



전남대학교  
CHONNAM NATIONAL UNIVERSITY

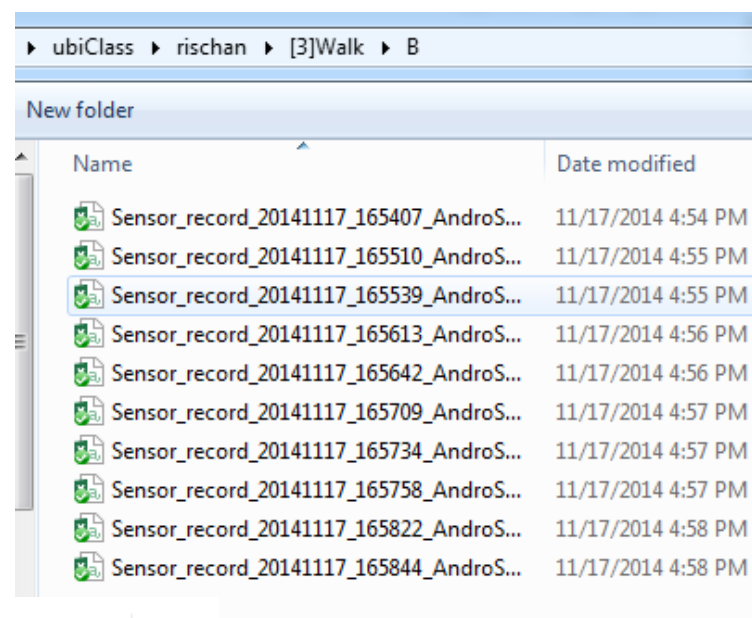
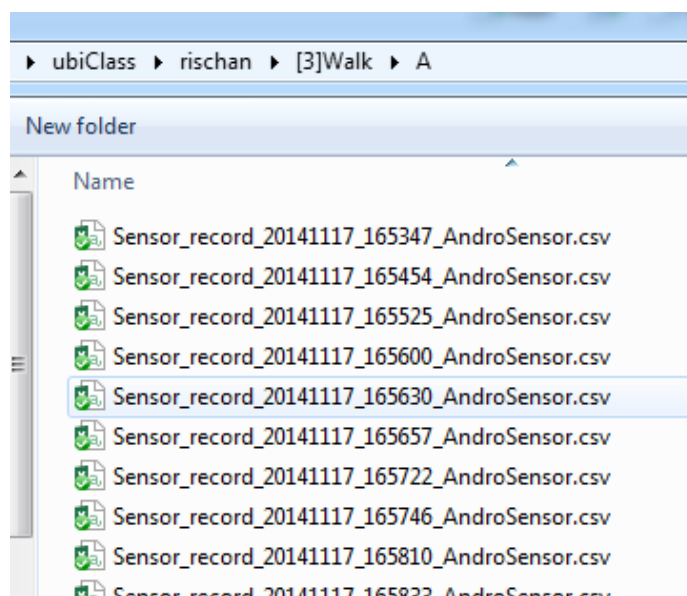
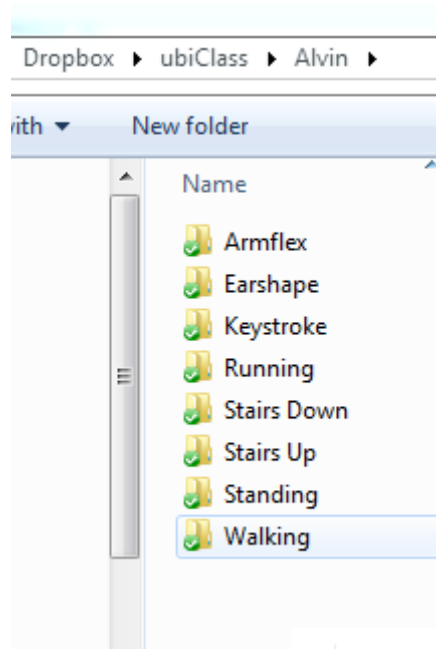
# Implementation of Human Gait Identification

