SmartSock: A Wearable Platform for Context-Aware Assessment of Ankle Edema

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Abstract— **Ankle edema is one the most significant symptoms for monitoring patients with chronic systematic diseases. It is an important indicator of onset or exacerbation of a variety of diseases that disturb cardiovascular, renal, or hepatic system such as heart, liver, and kidney failure, diabetes, etc. The current approaches toward edema assessment is conducted during clinical visits. In-clinic assessments, in addition to being greatly burdensome and expensive, are sometimes not reliable and neglect important contextual factors such as patient's physical activity level and body posture. A novel wearable sensor, namely SmartSock, equipped with accelerometer and flexible stretch sensor embedded in clothing is presented. SmartSock is powered by advanced machine learning, signal processing, and correlation techniques to provide real-time, reliable, and context-rich information in remote settings. Our experiments on human subjects indicate high confidence in activity and posture recognition (with an accuracy of $> 96\%$) as well as excellent reliability in edema quantification with intra-class correlation and Pearson correlation of 0.97.**

I. INTRODUCTION

Tens of millions of people in United Stated are currently diagnosed with various systematic diseases related to cardiovascular, renal, and hepatic system. Examples include chronic heart failure, COPD, chronic kidney and liver failure, and diabetes. Over five million American were diagnosed with heart failure in 2009 alone [1]. The total costs of heart failure treatment in the United States exceeded \$31 billion in 2012 and this figure is projected to reach \$70 billion by 2030 [2]. One of the most significant common symptoms among these diseases is peripheral edema. Edema is the acute accumulation of fluid in body tissues under the skin which appears as swelling mostly in lower leg and ankle. Monitoring edema has been practiced by clinicians due to its significant role in treatment of the disease. It helps clinicians and caregivers ensure the effectiveness of treatments and therapies, observe any severe changes in patient's condition and intervene if necessary.

Edema has been conventionally assessed in clinics through periodic patient-caregiver visits. The manual assessment includes methods such as using a tape measure, water displacement, and pitting. One issue with such methods is the reliability and consistency concern [3]. For instance, the manual assessment may be conducted by different caregivers. More importantly, such methods overlook the essential impact of patients daily activity level. In fact, the formation of edema is very dependent on patient's current body posture and physical activity level [4]. The type of body posture and the amount of time that it was maintained play a crucial role. In the cases that the contextual information is gathered, it is often via self-reports that are proved to be biased and inaccurate [5].

Wearables, as an enabling technology in pervasive computing, has been used before for various context-aware applications such activity recognition [6], [7], gait analysis [8], medication adherence [9], etc. Few pervasive and remote edema monitoring approaches have been proposed, to date, to overcome the shortcomings of manual assessments. Examples are blood-pressure monitoring and weight monitoring. Recent studies demonstrated the inefficiency of these methods as they are subject to high false positive rate [10]. Some prior studies investigated the possibility of using sensor for more accurate assessment of lower-limb edema. In [11], [3], [12], the authors used stain gauge and force sensors for leg volume measurement. Gaues et al. [3] developed an extensometer to measure the changes in surface of the body. Other studies reported using other solutions such as potentiometer and 3D cameras [13], [14]. Some of the prior works have focused on different applications such as edema in workplaces rather than in-home patient monitoring. Moreover, none of the other studies proposed any intelligence data processing, context-awareness, or wireless connectivity for enhanced edema monitoring.

We introduce a real-time and activity-sensitive wearable system for monitoring ankle edema. SmartSock is equipped with state-of-the-art technologies in terms of hardware design and intelligent data processing. This is a multi-faceted platform capable of accurate and reliable assessment of edema. The low-power accelerometer sensor feeds the ankle acceleration data to our machine learning pipeline for the purpose of accurate activity and body posture identification. It provides the basis for context-rich edema monitoring. Furthermore, the unique flexible stretch sensor embedded into the fabric, supported by signal processing and correlation techniques, enables SmartSock to reliably measure the changes in ankle edema in remote and in-home settings. The main contributions of our study are as follows: (1) introducing a wearable edema monitoring sock (SmartSock) with unique hardware/software design; (2) addressing the critical need for activity-sensitive edema monitoring; (3) validating the SmartSock using five participants in a comprehensive experimental procedure.

