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An Implemetation of Real-Time Wearable Monitoring of the Lower-Leg Edema Using Bioimpedance

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Abstract— **Cardiovascular disease is the leading cause of death in the United States. We propose a wearable sensor for continuous monitoring of edema in lower legs using bioimpedance. Bioimpedance devices are able to accurately measure Extra Cellular Water (ECW) and Total Body Water (TBW) using whole body measurements. This work details the implementation of a continuous real time, non-invasive wearable bioimpedance and activity monitoring system. The system collects a complex bioimpedance of the lower leg together with user's activity collected from an inertial sensor. The preliminary results indicate that activity state classification model achieved accuracy of 94.0 % based on bioimpedance only. We plan to use the system for monitoring of lower leg edema throughout the day as a part of diagnostic analysis of heart failure patients.**

***Keywords*—-Edema, Bioimpedance, Activity Monitoring, Wearable Monitoring, Cardiovascular Disease**

I. Introduction

Cardiovascular disease is the leading cause of death in the United States with 697,000 deaths in 2020—that's 1 in every 5 deaths [1], [2]. Cardiovascular disease is the most expensive direct health expenditure in the United States [3]. Population trends show the United States' population's mean age rapidly increasing and this increases the burden on our health care system [4]. The total projected cost of cardiovascular disease estimates a cost of over 1 trillion dollars by 2035 in the United States, almost double from the total cost of cardiovascular disease in 2015, which was 530 million dollars[3].

An edema is swelling caused by excess fluid trapped in body tissues. Severe edema in the lower leg is strongly correlated with heart failure[5]. However, current systems are unable to quantify the severity of the edema or edema index[6].

Real-time Bioimpedance-based edema and human activity monitoring applications have demonstrated promising potential for noninvasive cardiovascular disease monitoring and diagnostic applications. [5], [7], [8], [9], [10] . For this potential to be realized several challenges must be overcome: unobtrusive continuous monitoring of edema during activities of daily living, quantification of the edema index, determination of the clear cutoff points for important biomarkers such as phase angle and impedance ratio, accounting for subject variabilities across patients, and streamlining complex calibration processes that exist in current edema monitoring systems. Machine Learning techniques show promise in solving these challenges, but development, experimentation, and implementation is limited due to a lack of application specific data sets.

This project overcomes this significant problem by implementing a continuous real-time bioimpedance and activity monitoring device that can be applied to collect clinically relevant bioimpedance data. This project also lays the foundation for a future large scale clinical trial using this device to collect a large application specific dataset for bioimpedance based cardiovascular applications.

II. Background

Machine Learning (ML) techniques are currently being used to increase medical diagnostic accuracy, enable early disease detection, and to provide insight on underlying disease mechanisms that other disciplines can use to develop disease treatments and even cures[8]. Early detection of heart failure is strongly correlated with patient survival rate, and recently developed edema monitoring devices have greatly contributed to early detection[10].

Machine learning techniques require significant sets of clinical data. Advances in sensor manufacturing and in embedded computers have enabled high fidelity bioimpedance sensors to be integrated on a systems-on-a-chip equipped with an ADC to enable continuous real-time data to be collected and monitored from patients. By interfacing with these sophisticated systems-on-a-chip the data needed to train application specific machine learning models can be obtained. This work uses bioimpedance as the best noninvasive metric to assess edema index. Previous works have defined edema index as the ratio of extracellular water (ECW) to total body water (TBW) [7]. Bioimpedance devices are able to accurately measure ECW and TBW [8] using changes of complex bioimpedance of body segments at different stimulation frequencies. Typically, impedance at lower frequencies is correlated with TBW, and impedance at higher frequencies is correlated with ECW. The data collection will be accompanied by a survey to collect information such as gender, age, height, weight, obesity, and ethnicity which have been shown to affect individual bioimpedance measurements [8]. If patients have an edema assessment by a medical professional in an office visit during the duration of this survey the edema index this data will be time stamped and added to the collected data. Current edema monitoring devices require significant calibration from both engineering and medical

professions to receive data that is useful for an individual's body.

It is important to consider desired biometrics and foreseeable ML feature engineering during the design phase. During the literature review two particularly useful clinically significant biometrics were discovered.

