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Fuzzy Classifier Based Ingestive Monitor

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Abstract---*The observation of food intake and ingestive behavior remains an open problem that has significant implications in the study and treatment of obesity and eating disorders. A novel method of fusing a sensor and pattern recognition method was developed to detect periods of food intake based on non-invasive monitoring of chewing. A surface-type EMG electrode was used to capture the movement of the lower jaw from volunteers during periods of quiet sitting, and food consumption. These signals were processed to extract the most relevant features, identifying from 4 to 10 features most critical for classifying the type of food consumed. Fuzzy classifiers were trained to create food intake, detection models. The simplicity of the sensor may result in a less intrusive and simpler way to detect food intake. The proposed system is implemented using LabVIEW. The proposed methodology could lead to the development of a wearable sensor system to assess eating behaviors of individuals and also to calculate the quantity of food intake.*
Keywords---*EMG electrode, fuzzy classifier, labView.*

Introduction

Automatic dietary monitoring aims at simplifying the reporting of individual eating behavior for weight and diet coaching programs (Amft, 2010). Obesity is a global epidemic that imposes a financial burden and increased risk for a myriad of chronic diseases. A prototype automated ingestion detection (AID) process is implemented in a health monitoring system (HMS). The automated detection of ingestion supports personal record keeping which is essential during obesity management. Personal record keeping allows the care provider to monitor the therapeutic progress of a patient. (Amft & Troster, 2009), sensor fusion and pattern recognition method were developed for subject-independent food intake recognition. The device and the methodology were validated with data collected from various subjects wearing AIM during the course of 24 h in which both the daily activities and the food intake of the subjects were not restricted in any way. Results showed that the system was able to detect food intake with an average accuracy of 89.8%, which suggests that AIM can potentially be used as an instrument to monitor ingestive behavior in free-living individuals (Amft *et al.*, 2005). The proposed system deals with classifying the type of food intake which would be helping the hospitalized people to intimate a limit on the type and amount of food intake. Effective interventions are required to reduce the incidence of obesity and eating disorders and their life-threatening complications (Marimuthu & Ramesh, 2016).

Hardware and Methodology

An EMG electrode is fixed on the cheeks of the individual for monitoring the chewing of food (Beigl *et al.*, 2005). The bioelectrical activity inside the muscle of a human body is detected with the help of EMG electrodes. There are two main types of EMG electrodes: Surface (or skin electrodes) and inserted electrodes. The EMG electrode used here is of surface type electrode. Surface EMG assesses muscle function by recording muscle activity from the surface above the muscle on the skin. Surface electrodes are able to provide only a limited assessment of muscle activity. Surface EMG can be recorded by a pair of electrodes or by a more complex array of multiple electrodes (Brown, 1994). More than one electrode is needed because EMG recordings display the potential difference between two separate electrodes. Limitations of this approach are the fact that surface electrode recordings are restricted to

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superficial muscles, are influenced by the depth of the subcutaneous tissue at the site of the recording which can be highly variable depending on the weight of a patient, and cannot reliably discriminate between the discharges of adjacent muscles. These electrodes are simple and very easy to implement. Application of needle and fine wire electrodes require strict medical supervision and certification (Dacremont, 1995). Surface EMG electrodes require no such formalities. Surface EMG electrodes have found their use in motor behavior studies, neuromuscular recordings, sports medical evaluations and for subjects who object to needle insertions such as children. Apart from all this, surface EMG is being increasingly used to detect muscle. GenioGlossus (GG) muscle activity was measured with customized surface electrodes, while other muscles were recorded with conventional surface electrodes. EMG activities during tongue displacement and the articulation of long vowels, recorded by the customized electrodes, were consistent with the recordings obtained by fine wire electrodes placed in the GG muscle (Fontana & Sazonov, 2012; Fontana *et al.*, 2014; Paßler & Fischer, 2011).

DAQ Setup

Data acquisition is the process of sampling signals that measure real world physical conditions and converting the resulting samples into digital numeric values that can be manipulated by a computer. Data acquisition systems, abbreviated by the acronyms DAS or DAQ, typically convert analog waveforms into digital values for processing. The components of data acquisition systems include Sensors, to convert physical parameters to electrical signals. Signal conditioning circuitry, to convert sensor signals into a form that can be converted to digital values. Analog-to-digital converters, to convert conditioned sensor signals to digital values (Vickers, 1985; Walker & Bhatia, 2013).