II. SYSTEM AND METHODS

SmartSock is a combination of sensors and data processing pipelines designed for providing ankle edema quantifica-

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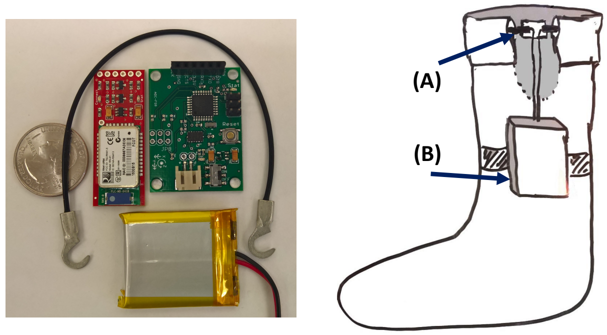


(a)

(b)

Fig. 1: (a) The hardware components embedded in SmartSock including a custom designed motion sensing and processing board, a flexible 12-inch stretch sensor, Lithium Ion battery, and a BLE transmission module. (b) Sketch design of SmartSock prototype. Area (A) shows the stretch sensor wrapped inside and around the elastic cuff. Area (B) has the rest of the hardware embedded inside the clothing.

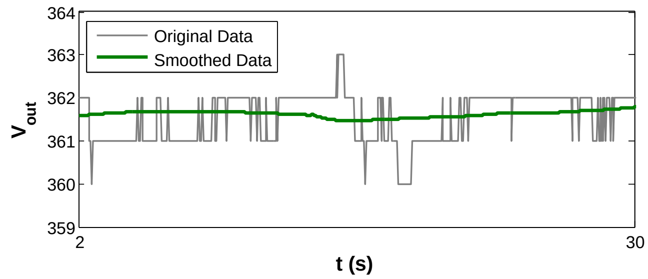


Fig. 2: Stretch sensor output being smoothed using a moving mean filter.

tion data annotated with activity/body posture information in a continuous manner. In this section, we elaborate on hardware/software design steps devised toward creating the SmartSock prototype.

A. Hardware Description

When designing the edema sensor, various design factors such as user adaptability, wearability, power efficiency, and accuracy need to be taken into account. Fig. 1a illustrates the components employed in our sensing hardware; it includes a custom designed printed circuit board (with an ATmega328 micro-controller and an ADXL345 accelerometer, on board), a 12-inch stretch sensor, a $500mAh$ Polymer Lithium Ion battery, and a Bluethooth low energy (BLE) transmission module. ADXL345 is a low power ($25-130\mu A$ at $2.5V$) three-axis 13-bit resolution accelerometer with $\pm16g$ sensing range. 13-bit digital output enables the sensor to have extremely high resolution ($4mg/LSB$).

The stretch sensor used for quantification of ankle circumference is a cylindrical cord made of unique polymer component. Its resistance will increase when stretched. The sensor has a nominal resistance of 1000 ohm per linear inch when un-stretched. Its resistance roughly doubles when stretched 50% [15]. Fig. 1b shows a design sketch of SmartSock prototype and the placement of different components. The stretch sensor is placed around the cuff and inside the elastic fabric in order to allow the sensor to get stretched freely. The remaining components including the board and battery are placed slightly above the ankle and embedded into the clothing therefore the components and circuitry are invisible when the sock is worn.

B. Circumference Measurement

The edema quantification procedure consists of a training phase where a correlation model is built and a measurement phase where the trained correlation model will be used to continuously estimate the current ankle circumference using the stretch sensor's readings.

1) Correlation Model Training: Fig. 3a shows the data flow in training phase. The input signal is the stretch sensor data annotated with actual ankle circumference. The readings are first smoothed using a moving mean filter described in Equation (1), where $S(t)$ denotes the signal amplitude at time t and n indicate the size of moving window. Moving mean is commonly used in time series to filter out the short-term fluctuations and highlight the long-term trends. The short-term fluctuations in the output of flexible stretch sensor are primarily caused due to unwanted events such as lower-leg muscle contractions.

$$\hat{V}(t) = \begin{cases} V(t) & \text{if } t \leq n \text{ or } t \geq \mid V \mid -n \\ \frac{\sum_{i=t-n}^{t+n} V(i)}{2n+1} & \text{otherwise} \end{cases} \tag{1}$$

A regression model is trained using the smoothed training data to convert the output voltage of stretch sensor into circumference measurements. The regression model is given by

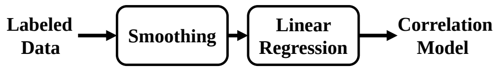
$$C(t) = \alpha \times \hat{V}(t) + \beta \tag{2}$$

where $C(t)$ and $\hat{V}(t)$ denote the correlated circumference and smoothed output voltage of stretch sensor at time t, respectively, and α and β are the coefficients of the model.

