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Analysis of Chewing Signals Based on Chewing Detection Using Proximity Sensor for Diet Monitoring

Authors: Nur Asmiza Selamat & Sawal Hamid Md. Ali

Presenter:Nur Asmiza Selamat (PhD Student)

Universiti Kebangsaan Malaysia & Universiti Teknikal Malaysia Melaka

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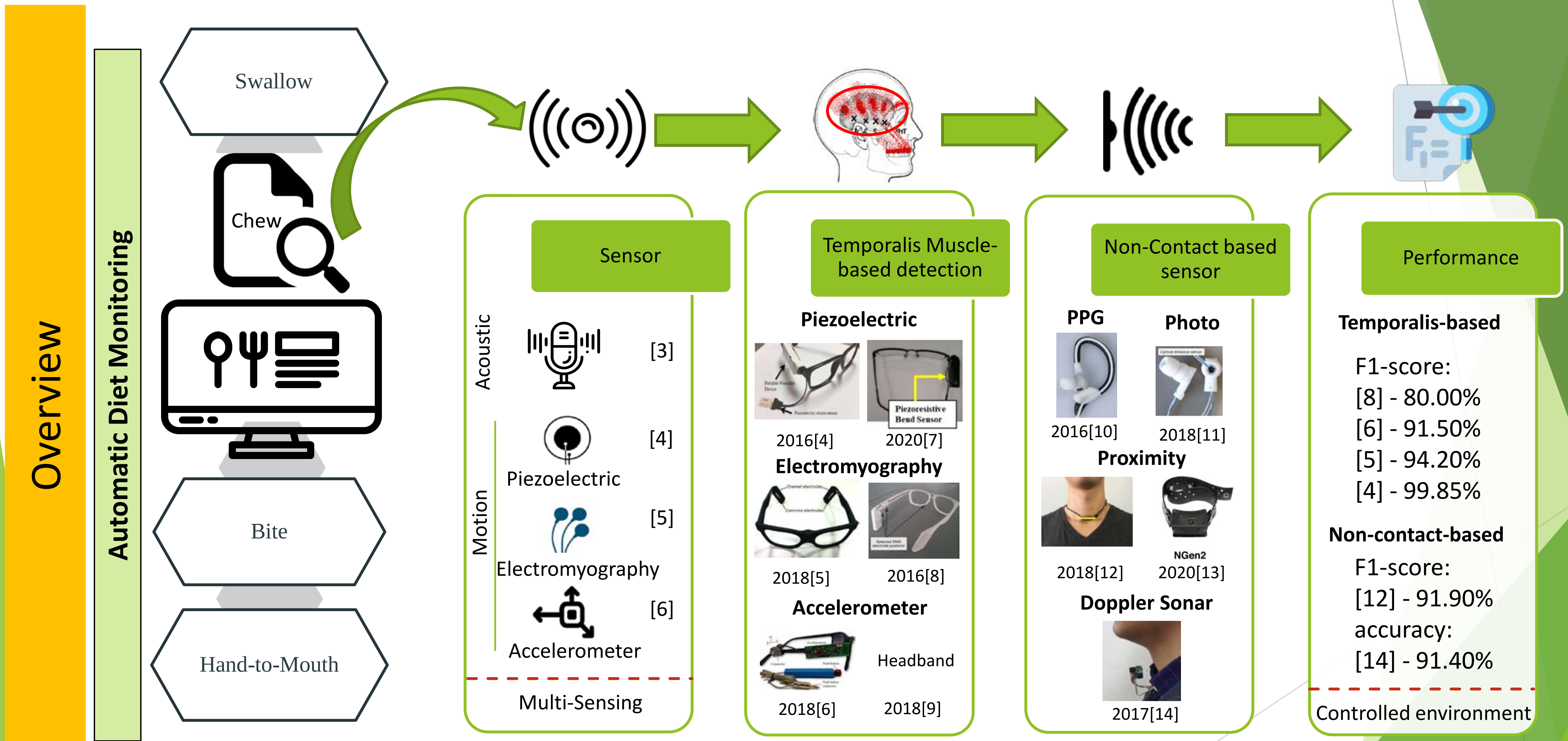
INTRODUCTION