By Rischana Mafrur

Advisor : Deokjai Choi

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# About Our Dataset



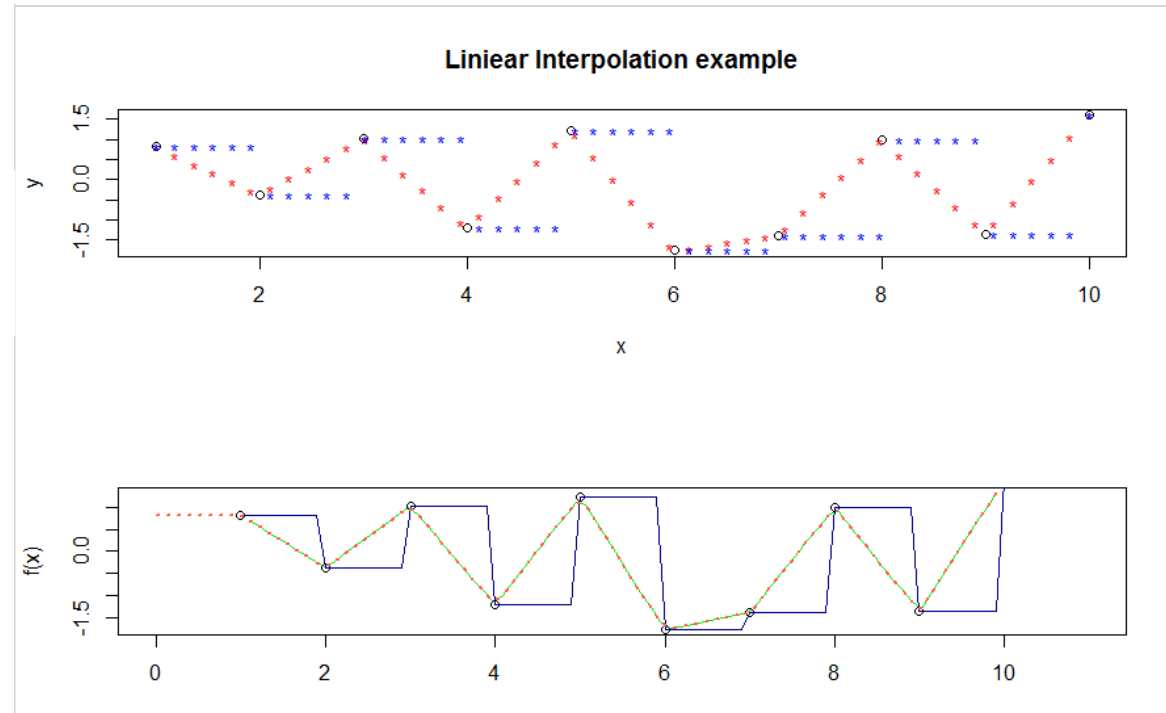
	A	B	C	AG	AH
1	ACCELEROMETER X (m/s??)	ACCELEROMETER Y (m/s??)	ACCELEROMETER Z (m/s??)	YYYY-MO-DD HH-MI-SS_SSS	
2	0.019154	-9.615114	1.455675	2014-11-17 16:53:57:173	
3	0.019154	-9.615114	1.455675	2014-11-17 16:53:57:223	
4	0.718261	-9.490616	1.168371	2014-11-17 16:53:57:276	
5	-0.047884	-9.940724	1.158794	2014-11-17 16:53:57:327	
6	0.651223	-9.346964	1.580173	2014-11-17 16:53:57:381	
7	-0.114922	-9.883264	1.934515	2014-11-17 16:53:57:437	
8	0.047884	-9.615114	0.871489	2014-11-17 16:53:57:500	
9	0.574608	-9.844956	1.063026	2014-11-17 16:53:57:560	
10	0.086191	-9.816226	1.254562	2014-11-17 16:53:57:624	
11	0.124498	-9.816226	0.593762	2014-11-17 16:53:57:675	
12	1.608904	-9.500192	0.986411	2014-11-17 16:53:57:738	
13	-0.086191	-10.28549	1.312023	2014-11-17 16:53:57:793	
14	1.053449	-8.801084	0.6608	2014-11-17 16:53:57:862	

# Experiment

- **Preprocessing**
  - Linear Interpolation
  - DB6 Level 1~3 De-noising (Noise Removal)
  - Gait Segmentation
- Features Extraction
- Identification