III. RELATED WORK

Fallanzadeh et al. implemented a Smart-Cuff to monitor ankle edema by using both accelerometers based human activity recognition and circumference derived data from a flexible fabric stretch sensor. The authors were able to obtain a 96% accuracy in human activity recognition and a Pearson correlation of 0.97 for edema detection.[6] The study revealed many of the current weaknesses with edema monitoring technology. The weaknesses of conventional in-clinic assessment of edema has several disadvantages which are in this paper: it is burdensome for older patients, it is expensive for patients, healthcare systems, and insurance companies, the lack on contextual activity information can result in unreliable information, and current assessment is prone to human error. Smart Sock applied a sliding window used for acceleration data which allowed for an 80% of overlap between successive segments. 10 statistical temporal features were chosen: amplitude, median, mean, maximum, minimum, peak to peak, standard deviation, variance, root mean square power, and start to end value from each segment. [8]

Calf edema monitoring has also been performed using a voltage strain gauge calibrated for each patient. After calibration the strain gate can detect changes in calf circumference.[11] One limitation of this device is that it requires calibration that could be prohibitive in a home patient setting.

A UAH Smart Water Bottle uses bioimpedance to facilitate real time hydration monitoring.[12] This work used a custom board with AFE4300 [13] weight-scale and body-composition measurement analog front end to implement bioimpedance monitoring. This research uses the same bioimpedance sensor.

Current monitoring approaches have significant limitations that need to be overcome. Current systems are unable to quantify the edema index. This information is important for medical diagnostic accuracy. Many current methods require complex calibration and setup which can make reliable monitoring outside of a clinical setting difficult for patients. Machine learning has yet to be applied to many problems in this domain such as edema index and calibration. This project works to solve these issues by collecting the clinical data sets required for ML applications and simplifying the calibration process.

IV. IMPLEMENTATION

In this project we use a Teensy LC controller to interface with a custom AFE4300 based bioimpedance sensor board that communicate using SPI protocol. Teensy LC provides the correct clock for the desired bioimpedance scan frequency and reads most recent measurement value at the desired measurement sampling frequency. We proposed the use of wearable sensor that can monitor relative changes in TBW and ECW in body segments throughout the day. Overall swelling depends on the time of the day and physical activity of the user. The device uses a standard 4-electrode configuration with two pairs of electrodes to source and sink measurement current to reduce noise.

Each measurement is then sent to a receiver over Bluetooth which logs the measured data for later analysis.

The device is powered using a battery and is enclosed in a case. The enclosure is attached to a leg brace using Velcro tape.

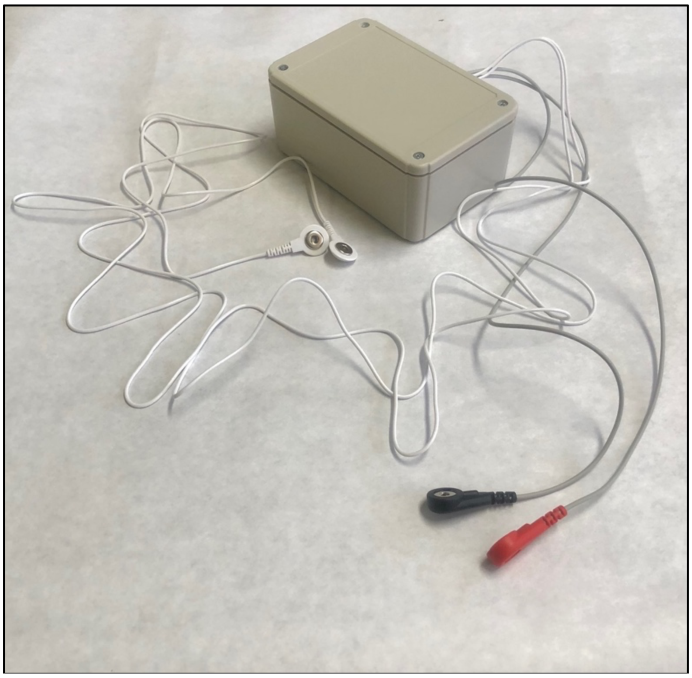

Figure 1: Wearable Real-time Bioimpedance Monitoring Device Enclosure

V. FEATURE ENGINEERING

Bioimpedance controller provides measures of complex bioimpedance components I and Q (resistance and reactance). [13]

Phase Angle (PA) is found as inverse tangent of reactance to resistance. Studies allege that it relates to important cellular characteristics including membrane capacitance, integrity, and permeability. Higher Pa has been interpreted to mean more intact cell membranes and a higher BCM. Lower Pa is associated with longer hospital stay, death, nutrition risk, and diseases. [8] [9] The primary challenge of using PA for clinical assessment is the lack of consensus on cut-points to be used to identify malnutrition. Clear cut-points need to be determined.