*PPG- photoplethysmography

INTRODUCTION

Objective

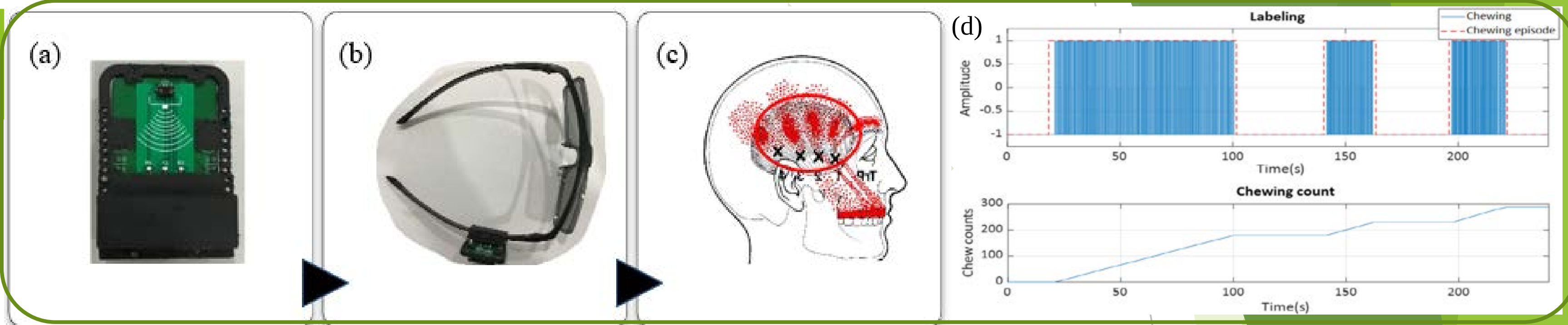
- To develop the non-contact based chewing detection system for diet monitoring applications
- To obtain and analyze the performance of the proposed approach in term of F1-score and accuracy
- To analyze chew count error based on proposed approach using automatic chew count label and chewing rate of different food hardness

METHODOLOGY

Data Collection

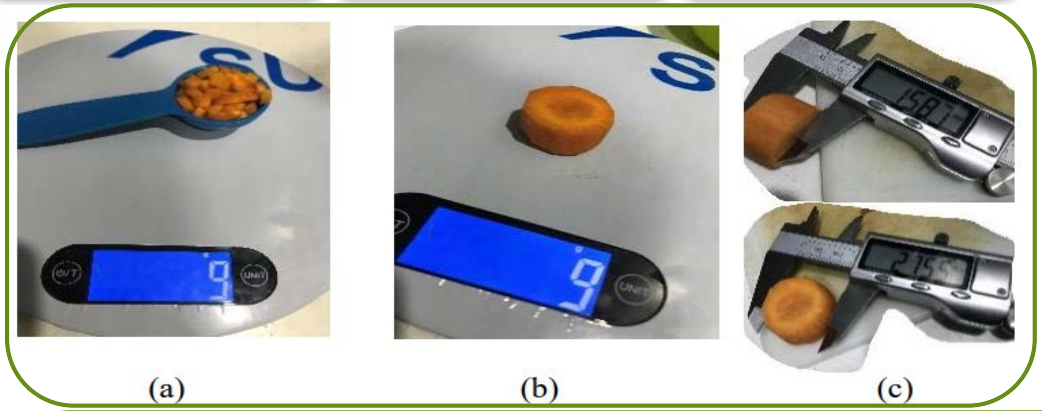
Chewing detection system

(a) The proximity sensor: VCNL4040, clickboard 9clicks from Mikro-E
(b) The wearable sensor: Arduino, Fs=50Hz
(c) Position of temporalis muscle
(d) Chewing, chewing episode & chewing count label