# Linear Interpolation

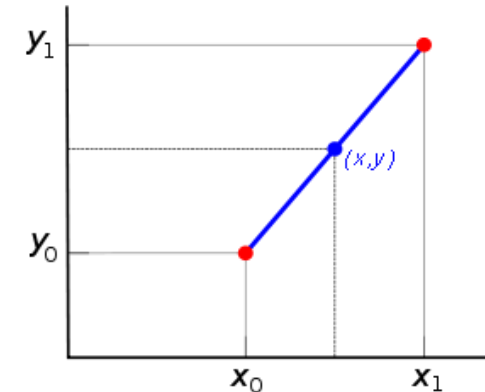
```
10 f <- approxfun(x, y)
11 curve(f(x), 0, 10, col = "green")
12 is.function(fc <- approxfun(x, y, method = "const")) # TRUE
13 curve(fc(x), 0, 10, col = "darkblue", add = TRUE)
14
15
```



The linear interpolation is calculated by:

$$s' = s_0 + \frac{(s_1 - s_0)(t' - t_0)}{t_1 - t_0} \quad (2)$$

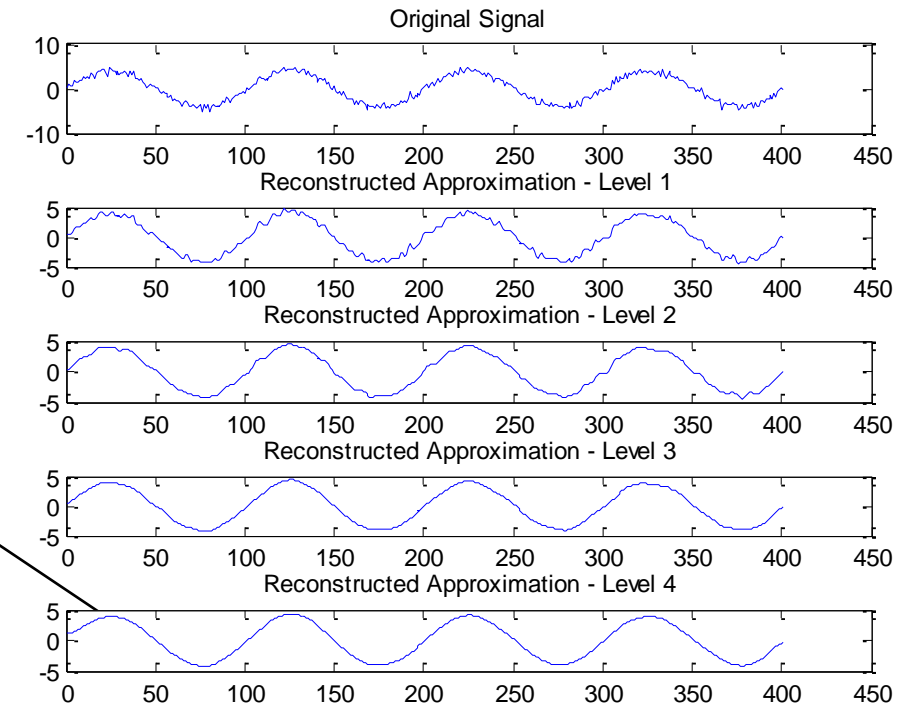
where  $s_0, s_1$  represents two samples collected at times  $t_0$  and  $t_1$ , respectively,  $(s', t')$  is the new generated point that lies between  $(s_0, t_0)$  and  $(s_1, t_1)$ .