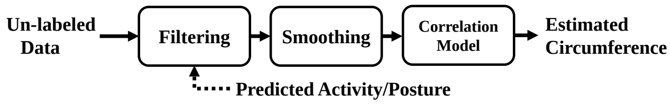
2) Quantification Phase: in this phase, as shown in Fig. 3b, the output of stretch sensor, before being smoothed, is fed to the filtering block. This block uses the predicted physical state in activity recognition pipeline as a control signal to decide whether or not to pass the current stretch sensor readings to the correlation model for further processing (i.e., circumference quantification using Equation (2)). The system categorizes the subject's physical state into 'valid' and 'invalid' states. The filtering block discards the edema sensor readings captured during invalid states. Fig. 4 illustrates an example of a portion of continuous output voltage cleaned by the filtering function. In this example, only the readings captured during the activity of interest (i.e., valid states: stand, sitting in chair as considered in this paper) is passed for smoothing and then into the correlation model.

C. Activity/Body Posture Detection

The contextual information regarding the patient's physical state is essential for reliable remote monitoring of edema. The activity recognition pipeline aims to provide an edema-specific body posture and activity recognition enabling the



(a) Training phase.



(b) Measurement phase.

Fig. 3: Data flow in training and measurement phases.

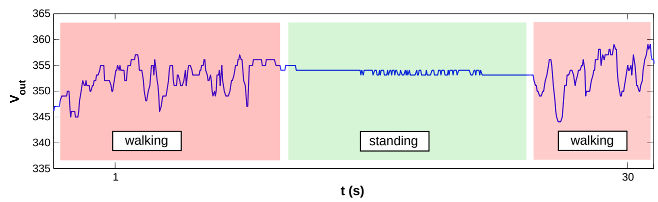


Fig. 4: Filtering block validates the circumference sensor readings by discarding the data captured during invalid physical states (e.g., walking, laying down, etc.). The segments highlighted in red will be discarded.

system to validate the edema sensor readings (taking place filtering block in Fig. 3b) and annotate the valid reading by their corresponding body posture. Fig. 5 illustrates a high-level description of our activity recognition model. Similar to circumference measurement procedure, it encompasses a training phase and measurement phase.

1) Training Activity Learner: This task is carried out using the three-axis acceleration data which are manually annotated with their actual physical state. The labeled data are first segmented into short windows of activity. Using the sliding window method, segments of 54 data instances (i.e., 3 seconds of activity at $18Hz$ sampling frequency) are extracted. The sliding window allows for 80% of overlap between successive segments. 10 statistical temporal features (i.e., amplitude, median, mean, maximum, minimum, peak to peak, standard deviation, variance, root mean square power, and start to end value) are extracted from each segment. These features provide an optimal trade-off between computational complexity and activity recognition accuracy [16] and, as a result, make the the data processing more adaptable for use in a wearable system which is constrained by limited energy source and computational capability. The extracted features and their corresponding activity labels are then used to train a standard machine learning algorithm (e.g., decision tree, nearest neighbor, etc.).

2) Continuous Activity Recognition: Once an activity learner is built, we use the trained model to predict the corresponding physical activity label of unlabeled data (i.e., 3-axis accelerometer readings). The unlabeled data (also referred to as test data) will go through the same segmentation and feature extraction process. The extracted features will be fed into the activity learner that ultimately outputs the predicted activity/ body posture.

Fig. 5: Data processing flow in physical activity detection. *In training phase, a classifier will be trained in this block. Also, the input data in training phase is labeled data.

TABLE I: The details of the movements performed in our experiment including light activities, transitional movements and body postures.

No.	Physical Movement	Details	Length
1	stand	standing naturally	$60s$
2	sit in chair	feet planted to floor	$60s$
3	sit on floor	legs parallel to floor	$60s$
4	lay on floor	back and leg parallel to floor	$60s$
5	sit to stand	from chair to upright stance	$10x$
6	bending at knees	pick up coin from floor	$10x$
7	bending at waist	pick up coin from floor	$10x$
8	jump	jump vertically	$10x$
9	climb stairs	one step per stride	6 flights
10	descend stairs	one step per stride	6 flights
11	walk	at normal pace	$60s$

III. VALIDATION

In this section, we first describe the experimental setup and then present the activity/ body posture classification accuracy and correlation results using various measures of reliability and repeatability.