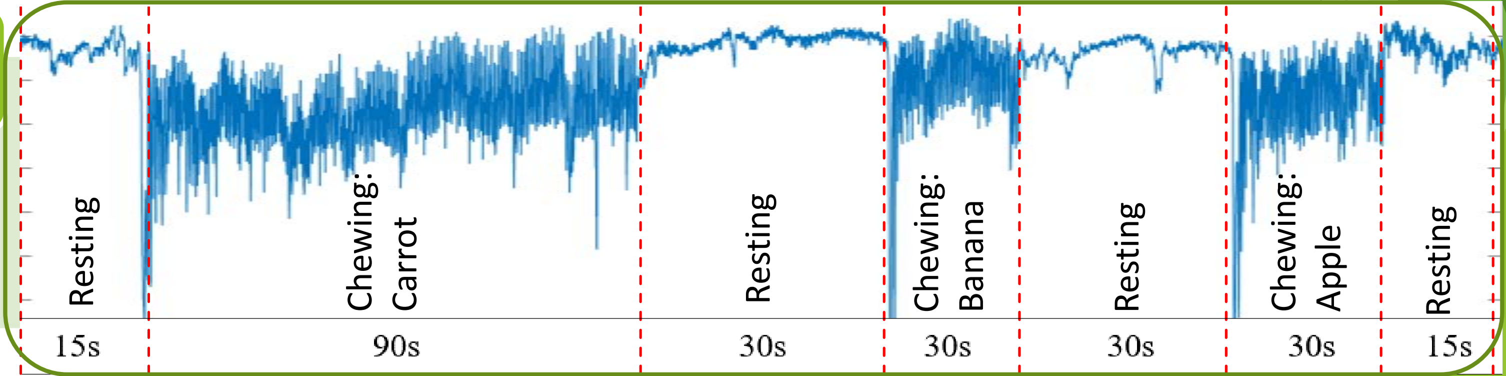
Test food selection & preparation

(a) A spoonful of test food being weight [9g]
(b) A cylindrical food being weight [9g]
(c) A cylindrical food being measure [thickness (±15mm), diameter (±27mm)]
(d) Different food hardness selection: Carrot, banana & apple [7]



Subject & activity

1) Subject: 1 with 10 data set
2) Activity: Eating and resting
3) Time: Each set of data takes 240s and a total of the 2400s for 10 set of data



