Printed Electrodermal Activity Sensor with Optimized Filter for Stress Detection

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ABSTRACT

This paper presents a tiny, flexible, and low-cost all-analog approach for measuring electrodermal activity, based on the conductance of the skin. We propose a tiny, fully-printed system on flexible substrates, which guarantees flexibility and simplifies attachment to the body, and allows for detection of high stress values in form of a binary classification. A major contribution of this paper is the design of the printed hardware, including a novel way to optimize the hardware parameters, which is done via an evolutionary algorithm.

CCS CONCEPTS

• Hardware → Sensors and actuators; **• Human-centered computing → User models**; **Mobile devices**; **• Computing methodologies → Machine learning approaches**.

KEYWORDS

stress detection, evolutionary algorithm, printed electronics, electrodermal activity, wearable computing

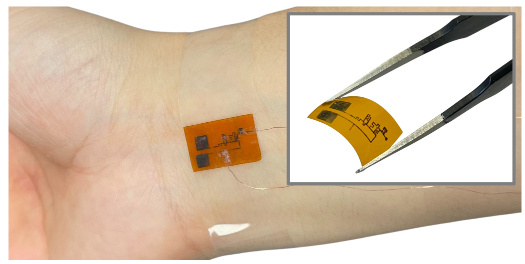


Figure 1: Photo of the proposed hardware design for stress detection. The copper wires are connected to power supply.

1 INTRODUCTION

Chronic stress can lead to several health risks [7]. Therefore, continuous and unobtrusive stress detection becomes important.

The most common wearable devices used for stress detection are smartwatches/wristbands [3, 10, 13]. Despite the considerable success of these devices and algorithms, there is still improvement to be made: The devices are pricey[1,2] and the hard housing of these devices prevents them from complete unobtrusiveness. Thirdly, the hardware for signal processing is sophisticated, when compared to full analog circuits. In this respect, printed electronics becomes a powerful candidate, as it allows flexibility, non-toxicity, ultra-low-cost, etc. In this work, we propose the design of a printed hardware system to do the binary classification for stress/non-stress of the users. Figure 1 shows the flexibility and ultra-small size of the printed prototype. Subsequently, we simulate the filtering behavior and optimize the filter using an evolutionary approach to achieve the best performance. Finally, we compare experimentally obtained measurement from the printed electrodermal activity (pEDA) sensor with an Empatica E4 wristband. It shows, that the sensor can obtain a comparable signal, using the proposed filtering approach.

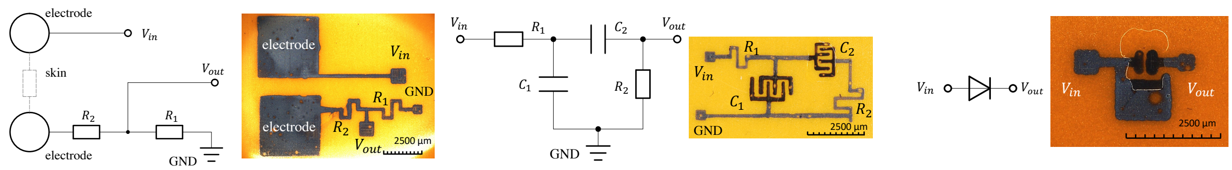
2 SYSTEM DESIGN

Here, we present the hardware design and its optimization. All proposed components can be printed (see Figure 2). The fabrication workflow and corresponding materials for the components can be found in [11, 12].

2.1 Hardware

Printed EDA sensor. As shown in Figure 2a, the pEDA sensor consists of two electrodes and two resistors for voltage division. As electrode material, we utilize graphene, which shows great potential as bio-compatible, wearable electrode material [1, 6].

[1] https://www.apple.com
[2] https://www.empatica.com/en-int/research/e4



(a) pEDA sensor (b) printed band-pass filter (c) printed diode-connected transistor

Figure 2: The schematics of the proposed hardware (left) and photos (right) of the hardware prototype. (a) printed EDA sensor. (b) printed band-pass filter for signal processing. (c) printed diode-connected transistor as threshold for stress detection.

