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Sensitivity Analysis of Wearable Textiles for ECG Sensing

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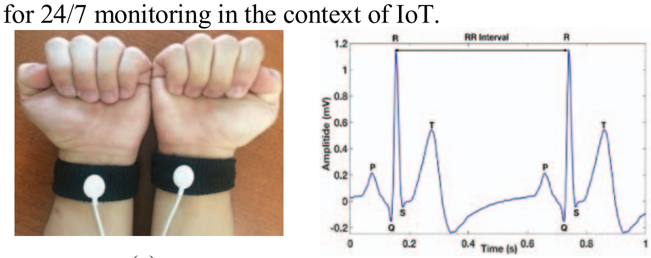
***Abstract*—Rapid advances in material science and mobile technology bring the new generation of wearable electrocardiogram (ECG) sensing systems. In particular, sensing textiles have been widely used in cardiac monitoring due to its high flexibility and reusability. Unlike conventional gel electrodes, sensing textiles are non-adhesive, which provide comfortable and stress-free experience. However, the quality of textile-based ECG sensing is more sensitive to external factors (such as sensor placement and contact pressure). There is an urgent need to investigate how the quality of ECG sensing is influenced by these factors and improve the design of wearable textiles. In the literature, little has been reported on the sensitivity analysis of textile-based ECG sensing. In this study, we experimentally investigate the sensitivity of textile-based ECG sensing to four factors, i.e., contact pressure, textile placement, user's activity, and muscle activity. Specifically, ECG signals are collected using sensing textiles under these four factors. Then, heart rate and ECG morphology are characterized from the obtained ECG signals and compared with true signals (obtained from standard gel electrodes). Experimental results show that the quality of textile-based ECG sensing is not sensitive to the contact pressure as long as it is ≥6N. When the patient is walking, nevertheless, the sensing quality can be strongly influenced by the textile placement. Furthermore, textiles placed on areas with fewer muscles achieve better signal quality. This study shows strong potentials of textile materials for the design of wearable ECG systems to empower smart and connected cardiac health.**

Keywords—Wearable devices, sensing textile, cardiac monitoring, sensitivity analysis, electrocardiogram (ECG) signals

I. Introduction

Recent advances in sensing and communication prompt the rapid growth of the Internet of Things (IoT). In the past few years, IoT technology has been increasingly adopted in various areas, including manufacturing, healthcare, transportation, and agriculture. In particular, IoT has been used in healthcare to monitor patients' conditions and improve treatment outcomes. For example, IoT devices are used by cardiologists for the continuous monitoring of patients' conditions. Patients' electrocardiogram (ECG) signals are collected by wearable sensors, which are transmitted seamlessly to the IoT cloud. Cardiologists are able to access the patient's data anywhere and anytime, and provide timely feedback to high-risk events. Prior research has shown that IoT-based cardiac monitoring provides a great opportunity to reduce the mortality, especially for patients with acute cardiac diseases [1].

Our previous studies [2-4] have developed an IoT technology that specific to cardiac care, namely, the Internet of Hearts. Advanced algorithms and analytical methods have been developed to effectively handle the big data from a large number of patients and extract vital signs to assist in the process of medical decision making. However, collecting patients' data in a more reliable way remains a significant challenge in the IoT-based monitoring. Traditional portable ECG monitors adopt disposable Ag-AgCl electrodes that require wet gel to attach to patients' body surface. In this way, they are effective only for a short period and not well-suited for 24/7 monitoring in the context of IoT.



(a) (b)

Fig. 1. (a) Sensing textiles used in this study; (b) 1-lead ECG.

With the rapid development of new materials and microelectronics, sensing textiles (see Fig. 1) have been increasingly used in the cardiac monitoring. Unlike gel electrodes, sensing textiles provide more comfortable experience and enable 24/7 continuous monitoring of cardiac conditions. For example, Gonzales et al. [5] integrated silver woven conductive fabric into a T-shirt to monitor ECG signals. Patients are able to wear the T-shirt on a 24-hour basis to detect heart abnormalities during daily life. Hitoe [6] is a shirt-based monitoring system. Wearable systems show a greater level of flexibility to collect, analyze ECG signals, and provide users with timely feedbacks on their cardiac conditions.