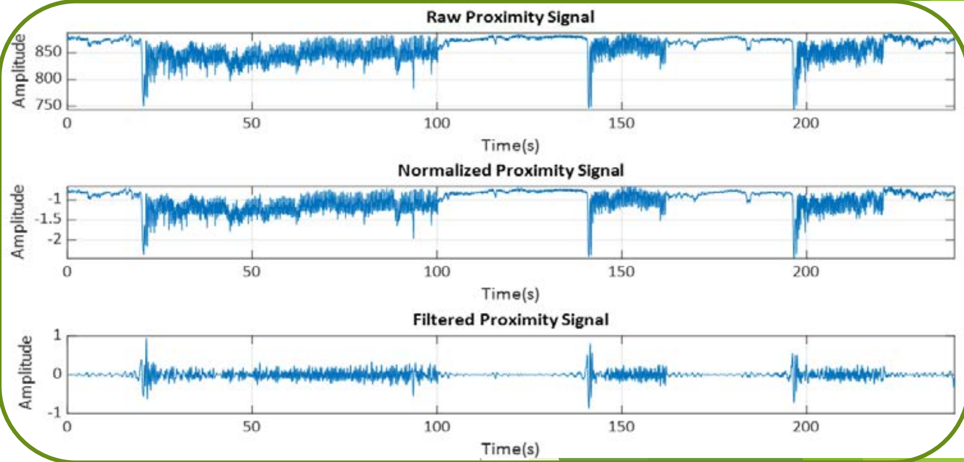
METHODOLOGY

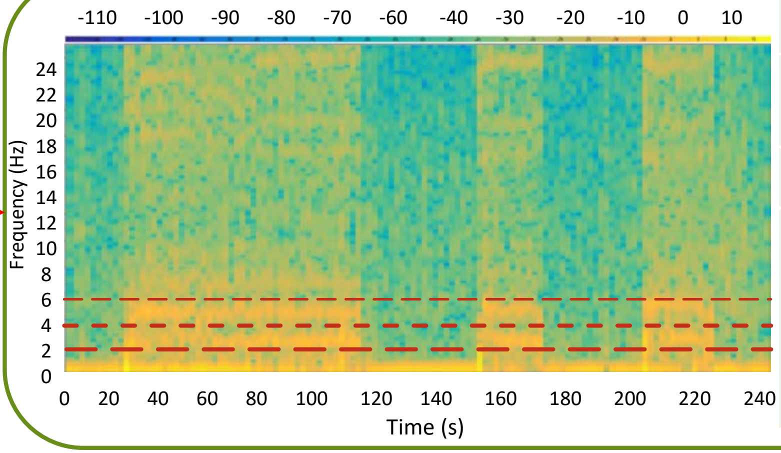
Summary

	Chew detection	Chew count & chewing rate analysis
Data Collection	Subject: one with ten set of data taken Test food: carrot, banana & apple (1 spoonful/9grams) Activity: Eating and resting	
Pre-Processing	Normalization: z-score BPF with fc1=0.5, fc2: 2.4Hz-20Hz	Normalization: z-score BPF with fc1=0.5, fc2: 2.3-2.5Hz, 5Hz & 6Hz
Segmentation /windowing	Type: Hanning Size: 3s Overlap:50%	Type: Hanning Size: 240s Overlap: 0
Feature extracted	Time-domain(TD), Frequency-domain (FD) & TFD (Spectrogram)	Chewing Count: Peak Detection Chewing rate
Performance	MATLAB 2020-Classifier learner; duration-based k-fold=10 Accuracy, F1-score	MATLAB 2020 Count: Mean of Error,

$$\mathrm{z-score} = \frac{x - \bar{x}}{S} \quad (1)$$

x = sample data
$\bar{x}$ = mean of the sample
S = standard deviation of the sample





Features Category	Features (features no. if more than 1)	#features
TD	Min., max., max-min, RMS, median, variance, standard deviation, skewness, kurtosis, interquartile range	10
FD	Mean frequency, power bandwidth, median frequency	3
TFD	Amplitude: ranges of frequency between 1Hz to 3 Hz (6), kurtosis & skewness, concentration measure. PSD: Min. max., mean, median, standard deviation, kurtosis, & skewness. Energy: sum, min, max, mean, energy in four bands of frequency (4).	27

$$Precision = \frac{TP}{TP + FP} \quad (2) \qquad Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F_1\ score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (4)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

TP: true positives, TN : true negatives,
FP: false positives, FN: false negatives

$$|\%Error| = \left| \frac{C_{Act}(n) - C_{Est}(n)}{C_{Act}(n)} \right| \times 100 \quad (6)$$

$$\text{mean } |\%Error| = \frac{1}{M} \sum_{n=1}^{M} \left| \frac{C_{Act}(n) - C_{Est}(n)}{C_{Act}(n)} \right| \times 100 \quad (7)$$

$$C_R = \frac{C_{Act}(n)}{C_T(n)} \times 100 \quad (8)$$

C_{Act}: actual chew count, C_{Est}: chew count estimation,
M: numbers of the chewing episode,
C_T:chewing episode time, C_R : chewing rate,
n: respective chewing episodes.

RESULTS & DISCUSSION

1. Chewing detection

- 2.5Hz gives the lowest accuracy of 92.6% using Medium Gaussian Support Vector Machine (SVM),
- 6Hz gives the highest accuracy value of 97.4% using Quadratic SVM classifier.
- The accuracies of the classifier decrease with a constant rate and maintain in the range of ±97% as the f_{c2} increase.
- The accuracy of the 2.5Hz does not gives comparable accuracy with 6Hz as the f_{c2}.
- This study only considered chewing food and resting, the signal noise due to the motion artifacts could be neglected.