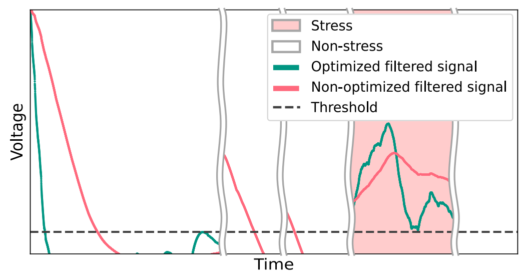


Figure 3: Simulated example of filter optimization, based on WESAD dataset. The gray vertical curves separate different temporal segments after removing meaningless time slots.

Band-pass filter. We use a band-pass filter for signal processing to filter out the skin conduction level part of the signal, thus minimizing differences between subjects, and leave only the skin conductance response part for stress detection. (See [9] for detail about EDA signal.)

Threshold diode. To do the binary classification, we implement the threshold by a diode (printed as a diode-connected transistor).

2.2 Optimization

Optimization of filter. Rather than simulating the filtering in frequency domain, we model and optimize the filter directly on the hardware level. The parameters to be optimized are the resistances and capacitances in Figure 2b. The relationship between input voltage V_{in} and output voltage V_{out} is described by:

$$\dot{z} = \begin{bmatrix} -\frac{R_1+R_2}{R_1R_2C_1} & \frac{1}{R_2C_1} \\ \frac{1}{R_2C_2} & -\frac{1}{R_2C_2} \end{bmatrix} \cdot z + \begin{bmatrix} \frac{1}{R_1C_1} \\ 0 \end{bmatrix} \cdot V_{in}, \quad V_{out} \quad = [1 \;\; -1] \cdot z\,,$$

where $z \in \mathbb{R}^2$ is the internal state of this system. Since we will classify the stress/non-stress by a threshold, the objective of the optimization is to increase the filtered signal when the user is under stress and vice versa, we optimize the parameters by CMA-ES [4], which is an evolutionary algorithm for optimizing challenging problems that are even non-convex and ill-conditioned. Figure 3 shows a simulation result of the filter optimization on *WESAD* [8]. We can see that, after the filter optimization, the output signal in stress time slots are increased and vice versa.

Optimization of threshold. search [2] for finding the best threshold. To avoid low recall or precision simultaneously, we take the F_1 score [5] as the objective and perform grid search [2] for finding the best threshold.

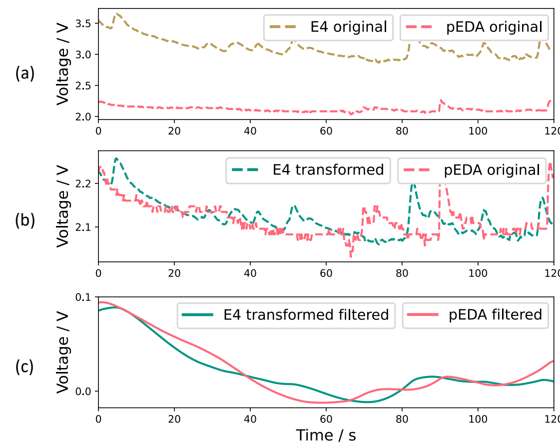


Figure 4: Signal alignment. (a) measured signals from E4 (transformed to voltage) and pEDA sensor. (b) signals after transformation. (c) filtered signals after transformation.

3 FEASIBILITY TEST

In this section, we test the feasibility of the pEDA sensor by comparing it with Empatica E4 wristband readings. Therefore, we equipped both, the E4 wristband and pEDA sensor on subjects' wrists (N=3) simultaneously, who read, play smartphones, and do other spontaneous activities for 30 min. To compare both obtained signals, we first transform the E4 signal from conductance to voltage, for comparability with our proposed hardware structure (see Figure 2a). Afterwards, we build a linear transformation to compensate the difference between both signals, which may be caused by different sensor specifications such as the shape/material of electrodes. We can see from an exemplary segment (Figure 4), the pEDA sensor signal is comparable to the E4 signal, especially after the band-pass filtering, which is done by the proposed method, using simulation and shows the feasibility of the proposed approach.

4 CONCLUSION

In this work, we proposed a printable, flexible, tiny, and cheap, all-analog circuit for stress detection. Moreover, we intend to show the possibilities of printed electronics in wearable computing.

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