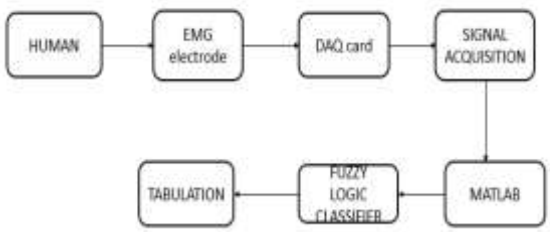

Figure 1. Block Diagram

The input is acquired using a DAQ card interfaced to a PC. The DAQ Assistant, included with NI-DAQmx, is a graphical, interactive guide for configuring, testing, and acquiring measurement data. With a single click, the code can even be generated based on the configuration, making it easier and faster to develop complex operations. Because DAQ Assistant is completely menu-driven, there will be fewer programming errors and drastically decrease the time from setting up a DAQ system to taking the first measurement. DAQ hardware acts as the interface between the computer and the outside world. It primarily functions as a device that digitizes incoming analog signals so that the computer can interpret them a DAQ device.

Figure 2. Surface electrode with NI-DAQ and measurement of the input signal

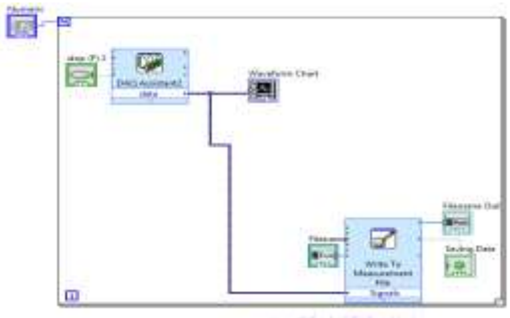

Figure 3. Block diagram to acquire the input signal in LabVIEW

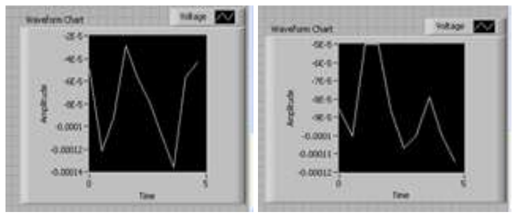

Figure 4. Reconstructed Input waveforms

The test system of fuzzy system designer for chew movement

Input values

When a person chews with EMG electrode fixed on his cheeks, the values of various parameters are obtained in the indicators in LabVIEW. These values viz., Arithmetic mean, RMS, Standard deviation and Variance are fed into MATLAB for fuzzy classifiers in order to classify the food. The block diagram to find statistical features in LabVIEW and the measured statistical features are shown in Figure 5.

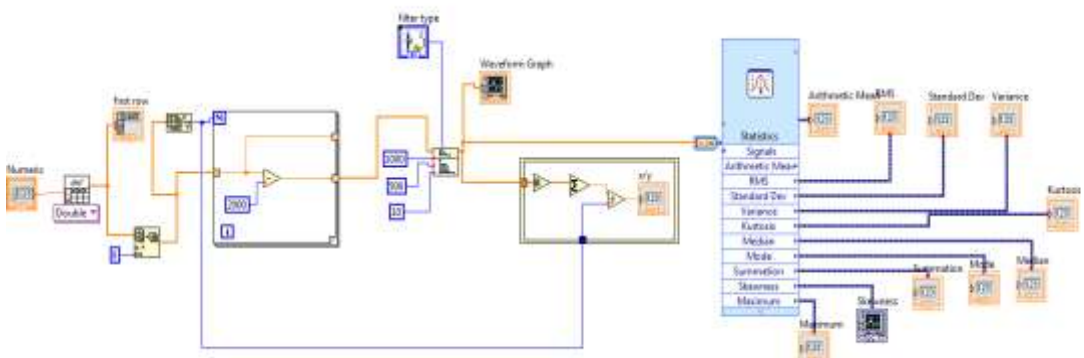

Fig. 5. Block Diagram to measure statistical features in labview

Table 1
Statistical parameters

Sample	Mean	Rms	Std Deviation	Variance	Summation	Mode	Kurtosis	Median
BIS1	-7.7269E-5	8.4487E-5	3.6016E-5	1.2971E-10	-0.0007	-5.7E-5	1.4626	-6.7949E-5
BIS2	-8.7147E-5	8.9656E-5	2.2200E-5	4.9285E-10	-0.00871	-0.0010	1.8702	-9.2915E-5
BIS3	-0.00010	0.00022	0.00021	4.5276E-8	-0.00102	-0.00069	6.0099	-3.5762E-5

BIS4	-0.00012	0.00015	8.7802E-5	7.7093E-9	-0.00126	-0.00026	1.7185	-0.00132
BUN1	-0.00020	0.00028	0.00020	4.0805E-8	-0.00209	-6.5664E-5	1.6240	-0.00013
BUN2	-6.5056E-5	7.9892E-5	4.8882E-5	2.3895E-9	-0.00650	-9.9418E-5	1.8645	-7.8678E-5
BUN3	-0.00020	0.00025	0.00015	2.3964E-8	-0.00204	-0.00286	1.9356	-0.000179
BUN4	-4.7924E-5	7.1596E-5	5.6051E-5	3.1418E-9	-0.00047	-5.8052E-5	1.80048	-4.6491E-5