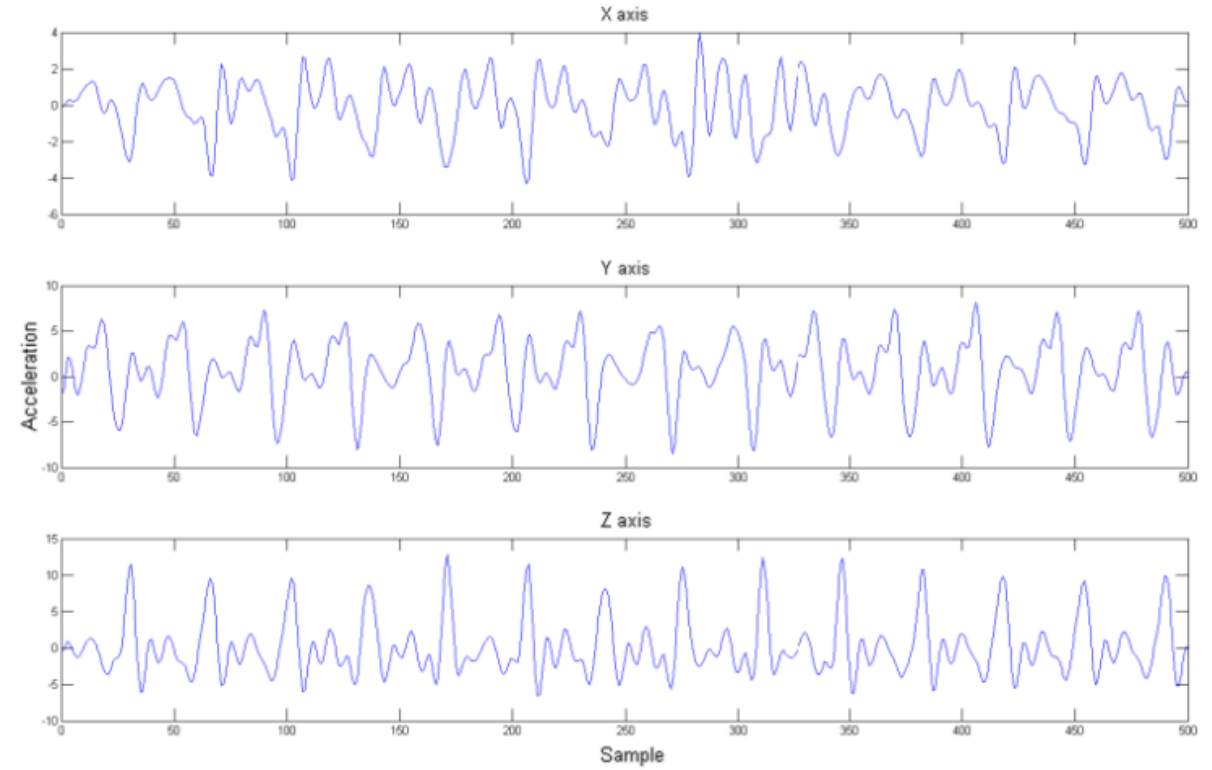
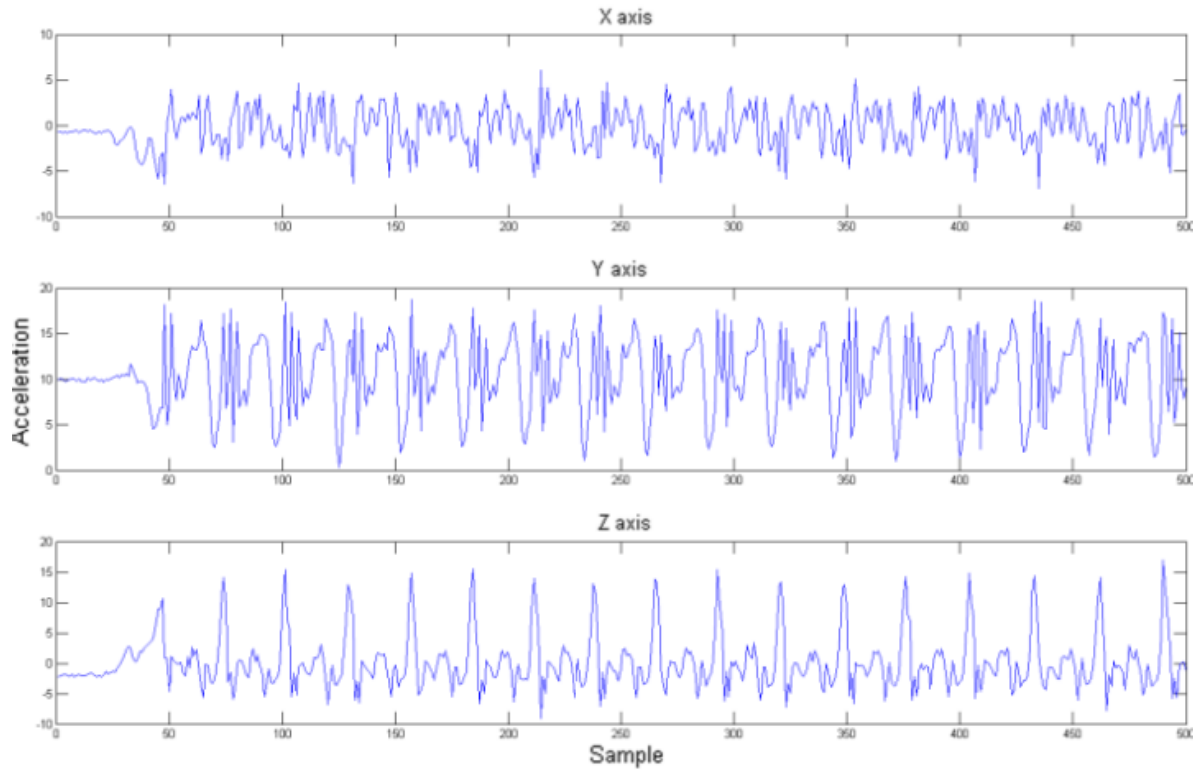
# De-Noising a Signal with Multilevel Wavelet Decomposition

```
5 [C,L] = wavedec(xn,4,'db6') #do a multi-level analysis to four levels with the Daubechies-6 wavelet
6 A1 = wrcoef('a',C,L,'db6',1) # Reconstruct the approximations at various levels
7 A2 = wrcoef('a',C,L,'db6',2)
8 A3 = wrcoef('a',C,L,'db6',3)
9 A4 = wrcoef('a',C,L,'db6',4)
10
11 subplot(5,1,1),plot(xn),title('Original Signal')
12 subplot(5,1,2),plot(A1),title('Reconstructed Approximation - Level 1')
13 subplot(5,1,3),plot(A2),title('Reconstructed Approximation - Level 2')
14 subplot(5,1,4),plot(A3),title('Reconstructed Approximation - Level 3')
15 subplot(5,1,5),plot(A4),title('Reconstructed Approximation - Level 4')
```