Impedance Ratio (IR) several studies have suggested that the differences between bioimpedance at high and low frequencies reflect the ratio between ECW/TBW fluid distribution. Additional research is needed to better identify standardized cut-points and to validate those cut-points in terms of current malnutrition criteria. [8]

PA, IR, ECW, and TBW can be determined using the metric logged from the device. The magnitude and phase angle have

been applied to train a classification model in this work. The other features will be evaluated in future work.

VI. Data Collection

Proof of concept data was collected from the lower leg of a subject in 4 activity states: laying down, sitting, standing, and walking. The electrodes sourcing current were placed on one side of the calf and the electrodes sinking current were placed across the calf on the opposite side of the leg.

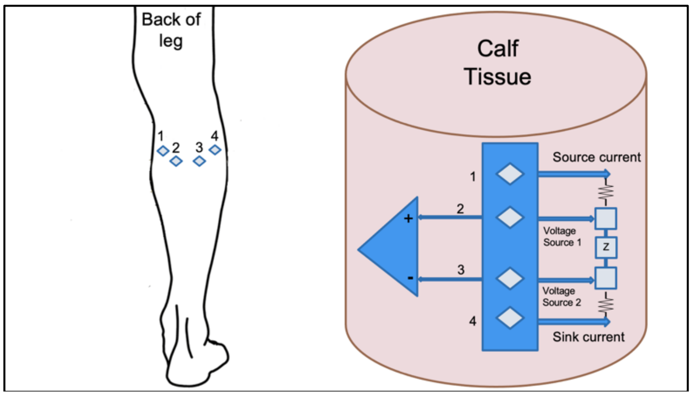

Figure 2: Electrode placement for a four electrode bioimpedance monitoring.

The validation data discussed in this manuscript measured the bioimpedance across the lower leg with a 16KHz sinusoidal current. Measurements were taken with sampling frequency of 15Hz.

VII. Data Analysis

The calibration constant and offset are derived using linear interpolation.

$$ax + b = y$$

a – Calibration constant
x – Raw measurement
b – Offset
y – Calibrated value

Linear interpolation was completed on the 100-ohm trial to find calibration equations for both magnitude and phase. For this trial, we know that the impedance we are measuring is 100 ohms and the phase is 0 degrees. These calibration constants have been applied to derive measurements in Table 1 and Table 2.

Trial	**Mean**	**Standard Deviation**	**coefficient of variation (CV)**
100 Ohm Mag. (Ω)	99.72	0.23	0.0023
100 Ohm Phase (rad)	-0.11	0.0028	-0.03
200 Ohm Mag. (Ω)	201.72	5.02	0.25
200 Ohm Phase (rad)	-0.01	0.0050	-0.50

Table 1: Validation results

The coefficient of variation is derived by taking the standard deviation divided by the mean, multiplied by 100%. The activity data is listed below.

Trial	**Mean**	**Standard Deviation**	**Variance**
Laying Down Mag. (Ω)	12.02	0.05	0.0026
Laying Down Phase (rad)	0.34	0.07	0.0053
Sitting Mag. (Ω)	12.30	0.04	0.0013
Sitting Phase (rad)	0.35	0.13	0.02
Standing Mag. (Ω)	13.42	0.06	3.8e-3
Standing Phase (rad)	0.30	0.0039	1.49e-05
Walking Mag. (Ω)	13.25	0.37	0.13
Walking Phase (rad)	0.31	0.01	1.17e-04

Table 2: Mean, Standard Deviation, and Variance by Activity

T-Tests are used to determine if differences between trials are due to stochasticity or differences in populations. Because the variances between the trials are unequal, I need to use the following formula to calculate the t-test.

The T-test is derived using the following equation.

$$T = \frac{\mu_1 - \mu_2}{\sqrt{\frac{V1}{N_1} + \frac{V2}{N_2}}}$$

μ_1 – Mean of set 1
μ_2 – Mean of set 2
$V_1 = (\sigma_1)^2$ – *Variance of set* 1
$V_2 = (\sigma_2)^2$ – *Variance of set* 2
N_1 – *Number of data points in set* 1
N_2 – *Number of data points in set* 2
Df = $N_1 + N_2$ – Degrees Freedom

T-Tests have been performed both magnitude and phase data from each activity state and all null hypotheses were rejected with a 1% significance level.