Algorithm for EMG Classification

The control of assistive devices and exoskeletons using EMG signals has been the focus of many researchers. As EMG signals are complex in nature, EMG classification for motion detection is a challenging task. The various approaches used to efficiently classify the EMG signals are summarized as follows (1) Neural network (2) Fuzzy logic (3) Hybrid fuzzy-neural approaches and (4) Particle swarm optimization-SVM based. In the presented work fuzzy logic approach is used for classification of EMG signals. Fuzzy logic has the ability to deal with imprecise, uncertain and imperfect information. The strength of fuzzy logic lies in the fact that it is based on the reasoning inspired by human decision-making. This fuzzy logic is used to handle the vagueness intrinsic to many problems by representing them mathematically. The fuzzy classifier for the proposed system is implemented using MATLAB software as shown in Figure 5.

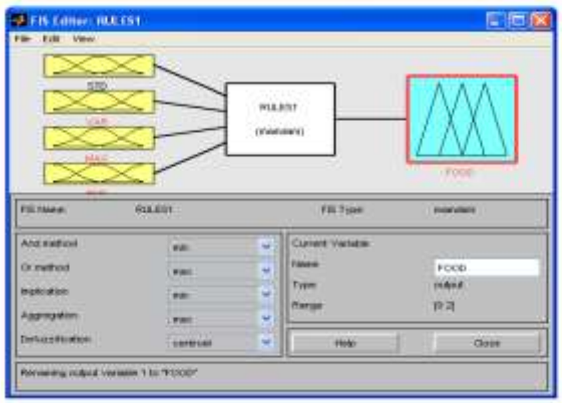

Figure 6. FIS Editor for the proposed system

Membership Function

The membership function of a fuzzy set is a generalization of the indicator function in classical sets. In fuzzy logic, it represents the degree of truth as an extension of valuation. Degrees of truth is often confused with probabilities, although they are conceptually distinct because fuzzy truth represents membership in vaguely defined sets, not the likelihood of some event or condition. Membership functions were introduced by Zadeh in the first paper on fuzzy sets (1965). Zadeh, in his theory of fuzzy sets, proposed using a membership function (with a range covering the interval (0,1)) operating on the domain of all possible values. For any set, a membership function on is any function from to the real unit interval.

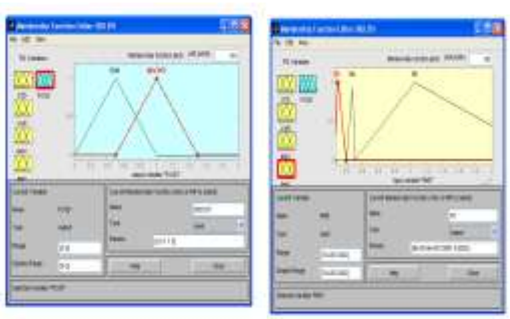

Fig.7 and Fig.8. Membership function value for food classification

The membership degree quantifies the grade of membership of the element to the fuzzy set. The value 0 means that is not a member of the fuzzy set; the value 1 means that is fully a member of the fuzzy set. The values between 0 and 1 characterize fuzzy members, which belong to the Fuzzy set only partially.

Fuzzy Rules

Human beings make decisions based on rules. Although we may not be aware of it, all the decisions we make are all based on the computer like if-then statements. If the weather is fine, then we may decide to go out. If the forecast says the weather will be bad today, but fine tomorrow, then we make a decision not to go today and postpone it till tomorrow. Rules associate ideas and relate one event to another (Sazonov *et al.*, 2008).

Fuzzy machines, which always tend to mimic the behavior of man, work the same way. However, the decision and the means of choosing that decision are replaced by fuzzy sets and the rules are replaced by fuzzy rules. Fuzzy rules also operate using a series of if-then statements. For instance, if X then A, if y then b, where A and B are all sets of X and Y.