Significant de-noising occurs  
with the level-4 approximation  
coefficients (Daubechies  
wavelets)



## Before and After Linear Interpolation and DB6 noise reduction



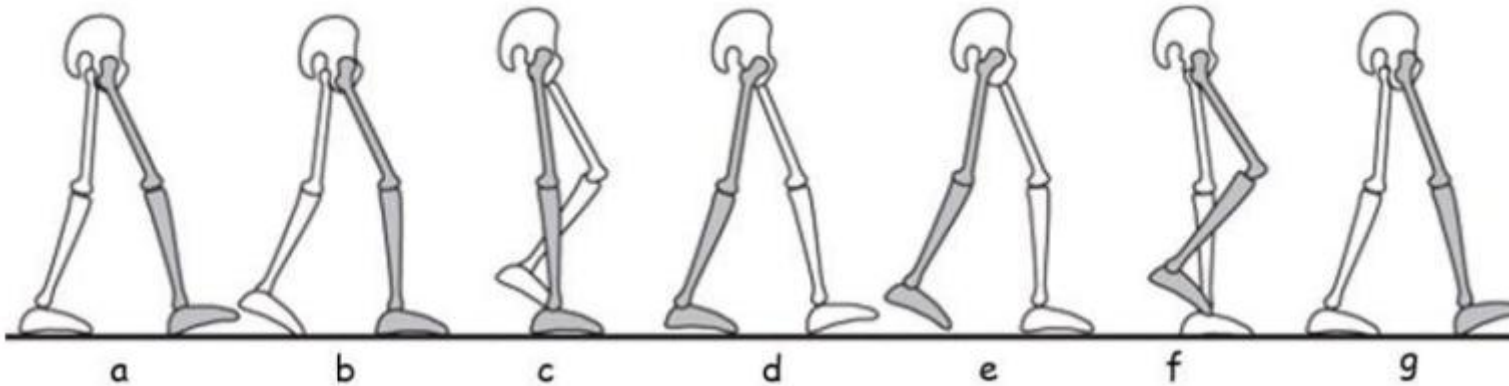
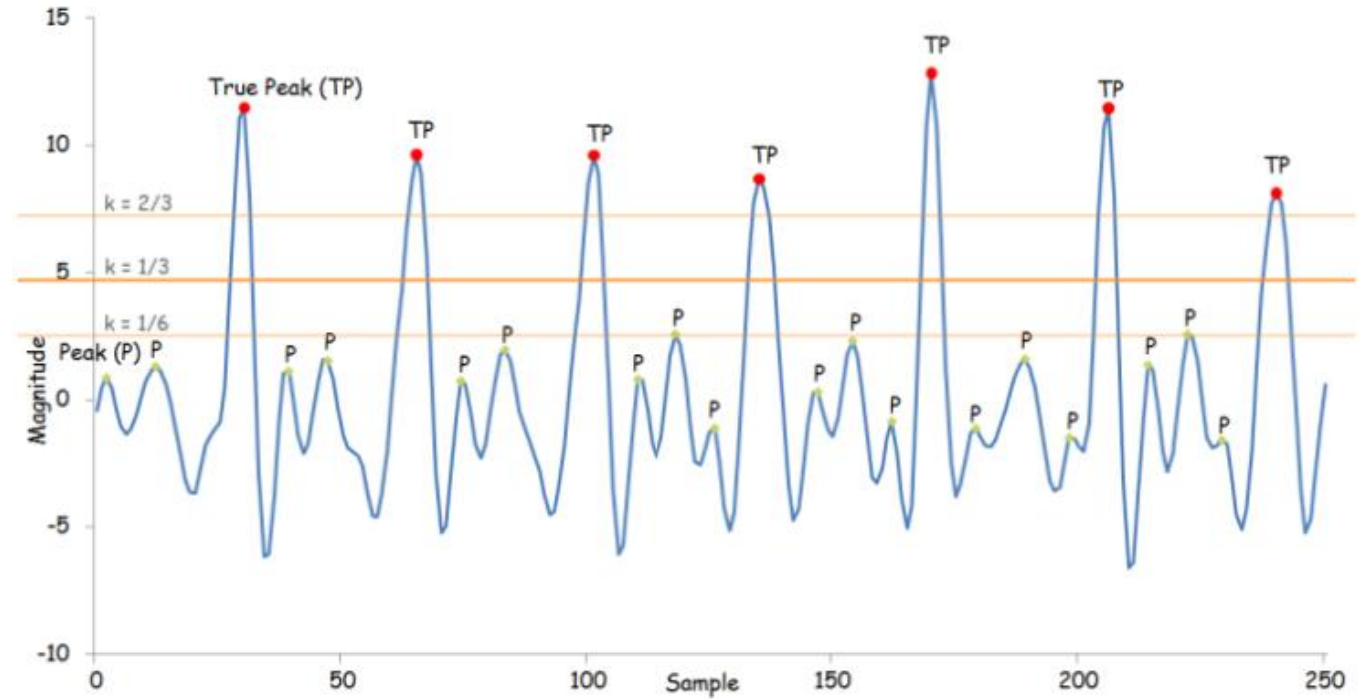
# Gait Segmentation