Table 1. Classifier and its performance for variation of the upper cutoff frequency

Fc1 (Hz)	Fc2 (Hz)	Classifier	Accuracy (%)	F1-score (%)
0.5	2.5	SVM: Medium gaussian	92.6	92.48
0.5	3	Ensemble: Boosted tree	93.9	93.79
0.5	3.5	SVM: Medium gaussian	94.8	94.71
0.5	4	SVM: Quadratic	95.3	95.25
0.5	4.5	SVM: Quadratic	96.7	96.66
0.5	5	SVM: Quadratic	97.4	97.35
0.5	5.5	SVM: Medium gaussian	97.1	97.04
0.5	6	Ensemble: Boosted tree	97.6	97.60
0.5	6.5	SVM: Quadratic	97.4	97.36
0.5	7	SVM: Quadratic	97.2	97.21
0.5	8	SVM: Quadratic	96.9	96.97
0.5	9	SVM: Quadratic	97.1	97.16
0.5	10	Ensemble: Boosted tree	97.0	97.01
0.5	15	SVM: Quadratic	96.7	96.70
0.5	20	Ensemble: Boosted tree	96.8	96.75

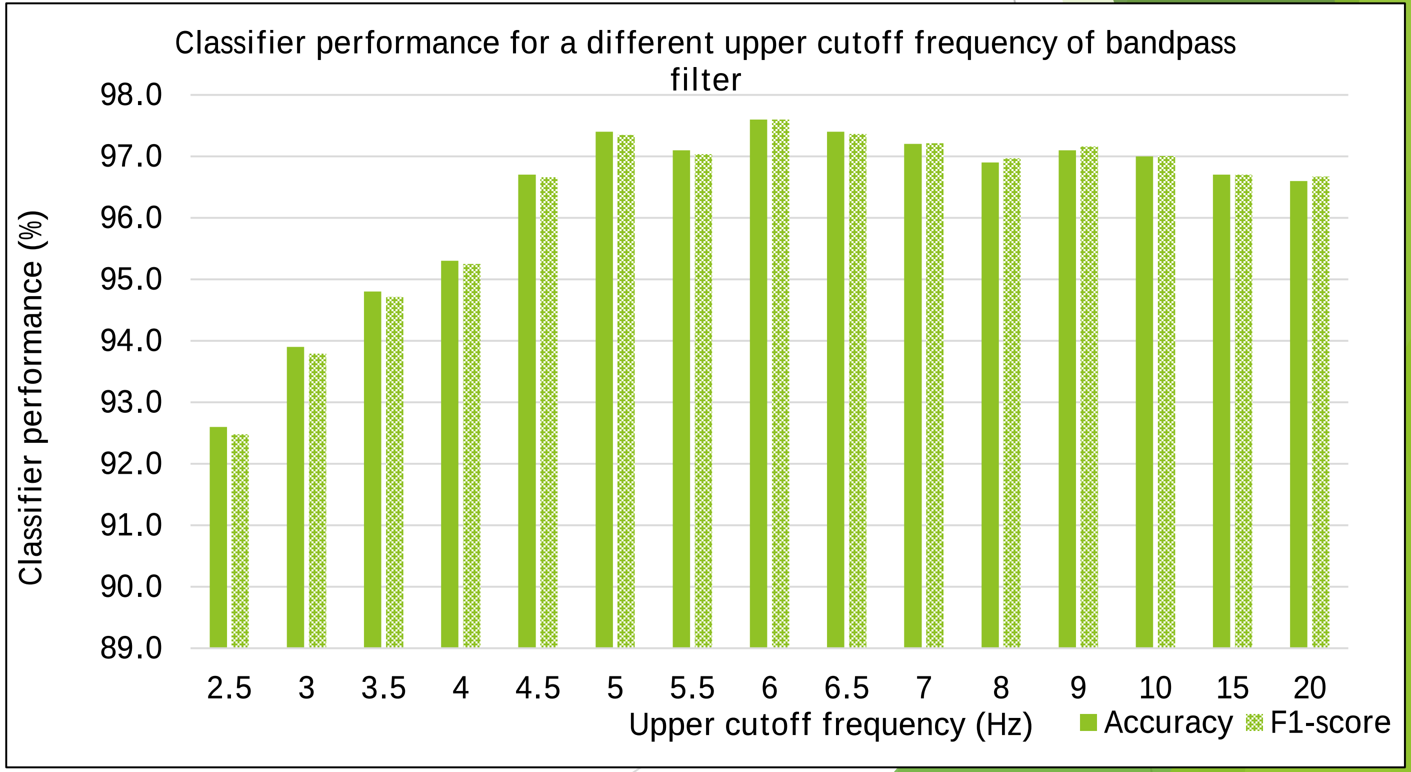


Fig. 1. Classifier performance for a different upper cutoff frequency of bandpass filter

RESULTS & DISCUSSION

2. Chewing count estimation

- For f_{c2} of 2.3Hz, 2.4Hz, and 2.5Hz, only the number of peaks that were in the range of chewing label episodes peaks value greater than 0 will be counted
- For 5Hz and 6Hz, an additional restriction of minimum peak prominence of 0.33 and 0.35 was implemented, respectively.