However, wearable monitoring is different from in-hospital monitoring, and the quality of textile-based ECG sensing can be significantly influenced by multiple factors. Skin-textile contact, textile placement, user's activity, and muscle activity can alter or even blur critical information in ECG. For example, when the ECG quality is low, the evidence of ischemia cannot be extracted [7]. This, in turn, will influence the diagnosis and impact the value of wearable ECG sensing systems. Limited work has been done to characterize how these uncertainty factors will impact the quality of textile-based ECG sensing. There is an urgent need to design and analyze experiments that help investigate how the quality of textile-based ECG sensing is influenced by these factors, thereby improving the design of wearable sensing systems.

In this paper, we perform the sensitivity analysis of textile-based ECG sensing. First, we study how the contact pressure between the sensing textile and skin surface impacts the signal quality. After determining the optimal pressure, we vary the location of sensing textiles under two user's activities: standing and walking. Further, the effect of muscle activity on the quality of ECG signals is investigated. The remainder of

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this paper is organized as follows: Section II presents the research methodology. Section III shows the experimental results. Section IV concludes this investigation.

II. Research Methodology

This paper focuses on how the variations of four experimental factors (i.e., contact pressure, textile placement, user's activity, and muscle activity) influence the quality of textile-collected ECG signals. Specifically, wearable textiles from Textronics (see Fig. 1a) and sensor from BITalino are used in our experiments. Experiments under each of four scenarios are repeated on 30 participants. Averaged results are reported in this study. Percentage error and normal-to-normal interval are used to characterize the variation from the benchmark signal (i.e., Gel-based ECG).

Sensing textile measures ECG signals by electrical conduction with user's skin. As such, the quality of ECG signals depends to a great extent on the skin-textile impedance. In physics, the skin-textile impedance R_C is defined as:

$$R_c = KA^{-1}P^{-1/2} \tag{1}$$

where K is the resistivity constant, A is the area of skin-textile contact, and P is the contact perimeter of the sensing textile [8]. Notably, the contact area is closely related to the contact pressure. In other words, a larger contact pressure will achieve a larger contact area (and hence better contact) between textile and skin. Thus, there is a need to investigate what contact pressure is required to achieve the optimal sensing quality.

Existing wearable ECG devices are oftentimes restricted to be placed on users' wrists and chest. They don't specifically consider the optimal placement. Therefore, the sensitivity of ECG sensing with respect to textile locations remains unsure. In this study, we measure the ECG signals from 5 equally separated locations under different user's activities and muscle activities.

Sensing textiles record cardiac electric potential that projected on the body surface. Thus, user's activity is also a factor that can impact the quality of ECG signals. In this study, we investigate how the quality of ECG sensing will be impacted by two kinds of activities, i.e., standing and walking. During walking, the user's body movements will introduce noisy components that will contaminate the ECG quality. To ensure a fair comparison, ECG signals are recorded under the same walking pace.

Textiles are more elastic than traditional gel electrodes. That is, textiles are easy to deform under muscle activities. When the muscle contracts, electromyography (EMG) signals are produced that resemble as noises to the ECG. Also, muscle activity results in the change of contact surface area (the parameter A in Eq. (1)). When holding hand gripper, Flexor carpi radialis muscles (located around L2) contract. Hence, we only conduct experiments regarding muscle activities from the L1, L2, and L3.

In this study, ECG signals obtained from sensing textiles are compared with standard ECGs (obtained using gel electrodes). The small differences between them give good measures on the quality of textile sensing. Therefore, we introduce two performance metrics:

1) percentage error of heart rate (Eq. (2)):

$$\text{Percent err} = \left|\frac{\mathrm{HR_{Textile}} - \mathrm{HR_{Gel}}}{\mathrm{HR_{Gel}}}\right| \times 100\% \tag{2}$$

2) normal-to-normal interval of the signal morphology: as shown in Fig. 2, normal-to-normal interval denotes the interval between the successive real R peaks [9].

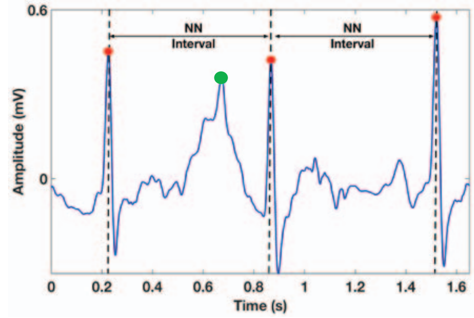


Fig. 2. Normal-to-normal (NN) intervals used to characterize ECG quality. Red dots are real R points and the green dot is a misdetection (false R point).