Fig.9. Fuzzy Rules for food classification

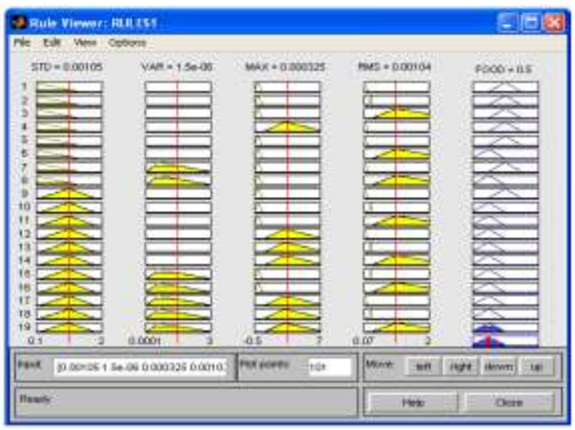

Fig.10. Rule Viewer for Bun

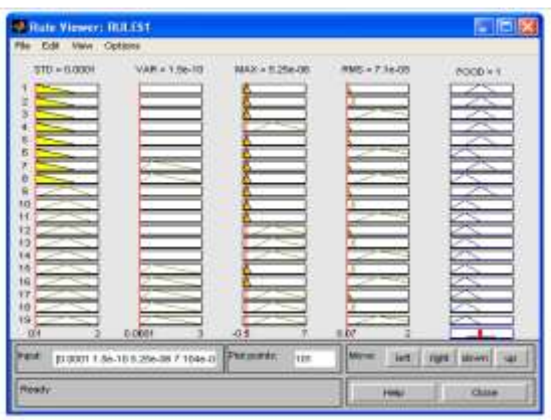

Fig.11. Rule Viewer for Biscuit

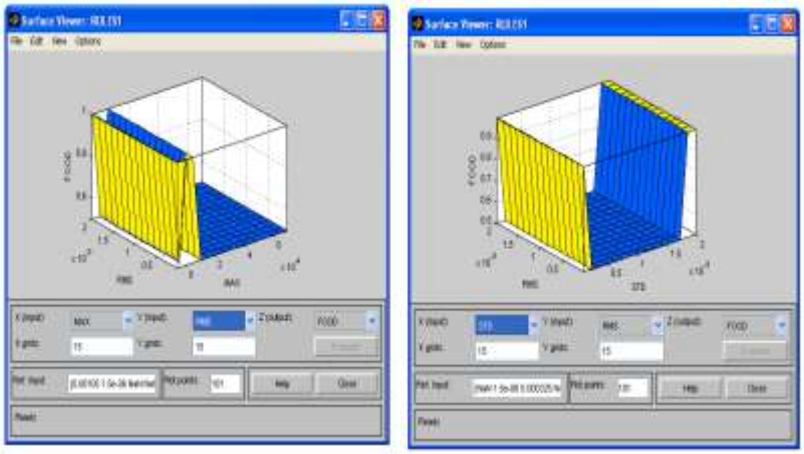

Fig.12. Surface Viewer

Validation of Output

The values obtained during chewing are compared with the threshold values and the type of food is indicated. In this case, 0.5 indicates bun and 1 indicates biscuit. Based on this value the output is displayed. Fuzzy logic classifiers are used for this purpose.

Table 2
Validation of output for consuming Bun

SAMPLE	STANDARD DEVIATION	VARIANCE	MAX	RMS	OUTPUT
1	0.0021	4.5e-8	7e-5	0.0003	1
2	5e-5	2e-9	4e-5	0.00012	1
3	8e-5	2e-8	0	0.00015	1
4	7e-5	3e-8	2e-5	0.0001	1
5	e-5	3e-11	-6e-5	0.00006	1
6	4e-5	5e-9	-2e-5	0.00012	1
7	9e-5	3e-8	-e-5	0.00019	1
8	0.00018	e-8	e-5	8e-5	1
9	0.00015	1.29e-10	-3e-5	8e-5	1
10	2e-6	4.3e-8	-8e-5	0.00005	NaN

$$Success\ Rate = \frac{No.of\ Successfull\ Trials}{Total\ number\ of\ Trials} * 100$$

$$=(9/10)*100$$

$$=90\%$$

Table 3
Validation of output for consuming Biscuit

SAMPLE	STANDARD DEVIATION	VARIANCE	MAX	RMS	OUTPUT
1	0.0010	1.5e-6	0.000325	0.00103	0.5
2	0.0005	2e-6	0.0001	0.001	0.5
3	0.0009	5e-8	0.0002	0.00035	0.5
4	0.00075	5e-7	1.8e-5	0.0004	0.5
5	0.0012	7e-7	0.00015	0.0008	0.5
6	0.00035	3e-8	0.00052	0.0019	NaN
7	0.00065	2.5e-8	0.0006	0.0008	NaN
8	0.00059	6e-8	8e-5	0.0007	0.5
9	0.0008	1.5e-6	0.0007	0.0005	0.5
10	0.0014	8e-7	9.5e-5	0.0011	0.5

$$Success\ Rate = \frac{No.of\ Successfull\ Trials}{Total\ number\ of\ Trials} * 100$$

$$=(8/10)*100$$

$$=80\%$$

Conclusion and Future Scope

The proposed system can be used to classify the type of food intake by the humans which in turn can be used to monitor the dietary behavior of hospitalized people and others suffering from obesity. It would also intend to serve as a behavioral modification tool for correcting known ingestive behaviors leading to weight gain (snacking, night eating, and weekend overeating) and would help to advance the study of free-living food consumption in obesity and in other eating disorders. It can also be extended to find out the amount of food consumed and many classifier algorithms can be implemented to improve the accuracy of the classifier output.

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