- 2.4Hz gives the smallest total absolute error of 2.69% compared to other f_{c2}
- The total absolute error obtained is comparable or even smaller compared to the previous study 8.09±7.16%[25], 10.4%±7.0%[21], 9.66%[26], 3.83%[27], and 12.2%[9] which used method of the peak detection algorithm, histogram-peak detection algorithm, multiple regression model, multivariate regression model, and maximum frequency component (MFC), respectively

Table 2. Mean absolute error of chewing count estimation

F_{c2}	Chewing episodes											
	Carrot			Banana			Apple			Total		
	Mean			Mean			Mean			Mean		
	C_{Est}	%error	|%e|	C_{Est}	%error	|%e|	C_{Est}	%error	|%e|	C_{Est}	%error	|%e|
2.3	168.5	0.14	3.91	41.00	-2.16	5.00	49.20	7.70	11.38	258.70	1.46	3.90
2.4	171.30	-1.52	3.16	42.2	-4.54	6.02	52	2.79	6.41	265.50	-1.04	2.69
2.5	172.20	-2.03	2.90	42.90	-6.66	7.25	54.30	-1.11	6.90	269.40	-2.41	3.21
5	177.10	-5.11	14.13	37.50	7.36	9.61	48.70	9.04	18.17	263.30	-0.23	11.77
6	175	-3.92	13.62	37.5	7.56	9.42	51.50	3.56	14.99	264	-0.43	12.11