A. Experimental Setup

The experiment aims to provide proof of functionality of SmartSock system in terms of accuracy of activity detection and ankle circumference quantification. Five healthy individuals aged between 23 and 31 were recruited on Washington State University (WSU) campus. Participants were informed of the experiment procedure and goals and were required to sign a consent form approved by WSU IRB ($\sharp$14522-001). We asked each participant to perform 11 different physical tasks while wearing the SmartSock prototype on the right foot. These tasks (detailed in Table I) include three categories: transitional movements, physical activities, and maintained body postures. These tasks are selected such that they cover main physical states in their categories with most impact on activity aware edema assessment. Fig. 6 shows a picture of a participant wearing the prototype. SmartSock was paired with a password protected Microsoft Surface device through Bluetooth connectivity and the collected data were stored on the device during the experiment at $18.7Hz$ frequency. At the end of the experiment, the actual circumference on the exact location of stretch sensor was manually measures using a tape measure.

B. Activity Recognition Results

The collected acceleration data were segmented into windows of 54 instances (i.e., 3 seconds of activity). Ten statistical features were extracted from each data segment resulting in a total of 174×10 annotated features. A Matlab tool was developed to perform off-line segmentation and

Fig. 6: A participant wearing the SmartSock prototype.

feature extraction. The annotated feature set was then fed into various machine learning algorithms. We used Weka machine learning toolkit for training and evaluation of our classification models. We chose Decision Tree algorithm (DT), Nearest Neighbor (NN), and Naive Bayes learner (NB) which offer computationally simple (therefore more suitable) solutions for activity identification in wearable systems.

In order to evaluate the performance of our classification models, we ran two tests using 10-fold cross-validation and 66%-test split methods. 10-fold cross-validation uses one tenth of data as the supplied test in each iteration and reports the average performance. Test split method trains the model using a portion of data and tests the model using the rest. Fig. 7 shows the performance of the activity recognition models in terms of precision and recall accuracy and the area under ROC curve. Precision metric measures the fraction of identified labels that are relevant where recall measures the proportion of labels that are correctly identified as such. ROC is true positive rate vs false positive rate plot. ROC area is an indication of the probability that the current model is making an informed decision. As it can be observed in Fig. 7, decision tree and nearest neighbor models showed sufficiently high performance (≥ 0.95) outperforming naive Bayes model. The reason is that probabilistic models such as naive Bayes often fail to offer significant performance on smaller data sets. Cross-validation method slightly outperforms the 66%-test split due to its advantage in using the entire data set.

Table II reveals more details of activity recognition results. It shows the confusion matrix and the precision and recall accuracy of the decision tree model for each movement evaluated using 10-fold cross-validation evaluation method. While the overall accuracy of the model is high (with weighted average accuracy of 0.97), some instances of movements 9 and 10 (i.e., climbing and descending stairs) were misclassified by the activity recognition model.

C. Circumference Measurement Results

Using the stretch sensor data collected during the experiments, we developed a regression model to correlate the validated smoothed output with actual ankle circumference. As discussed in Section II-B, we first exclude the stretch sensor readings captured during invalid physical states. Similar to in-clinic edema assessment, we consider movements 1 and 2 (i.e., standing and sitting in chair) as the only medically relevant inputs (i.e., valid states) to our edema quantification module. The valid voltage output is then smoothed using the window size of $n = 10s$ to discard the unwanted fluctuations

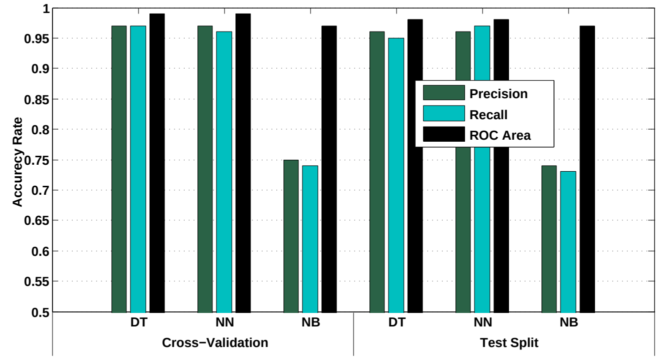


Fig. 7: Performance of different classifiers using 10-fold cross-correlation and 66%-test split evaluation methods.

TABLE II: Confusion matrix and precision and recall accuracy of each movement using DT classifier and 10-fold cross-validation method.

