PredictPlot("TS15Walking.csv", 0, 2600, 10000)
```

```
Trimmed Time Series
```





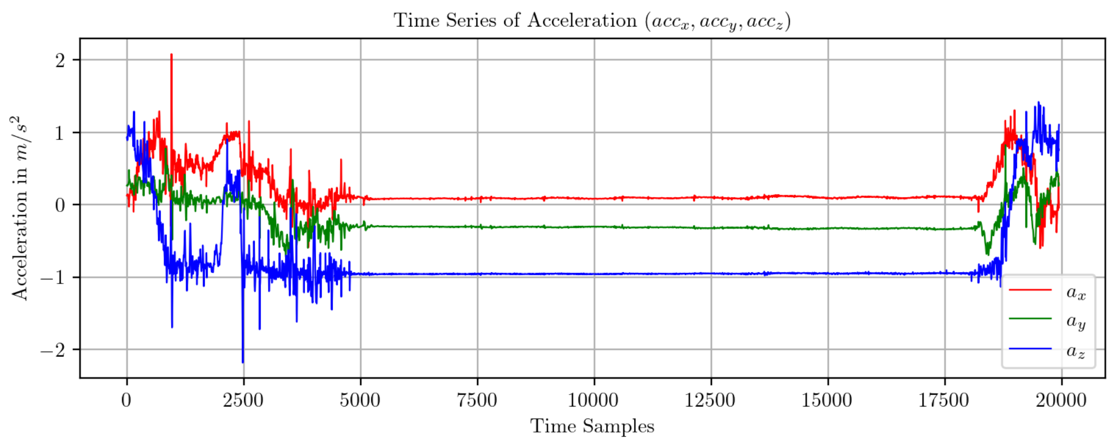
```
*** Feature extraction started ***
```

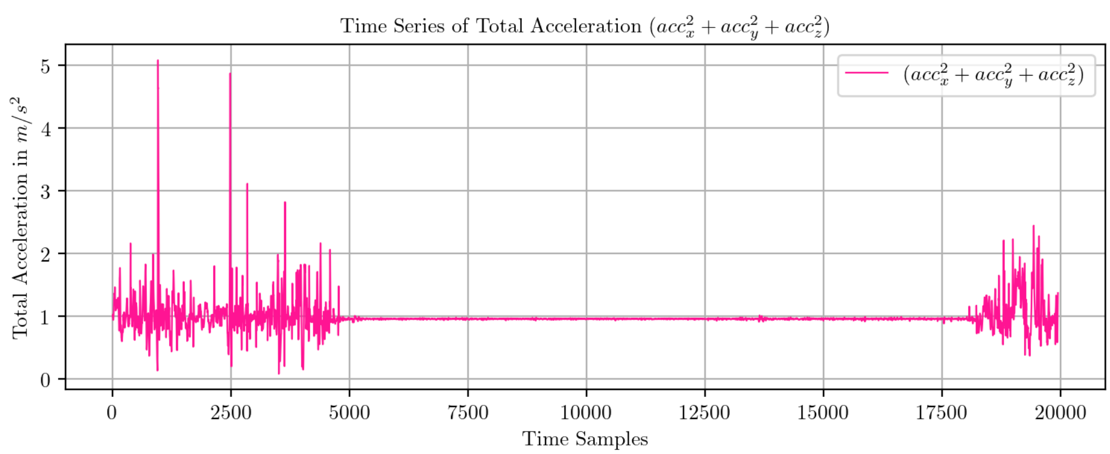
<IPython.core.display.HTML object>

```
*** Feature extraction finished ***
WALKING
```

[65]:
```python
PredictPlot("TS16Laying.csv", 1)
```

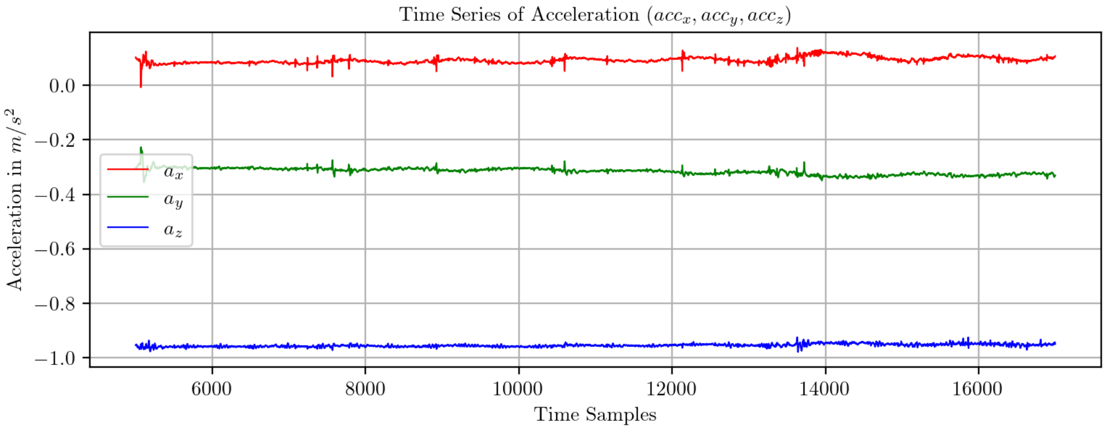
```
Original Time Series
```

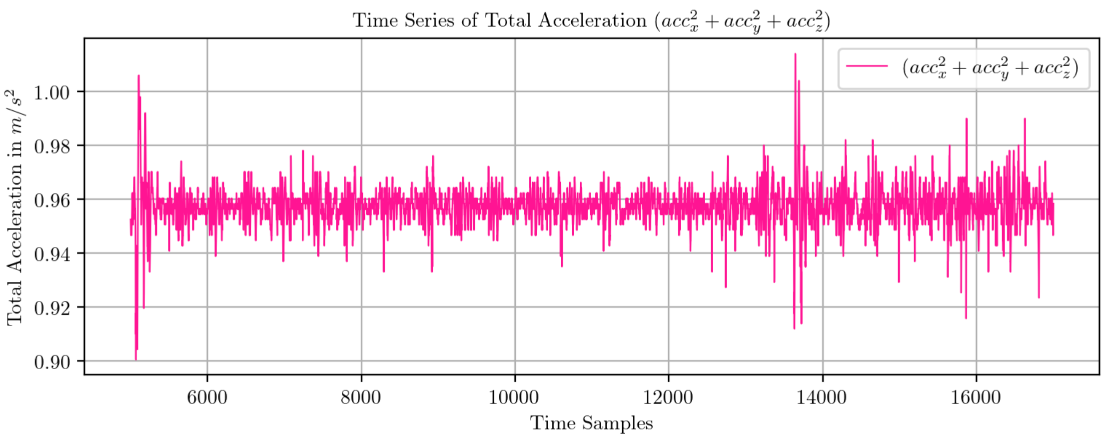




[72]:
```python
PredictPlot("TS16Laying.csv", 0, 5000, 17000)
```

```
Trimmed Time Series
```






```
*** Feature extraction started ***
<IPython.core.display.HTML object>


*** Feature extraction finished ***
SITTING
```

```
[ ]:
```