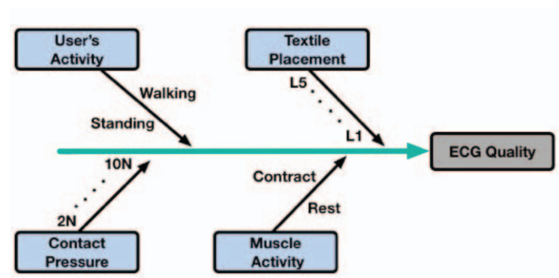


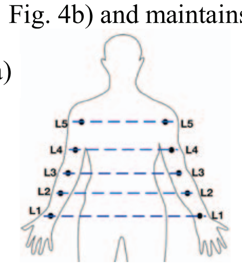
Fig. 3. The cause-and-effect diagram of experimental design.

III. Experimental Results

Fig. 3 shows the design of experiments with four factors:

1) *Contact Pressure*: Five pressure levels (2N, 4N, 6N, 8N, and 10N) are applied on the textile to vary the condition of skin-textile contact. The contact pressure is measured using digital hanging scales.
2) *Textile Placement*: Five locations (L1 to L5) are selected to place sensing textiles. As shown in Fig. 4a, the locations are separated by the same distance. L1 is close to the wrist and L5 is close to the chest.
3) *Users' Activity*: Standing and walking are also considered when recording the ECG signal using sensing textiles. When walking, the variability of ECG sensing comes from the upper body movements.
4) *Muscle Activity*: We record the ECG signals using sensing textiles when muscle contracts and rests. To simulate muscle activity, users hold hand gripper (see Fig. 4b) and maintains 50N force.

(a)



(b)

Fig. 4. (a) Five locations of the sensing textiles; (b) hand gripper used to evaluate the effects of muscle activity.

A. *Percentage Error of Heart Rate*

TABLE 1. PERCENTAGE ERROR OF HEART RATE FOR FIVE PRESSURES

	2N	4N	6N	8N	10N
Percent. Err. (%)	10.8	8.60	3.79	3.78	3.66
Standard deviation	3.81	2.34	1.94	2.16	1.73
Max Error (%)	24.1	15.2	12.9	12.67	10.4
Min Error (%)	1.22	1.16	1.05	0	0

TABLE 2. ANOVA FOR CONTACT PRESSURES

Source	SS	DF	MS	F_{Stat}	*P*
Between Group	865	4.00	216	21.5	<0.001
Within Group	1460	145	10.1		
Total	2325	149			

Table 1 shows the percentage error of heart rate measurement under five levels of contact pressures compared with gel electrodes. Notably, sensing textiles are able to obtain accurate heart rate (< 5% error) when the pressure is ≥6N. Further, the analysis of variance (ANOVA) is performed to investigate the difference on the five pressure levels. As shown in Table 2, a small p-value indicates there is a significant difference between pressure levels on the heart rate accuracy. In addition, Scheffe's test [10] shows that there is no difference between 6N and 8N, 6N and 10N, and 8N and 10N, but differences are found between 2N and 4N, 2N and 6N, and 4N and 6N. This result shows that applying pressure ≥ 6N to sensing textiles helps acquire high accuracy on heart rate measurement and increasing pressure does not result in higher accuracy.

TABLE 3. PERCENTAGE ERROR OF HEART RATE FOR TWO ACTIVITIES

		L1	L2	L3	L4	L5
Percent. Err. (%)	**Stand**	2.79	2.68	2.97	2.75	2.33
	Walk	7.70	6.24	9.30	4.15	5.14
Standard deviation	**Stand**	1.94	1.60	1.44	1.40	2.23
	Walk	3.20	2.43	2.91	1.23	1.60
Max Error (%)	**Stand**	8.99	9.33	8.07	8.45	8.66
	Walk	13.2	9.61	19.65	8.41	11.4
Min Error (%)	**Stand**	1.05	0	0	0	0
	Walk	1.09	1.02	2.17	1.01	1.00

Table 3 shows the percentage error of heart rate at five locations on arms while the user is standing or walking. It is noteworthy that when the user is standing, textiles obtain accurate heart rate and the percentage error does not vary significantly with different locations. Walking, however, results in larger errors when sensing textiles are placed at lower arms (i.e., errors in L1~L3 are larger than L4 and L5) and joints (i.e., error in L3 is larger than L1 and L2). Further, ANOVA results suggest that the difference between five locations of textile placement for walking is more significant than that of standing.