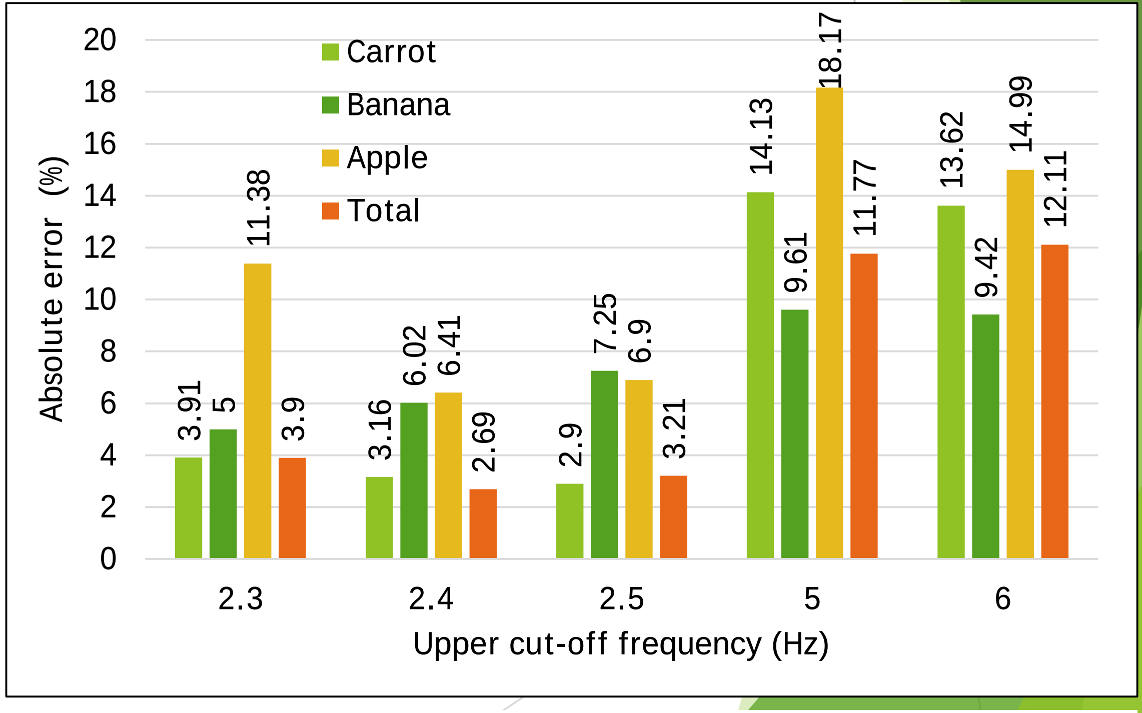


Fig. 2. The absolute error of chewing count for different upper cut-off frequency

RESULTS & DISCUSSION

3. Chewing rate

- The chewing rate for all food types was in the range of 1.7Hz to 2.3Hz.
- the total chewing count could be used to differentiate the food hardness.
- The chewing rate does not show an obvious pattern during chewing food with different hardness

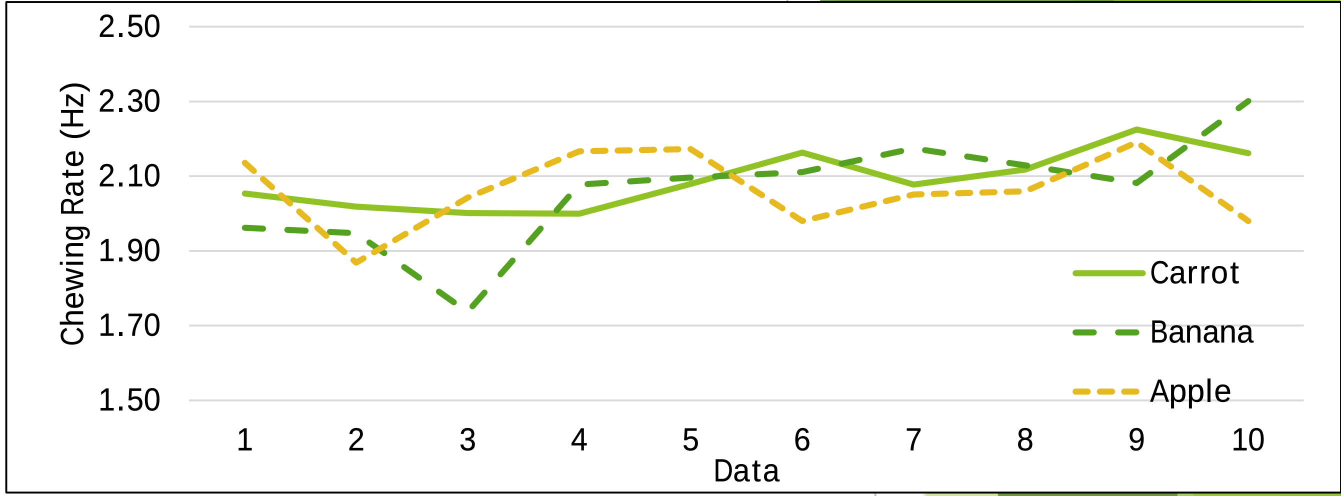


Fig. 3. The chewing rate based on food type for f_{c2} equal to 2.4Hz

Table 3. Percentage of error based on total chewing count for f_{c2} equal to 2.4Hz