Classified as →	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(10)**	**Precision (%)**
(1)	388	0	0	0	0	0	0	0	0	0	0	1
(2)	3	385	0	0	0	0	0	0	0	0	0	99
(3)	0	2	385	1	0	0	0	0	0	0	0	99
(4)	0	0	4	384	0	0	0	0	0	0	0	99
(5)	0	0	0	0	44	0	2	0	0	2	0	91
(6)	0	0	0	0	1	47	0	0	0	0	0	97
(7)	0	0	0	0	1	0	47	0	0	0	0	97
(8)	0	0	0	0	0	0	0	43	1	4	0	89
(9)	0	0	0	0	0	0	0	1	241	15	3	92
(10)	1	0	0	0	0	0	0	3	18	231	7	89
(11)	0	0	0	0	0	0	0	0	3	2	283	98
Recall (%)	99	99	99	99	95	100	95	91	91	90	97	-

TABLE III: Details of regression models and their corresponding R-squared value.

Included Physical States	**Regression Model**	R^2
"stand"	$C(t) = -14.2 \times \hat{V}(t) + 818$	0.94
"sit in chair"	$C(t) = -15.2 \times \hat{V}(t) + 859$	0.90
"stand" & "sit in chair"	$C(t) = -14.7 \times \hat{V}(t) + 838.5$	0.91

caused by irrelevant sources such as muscle contractions. In the next step, the preprocessed data collected from each participant (i.e., $60s$ of standing and $60s$ of sitting in chair) were split into three 20-second segments of continuous data. We refer to each data segment as one trial. Trails are annotated with participants' actual ankle circumference measured at the time of experiment. We used these trails to (1) build the linear regression model and (2) calculate the reliability and repeatability measures to evaluate the usability of flexible stretch sensor.

Using the median value of each trial and its corresponding circumference label, we developed a linear regression model as described in Equation (2). Three regression models were built using instances of movement (1), movement (2), and combinational of those two. Table III presents the details of constructed models and their corresponding R^2 values. A high correlation of sensor output and actual circumference (> 0.90) was reported. However, data instances captured during "stand" state, shows comparatively higher correlation. One explanation could be the higher chance of deviation from upright position in lower leg, when sitting in chair that could

TABLE IV: Reliability measures for each pair of trials

Subjects	1		2		3		4		5	
Trial pairs	1-2	2-3	1-2	2-3	1-2	2-3	1-2	2-3	1-2	2-3
Typical Error	0.18	0.11	0.14	0.12	0.15	0.09	0.08	0.14	0.14	0.18
Pearson Correlation	0.96	0.97	0.96	0.99	0.97	0.98	0.96	0.96	0.97	0.98
Intraclass Correlation	0.98	0.96	0.97	0.97	0.96	0.97	0.99	0.96	0.98	0.96

cause possible inconsistencies in stretch sensor readings.

In order to further explore the usability of the stretch sensor in terms of reliability and repeatability in readings, we calculated the Pearson correlation and intraclass correlation (ICC) measures. Table IV shows the metrics calculated for each subject collected from stance posture. Pearson correlation measures the level of consistency between each trial where any value greater than 0.9 is considered excellent reliability. The intraclass correlation measures the absolute agreement between output of different trials. The average reported number for ICC is 0.97. Similar to Pearson correlation, any ICC value above 0.9 indicates excellent repeatability. This result suggests that the proposed sensing device is capable of reproducing the same output in different trials with excellent reliability. The minor difference in each trial can be explained by human errors or irrelevant sources of distortion (Standard error of measurement a.k.a typical error). Typical error of around 0.1 results in 95% confidence interval of $[V \pm 2.65 * SEM] = [V \pm 0.26]$ which is sufficient for detecting meaningful changes in ankle circumference (i.e., it lies outside the margin of error) for the purpose of edema monitoring.

IV. Conclusion

An activity-aware remote edema monitoring platform, namely SmartSock, was presented in this paper. SmartSock is a fully wearable sensing system that takes advantage of advanced techniques in machine learning and signal processing. As mentioned, ankle edema is an important symptom of several chronic and systematic diseases such as heart failure, kidney and liver failure, diabetes, etc. Conventional in-clinic assessment of edema has several disadvantages: (1) it is burdensome for edema patients (especially older adults); (2) it is very costly for health-care system, patients, and insurance companies; (3) it offers incomplete and often unreliable information in terms of contextual information such as daily physical activity level; (4) it is prone to human error and fails to provide accurate, comprehensive, and continuous assessment. SmartSock is a remote monitoring solution to disadvantages of in-clinic assessments. It provides a means for context-rich, accurate, and reliable edema monitoring in remote settings which makes it a better, more affordable, and more convenient alternative to current methods.

Our experimental results demonstrate that SmartSock is capable of identifying a wide range of physical activities with an accuracy of 97%. Furthermore, the unique flexible stretch sensor employed in our device is capable of measuring ankle circumference with high correlation ($R^2 = 0.94$) and excellent test-retest repeatability ($ICC = 0.97$).

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