TABLE 4. PERCENTAGE ERROR OF HEART RATE FOR MUSCLE ACTIVITIES

	L1		L2		L3	
	Contract	**Rest**	**Contract**	**Rest**	**Contract**	**Rest**
Percent. Err. (%)	5.25	2.79	8.35	2.68	4.66	2.97
Standard deviation	3.85	1.94	4.58	1.60	2.51	1.44
Max Error (%)	20.25	8.99	17.0	9.33	23.88	8.07
Min Error (%)	2.15	1.05	1.83	0	2.75	0

Table 4. shows the percentage error in heart rate when muscle contracts and rests. Notably, when sensing textiles are placed at L2, the highest percentage error is obtained when muscle is contracting due to the activity of flexor carpi radialis muscle. Furthermore, ANOVA is applied to evaluate the difference between textile placement when muscle is contracting. As shown in Table 5, the p value is 0.001, which indicates a significant difference. In addition, results from Scheffe test indicate that the differences exist between L1 and L2, and L2 and L3.

TABLE 5. ANOVA FOR MUSCLE ACTIVITY

Source	SS	DF	MS	F_{Stat}	P
Between Group	398.9	2	199.5	6.89	0.001
Within Group	2516	87	28.92		
Total	2915	89			

B. *ECG Morphology*

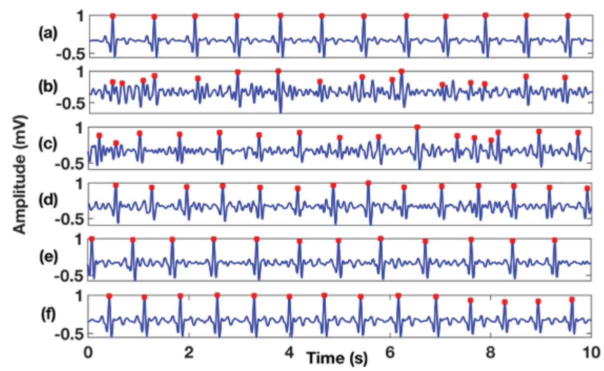


Fig. 5. Collected ECG (at the location of L1) under different pressure levels: (a) standard ECG (obtained from gel electrodes), (b) 2N, (c) 4N, (d) 6N, (e) 8N, (f) 10N.

As shown in Fig. 5, ECG signals collected under contact pressures of 6N, 8N, and 10N are more close to the standard ECG (obtained from gel electrodes). Red dots are detected R peaks using the Pan Tompkins algorithm. Notably, some noise-induced waves with large amplitudes are detected as false R peaks. This mainly happens when the contact pressure is low (see Fig. 5b and c).

TABLE 6. NN INTERVAL STATISTICS FOR VARYING CONTACT PRESSURES

	2N	4N	6N	8N	10N	Gel
Max NN	887	878	791	816	782	784
Min NN	289	212	732	715	725	722
Std NN	215	205	21.0	21.0	23.0	23.0

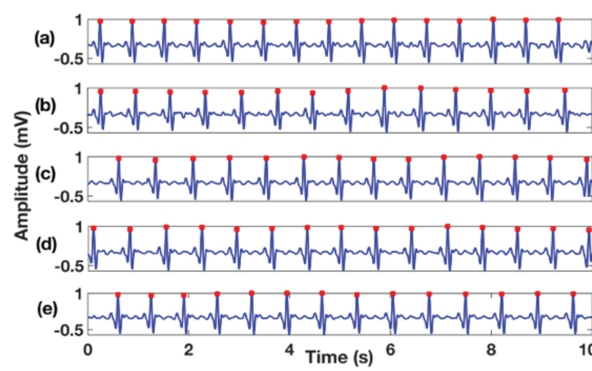


Fig. 6. Collected ECG at five locations: (a) L1, (b) L2, (c) L3, (d) L4, (e) L5, while the user is standing still.

Furthermore, normal-to-normal interval statistics (i.e., maximum NN, minimum NN, and standard deviation of NN) are extracted and compared with those of standard ECG. As shown in Table 6, minimum normal-to-normal intervals under 2N and 4N are significantly smaller than that of standard ECG. This is because under small contact pressures, noises with high amplitudes can be recognized as R peaks. Also, the standard deviation of normal-to-normal interval under small contact pressures (2N and 4N) is larger. When the contact pressure is ≥ 6N, the obtained signal has similar morphology as standard ECG signals.