The results of these T-Tests indicate that the differences between activity states are not due to noise. Values of magnitude and phase during different states and postures are represented in Figs. 3 and 4.

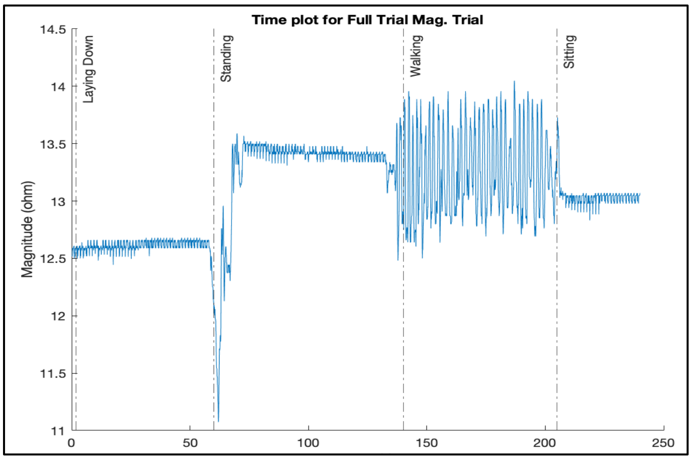

Figure 3: Measured impedance magnitudes by activity.

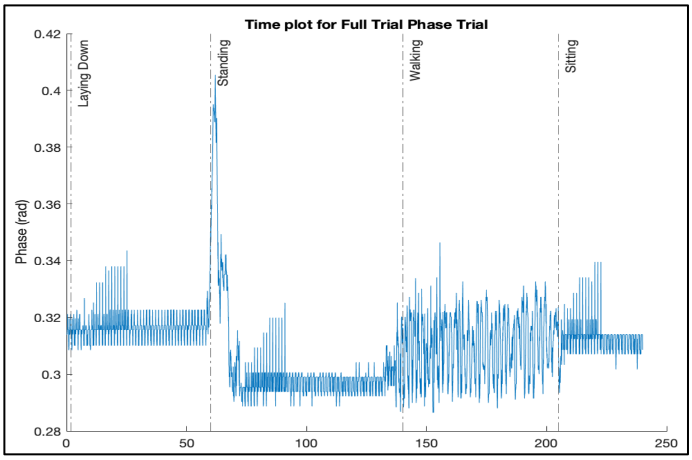

Figure 4: Measured impedance phase by activity

VIII. Machine Learning Classification Implementation

K-nearest neighbor machine learning model was trained on label activity state data with the following four features: Imaginary Component, Real Component, Magnitude, Phase Angle. After training the model achieved an accuracy of 94.0 percent.

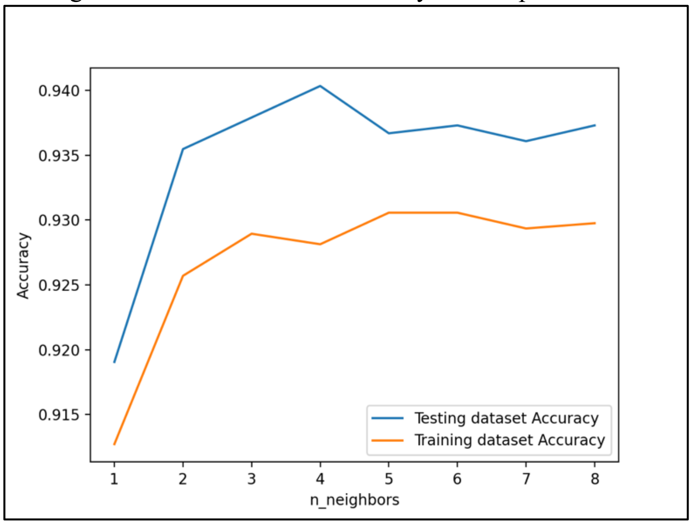

Figure 5: K-Nearest Neighbor Classification Accuracy

The model does not accurately categorize the sitting state. We believe that the reason is similarity of lower leg swelling in sitting and standing state.

IX. Conclusion

In this paper we present a prototype wearable sensor for monitoring of lower leg edema using complex bioimpedance of calf muscle. We implemented a real-time wearable sensor that collects lower leg bioimpedance and human activity from inertial sensors. We plan to use the system to assess edema of lower legs in heart failure and kidney patients. We plan to use machine learning for assessment of changes in different postures and improve diagnostic procedures for cardiovascular and kindey patients. We will apply machine learning techniques to quantify edema severity and account for subject variability.

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