Use **Z** value of Accelerometer to define gait cycle

$$P = \{d_i \mid d_i > d_{i+1} \wedge d_i > d_{i-1}\} \text{ with } i \in [1 \dots n] \quad (1)$$

$$T = \mu + k\sigma \quad (2)$$

$$R = \{d_i \in P \mid d_i \geq T\} \quad (3)$$



# Features Extraction

## ***Time domain feature:***

1. Mean from each gait signal (X,Y,Z,M signals)
2. Average maximum acceleration from (X,Y,Z,M signals)
3. Average minimum acceleration from (X,Y,Z,M signals)
4. Average absolute different from (X,Y,Z,M signals)
5. Standard deviation
6. RMS (Root Mean Square)

## ***Frequency domain features:***

The first 40 FFT coefficients form a feature vector



# Features

## Time domain Features

Mean, Max, Min, Sd, Abs, Rms (6 features) with 4 signals (X,Y,Z, and M), total features from time domain features are 24 features.

## FFT Features

FFT features is the 40 first FFT coefficient from each gait signal. In this experiment we use 4 accelerometer signals (X,Y,Z, and M) so total FFT features are 160 features.

## All Features

Combine between time domain features and FFT features. Total :  $24+160 = 184$  features

	A	B	C	D	E	F	G	H	I	J	K	L
1	MeanX	SdX	MaxX	MinX	AbsX	RmsX	MeanY	SdY	MaxY	MinY	AbsY	RmsY
2	0.555395	1.098373	2.585991	-1.08811	1.252715	1.215395	-9.51746	2.921483	-3.84992	-13.631	2.110561	9.94235
3	0.589866	1.674695	2.342881	-1.7251	1.877133	1.702228	-9.53034	4.4986	-2.73963	-17.1231	4.310039	10.4510
4	-0.57362	1.973134	5.313475	-5.58799	1.535156	2.029057	-9.0482	3.819357	0.18906	-17.1231	1.998044	9.80118
5	0.046401	1.333856	1.680272	-3.22602	0.503896	1.31431	-10.4238	4.875651	-4.62248	-16.5488	7.807723	11.4763
6	0.59743	2.15929	5.780469	-4.10599	1.58677	2.216083	-10.9544	2.195639	-6.95364	-17.8585	1.775844	11.1672
7	0.460256	1.466863	2.977381	-3.45786	1.272482	1.513052	-9.79361	4.176959	-4.37038	-14.5361	6.159178	10.6188
8	0.076862	3.499743	7.005158	-9.98727	2.63952	3.447166	-9.5194	3.639357	-0.46927	-14.8035	3.37587	10.1716
9	-1.3334	1.008193	0.501548	-2.83548	0.983463	1.65126	-11.7156	1.578985	-9.67843	-14.4889	2.100525	11.8144
10	0.391567	1.444585	2.786917	-2.83548	1.855781	1.474053	-10.1042	4.67004	-3.88231	-15.2468	6.137039	11.0995
11	1.08488	1.408252	3.484808	-0.94153	2.044802	1.758338	-8.74339	4.155428	-1.59603	-17.1275	3.769392	9.64982
12	-0.51043	0.674269	0.81719	-1.22429	0.539701	0.832133	-10.8278	1.174787	-8.95463	-12.4584	1.475132	10.8882
13	0.35861	2.336641	3.258774	-4.91309	1.075629	2.327632	-10.0079	4.256948	-3.78951	-15.8723	6.268378	10.8495
14	1.831153	1.013319	3.485867	0.699891	1.053489	2.057486	-10.2371	2.13004	-7.52693	-13.2058	2.795151	10.4252
15	4.595901	1.188852	6.851176	3.485867	0.66244	4.725861	-8.49996	4.635166	-4.2969	-17.5652	2.126148	9.52180
16	0.92104	3.355269	6.851176	-2.75926	2.460915	3.27092	-9.52298	7.088065	0.304573	-17.5652	7.028253	11.6037
17	-0.6693	0.38319	-0.15324	-1.31823	0.431065	0.76058	-10.409	2.502866	-8.06672	-16.0147	0.89282	10.6731
18	-0.26855	0.202324	0.097024	-0.47175	0.177996	0.328536	-9.49025	0.221543	-9.29248	-9.90878	0.185577	9.49251
19	0.172826	0.432426	0.547773	-0.68017	0.335536	0.43606	-9.75276	0.130861	-9.60609	-9.91369	0.160027	9.75350
20	-0.54613	0.552443	0.421373	-1.29695	0.674968	0.765833	-9.49886	0.210116	-9.08911	-9.91369	0.193713	9.50105
21	0.334047	0.269243	0.537492	-0.04947	0.143337	0.407377	-9.402	0.090068	-9.29508	-9.4855	0.092643	9.40232
22	0.17121	0.200362	0.344133	-0.13422	0.151396	0.247848	-9.45391	0.020268	-9.41957	-9.4669	0.001635	9.45392
23	0.312653	0.269433	0.681938	-0.13422	0.310558	0.404657	-9.37638	0.020055	-9.34769	-9.41957	0.017913	9.37640
24	0.249499	0.096882	0.360068	0.101849	0.08727	0.265132	-9.34003	0.018024	-9.314	-9.36328	0.022763	9.34004
25	0.249998	0.028222	0.27626	0.220157	0.033632	0.251058	-9.30377	0.010308	-9.29338	-9.314	0.01492	9.30377
26	0.312859	0.035744	0.34651	0.220157	0.018518	0.314824	-9.34379	0.050858	-9.29256	-9.43376	0.026749	9.34392
27	0.330673	0.807715	2.625555	-2.01434	0.452796	0.864246	-10.0095	1.208931	-8.99344	-13.322	0.267905	10.0806
28	-0.12814	2.019406	1.901591	-4.67069	1.104262	1.99361	-9.55233	3.856989	-3.54766	-13.9149	4.207983	10.2803