To evaluate the influence of user's activity on the signal morphology, ECG is firstly measured when the user is standing still and we vary the location of sensing textiles. As shown in Fig. 6, ECG measured at different locations show similar morphology to standard ECG (see Fig. 5a) when the user is standing still. Second, ECG signals are measured when the user is walking. As shown in Fig. 7, ECG signals obtained from L1, L2, and L3 are contaminated by strong noises, which generate false R peaks. Although ECG measured at L5 has correct normal-to-normal interval, it contains large baseline wandering due to the movement of upper arms and shoulders.

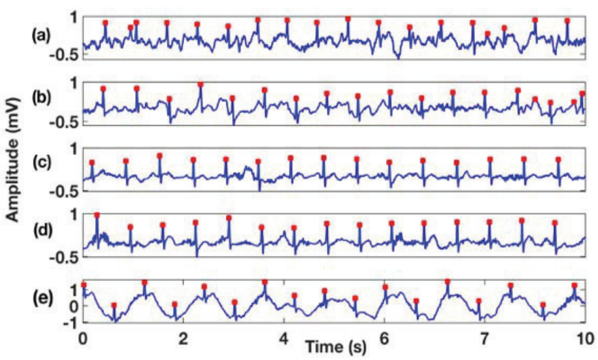


Fig. 7. Collected ECG at five locations: (a) L1, (b) L2, (c) L3, (d) L4, (e) L5, when the user is walking.

As shown in Table 7, normal-to-normal interval statistics extracted from textile-based sensing are similar to those from standard ECG when the user is standing. When the user is walking, ECG signals obtained at L1, L3, and L5 show more differences compared with standard ECG. This is because textile-based sensing is more sensitive to the body movement, especially when textiles are placed near the joints.

TABLE 7. NN INTERVAL STATISTICS UNDER DIFFERENT USERS' ACTIVITIES: STANDING AND WALKING

		L1/Gel	L2/Gel	L3/Gel	L4/Gel	L5/Gel
Max NN	Stand	771/771	737/737	667/667	795/797	756/756
	Walk	615/600	643/666	803/828	710/699	610/607
Min NN	Stand	587/587	519/518	548/548	516/514	653/652
	Walk	301/541	486/526	206/501	466/584	422/533
Std NN	Stand	18.4/18.4	24.0/24.0	28.0/28.0	38.6/38.6	14.5/14.5
	Walk	149/17.5	49.5/10.0	255/16.5	78.5/11.0	106/13.0

When muscle contracts, EMG signals will be introduced as noises for the ECG sensing. As shown in Fig. 8a and 8b, heavier noises are obtained at L1 and L2 due to flexor carpi radialis muscle. Correspondingly, minimum normal-to-normal intervals obtained at L1 and L2 show a bigger difference between muscle contraction and rest, compared with the smaller difference obtained at L3 (see Table 8). Notably, the contraction of flexor carpi radialis muscle (L1 and L2) not only generates EMG signals, but also deforms the skin-textile contact surface. As a result, the contact area changes, which impacts the quality of ECG sensing.

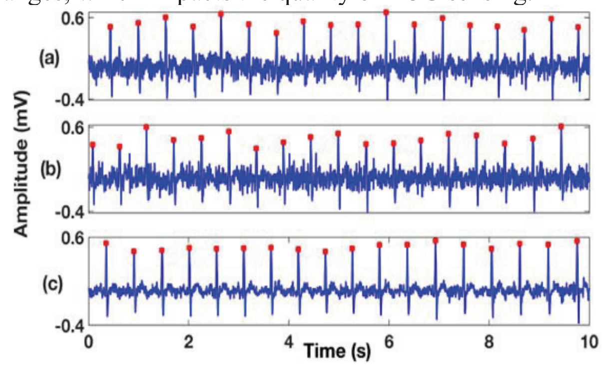


Fig. 8. ECG under muscle activity at: (a) L1, (b) L2, (c) L3.

TABLE 8. NN INTERVAL STATISTICS FOR MUSCLE ACTIVITIES

	L1		L2		L3	
	Contract	Rest	Contract	Rest	Contract	Rest
Max NN	695	771	782	737	644	667
Min NN	493	587	422	519	543	548
Std NN	78	18.4	128	24	19	28

IV. CONCLUSION

The rapid growth of material science, mobile technology promotes the increasing popularity of sensing textiles and the Internet of Health Things. However, the quality of textile-based ECG sensing is sensitive to uncertain factors. Limited work has been done on the sensitivity analysis of textile-based ECG sensing. Results of this study have strong potentials to serve as references for the design and development of new generation of wearable ECG monitoring systems. This, in turn, will realize the full potential of wearable ECG monitoring for smart and connected healthcare.

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