	Carrot	Banana	Apple	Total
C_{Est}	1713	429	520	2655
C_{Act}	1697	402	536	2635
|%error|	0.94	6.72	2.99	0.76

Table 4. The details of the chew count estimation in a dataset for f_{c2} equal to 2.4Hz

	Chewing episodes											
	Carrot			Banana			Apple			Total		
	C_{Est}	%e	|%e|	C_{Est}	%e	|%e|	C_{Est}	%e	|%e|	C_{Est}	%e	|%e|
Sum	1713			429			520			2655		
Mean	171.3	-1.52	3.16	42.20	-4.54	6.02	52.00	2.79	6.41	265.5	-1.04	2.69
STD	19.36	4.86	3.88	10.10	6.77	5.33	12.95	9.34	7.09	28.83	3.59	2.45

Table 5. The chewing rate for f_{c2} equal to 2.4Hz

Data	Chewing rate (Signal)					
	Carrot		Banana		Apple	
	C_T(s)	C_R(Hz)	C_T(s)	C_R(Hz)	C_T(s)	C_R(Hz)
1	74.52	2.05	18.86	1.96	33.72	2.14
2	62.42	2.02	17.98	1.95	18.74	1.87
3	83.44	2.00	14.40	1.74	24.00	2.04
4	86.54	2.00	19.74	2.08	33.70	2.17
5	85.62	2.08	17.18	2.10	20.26	2.17
6	90.62	2.16	24.64	2.11	17.68	1.98
7	85.68	2.08	26.68	2.17	25.36	2.05
8	85.00	2.12	22.08	2.13	27.20	2.06
9	81.80	2.23	18.26	2.08	24.20	2.19
10	83.28	2.16	23.04	2.30	25.76	1.98
Mean	81.89	2.09	20.28	2.06	25.06	2.06
SD	7.98	0.08	3.75	0.15	5.52	0.10

CHALLENGES

- By focusing on the use of f_{c2} of 2.4Hz and 6Hz and referring to the classification stage results and chewing count estimation results, an inference can be made that the chewing frequency is in the range of 2.5Hz.
- The 2.5Hz does not give good accuracy in the classification stage as the labeling of the chewing signal is based on the self-reporting (using pushbutton).
- There chewing signal and the chewing label does not tally, due to delay in pushing the pushbutton or during data collection (obtaining the label data) as the self-reporting label approach was used.
- The unsynchronized data and label would affect when shorter window segmentation was used as the chewing data wrongly label.
- This was proven as the chewing classification stage used a shorter window of 3s compared to the chewing count estimation of 240s.

CONCLUSION

- The proposed system was able to give high accuracy with 97.6% and F1-score of 97.6% of chewing detection using f_{c2} equal to 6Hz in its bandpass filter.
- As f_{c2} is set to 2.5Hz the accuracy reduced to 92.6%, however, the percentage of mean absolute error gives a good value of 3.21% compared to 6Hz with 12.11%.
- The f_{c2} was then changed to f_{c2} of 2.4Hz aiming to find the optimal f_{c2}, and the results do improve with the percentage of error of 2.69%.
- While the results of relating the chewing count with the different food hardness show a potential and could be further investigated. The results suggest that the proposed approach could be used in characterizing the chewing activity.
- Future work: further modification of labeling methods by either using manual or improving the current self-reporting labeling method is required. Besides, more data will be collected with different subjects in proving the effectiveness of the systems.

ACKNOWLEDGEMENT

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THANK YOU