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FU	FV	FW	FX	FY	FZ	GA	GB	GC	
FFT153	FFT154	FFT155	FFT156	FFT157	FFT158	FFT159	FFT160	label	
-0.60934	0.144611	-0.405	-0.88437	-0.67508	-0.40843	-0.55527	-0.59382	agung	
-2.61995	-2.79797	-2.47035	-2.78383	-2.50306	-2.71729	-2.16354	-2.44152	agung	
2.700932	1.954585	2.055435	1.902533	1.679828	2.059306	2.190261	2.336578	agung	
-0.95285	-0.17715	-0.38109	0.241818	-0.72403	-0.65203	-1.93696	-1.98026	agung	
4.808676	2.777703	4.670166	6.669613	3.334803	0.89254	2.977633	2.611604	agung	
-1.17916	-2.04098	-2.44121	-3.28289	-3.10196	-3.18561	-2.60327	-2.40219	agung	
5.966523	5.999911	7.502656	6.85634	6.760834	4.302868	5.591767	6.273775	agung	
-2.77245	-2.62142	-2.8757	-2.84504	-2.84814	-2.64578	-2.8176	-2.83888	agung	
-0.542	-0.30119	-1.41766	-0.92355	-1.59163	-1.09617	-1.03317	-0.8322	agung	
4.431904	5.628292	3.171458	3.831947	3.641558	4.807209	3.801818	4.083849	agung	
-2.17362	-2.24252	-2.24948	-2.14989	-2.24958	-2.38743	-2.40747	-2.3552	agung	
-2.25839	-2.31592	-1.74282	-1.40156	-1.70077	-2.06582	-3.03182	-3.14669	agung	
5.516083	5.465489	5.449561	5.577563	5.453935	5.588735	5.49983	5.456692	agung	
-7.31496	-7.15132	-7.27213	-7.14189	-7.50581	-7.05846	-7.38461	-7.2666	agung	
4.172495	4.292497	4.836977	4.363838	4.718246	4.136125	4.193529	4.255587	agung	
3.404821	3.567294	3.555427	3.487997	3.510887	3.555237	3.485073	3.577724	agung	
-1.13499	-1.17272	-1.15514	-1.20356	-1.15912	-1.17396	-1.15804	-1.15923	agung	
0.86713	0.803363	0.846054	0.860618	0.813731	0.868544	0.851388	0.805035	agung	
0.482515	0.404696	0.39354	0.415888	0.438225	0.346379	0.415751	0.453539	agung	
0.062353	0.048932	0.058648	0.060265	0.048935	0.05705	0.058647	0.048939	agung	
0.02446	0.026294	0.024354	0.026032	0.02446	0.025875	0.024375	0.025682	agung	
-0.03734	-0.03736	-0.03715	-0.03729	-0.03725	-0.03737	-0.03759	-0.03747	agung	
-0.06281	-0.06267	-0.06287	-0.06285	-0.06306	-0.06288	-0.06288	-0.06279	agung	
-0.02659	-0.02656	-0.02659	-0.02657	-0.02659	-0.02657	-0.02659	-0.02657	agung	
0.042131	0.043772	0.042679	0.034298	0.04193	0.040868	0.040933	0.040135	agung	
-4.05089	-4.31722	-3.92748	-3.66853	-3.67108	-3.95814	-4.09392	-3.91254	agung	
1.044144	1.04149	1.479194	1.546559	1.572899	1.5814	1.246371	1.176803	agung	

Result

## Time Domain Features

List Features after SFFS:

"MeanX", "AbsX", "MeanY", "MinY", "MeanZ", "SdZ"

Best SVM Parameters: gamma = 0.5, cost = 10

	Original	SFFS
Time Loading	0.48	0.37
Time Prediction	0.11	0.02
Accuracy	0.7614	0.8267

## FFT Features

List Features after SFFS:

"FFT1", "FFT13", "FFT71", "FFT81", "FFT82", "FFT121"

Best SVM Parameters: cost=1, gamma=1

	Original	SFFS
Time Loading	1.73	0.87
Time Prediction	0.45	0.03
Accuracy	0.4821	0.7178

## All Features

List Features after SFFS:

"MeanX", "AbsX", "MeanY", "MinY", "MeanZ", "SdZ"

Best SVM Parameters: gamma = 0.5, cost = 10

	Original	SFFS
Time Loading	2.45	0.37
Time Prediction	0.55	0.02
Accuracy	0.4155	0.8267

*SFS (Sequential Forward Selection)*

*SFFS (Sequential Floating Forward Selection)*

# Naïve Bayes and Random Forest

	SVM SFFS	Naïve Bayes	Naïve Bayes with SFFS
Time Loading	0.37	91.36	4.09
Time Prediction	0.02	8.58	0.31
Accuracy	0.8267	0.5297	0.6287

	SVM SFFS	Random Forest	Random Forest with SFFS
Time Loading	0.37	2.53	0.62
Time Prediction	0.02	0.36	0.23
Accuracy	0.8267	0.848	0.7966

# Conclusion

- If we want to **play** with **sensor** data, we have to consider deeply about **sampling rate**.
- **Features selection** is very useful method, we can use it to find which is the **best features**.
- **Many features** does **not** mean **good accuracy**, but **many features** means take **more time** to load and predict.

Thank you,