

Poster: Unobtrusive User Verification using Piezoelectric Energy Harvesting

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ABSTRACT

With the capability to harvest energy from low frequency motions or vibrations, piezoelectric energy harvesting has become a promising solution to achieve self-powered wearable system. Apart from generating energy to power the wearable devices, the output electricity signal of the PEH can also be used as an information source as it reflects the activity or motion patterns of the user. In this paper, we have designed and built an insole-based user authentication system by leveraging the AC voltage generated by the PEH during human walking. Meanwhile, the generated power is also collected and stored, which could be later used as the power source of the mobile system. By using a dataset of 20 subjects, we have demonstrated that our system can achieve 89.76% of human recognition accuracy when using only one gait cycle signal, and the accuracy can be further increased to 95.86% when two gait cycles are utilized.

CCS CONCEPTS

•Computer systems organization →Embedded systems; Redundancy; Robotics; •Networks →Network reliability;

KEYWORDS

Energy-efficiency, Gait Verification, Sparse Representation, Wearable Device

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1 INTRODUCTION

The limited battery lifetime is one of the major barriers of achieving sustainable operation for the wearable devices nowadays. Fortunately, as ambient motions or vibrations are easily accessible in people's daily life, kinetic energy harvesting (KEH) has been considered as a promising technique which could be utilized as a viable power source to extend or even replace the batteries. One of the most attractive option to harvest energy from human motion is insole-based piezoelectric energy harvesting because it produces significant amount of energy and can be assembled in shoes unobtrusively [1]. Moreover, human walking contains unique gait pattern of each individual, which can be reflected from the output signal of the PEH [3]. We can thereby assume that the signal can be useful for some security or classification applications, such as user verification for door opening in smart home, automated ticket checking in public events, client verification in automated teller machines, and many more. Thus, by collecting the output AC voltage of the PEH, the novelty of the system is simultaneous energy scavenging and information collection.

In this work, we have designed and built an insole-based PEH prototype. Using this prototype, we have collected the actual AC voltage signal generated from the PEH during human walking from 20 subjects. In addition, a sparse representation based algorithm has been designed, which efficiently leverages the AC voltage signal for user recognition.

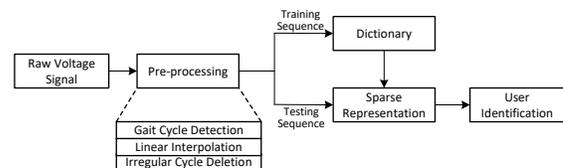


Figure 1: System Overview

2 SYSTEM ARCHITECTURE

Figure 1 illustrates the system overview, which includes raw voltage collection, signal pre-processing and sparse representation based classification.

2.1 Data Pre-processing

- **Gait Cycle Detection:** To detect the periodic gait cycles, we first applied a band pass filter to the original time serial

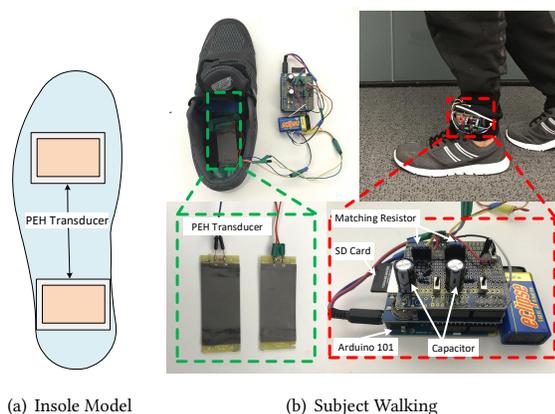


Figure 2: The Design and Appearance of the prototype voltage signal to remove the noise. We then obtain the gait cycles by finding the consecutive peaks, which correspond to the heel-strike time or the heel-off time, in the filtered signal.

- **Linear Interpolation:** To deal with variable walking speed which may occur among different subjects or one subject in different walking scenarios, we perform the linear interpolation on the detected gait cycles. According to the distribution of the gait cycle length, which ranges from 80 to 130 samples when sampling at 100Hz, we interpolate the gait cycles to equal length of 130 samples.
- **Irregular Cycle Deletion:** Unusual cycles caused by occasional abnormalities like temporary walking pauses or turning contains much noise that will deteriorate the recognition accuracy. Therefore, we calculate the Dynamic Time Warping (DTW) distance for each subject to remove outliers from a set of cycles.

2.2 Sparse Representation based Classification

We utilize SRC as it is more robust compared to other classifiers [3]. To model gait recognition as a sparse representation problem, one needs to first build a training dictionary A . Assume that we have acquired a set of M training vectors. We can obtain the corresponding estimated coefficients vectors $\hat{X} = \{\hat{x}_1, \hat{x}_2, \dots, \hat{x}_M\}$ by solving the ℓ_1 optimization problem as in [2].

By exploiting the coefficients vectors $\hat{x} \in \mathbb{R}^n$, the class results can be determined by checking the residuals based on the Euclidean distance. The definition of the residual for class i is:

$$r_i(y) = \|y - A\delta_i(\hat{x})\|_2 \quad (1)$$

where $\delta_i(\hat{x}) \in \mathbb{R}^{N \cdot K}$ contains the coefficients related to class i only (the coefficients related to other classes are set to be zeros). Then the final result of the classification will be:

$$\hat{i} = \arg \min_{i=1, \dots, K} r_i(y) \quad (2)$$

i.e., the correct class produces the minimal residual.

3 IMPLEMENTATION AND EVALUATION

Figure 2 shows the design and appearance of the prototype. We mount two PEHs from Piezo System¹ in the front and rear position

¹Piezo System: <http://www.piezo.com/>.

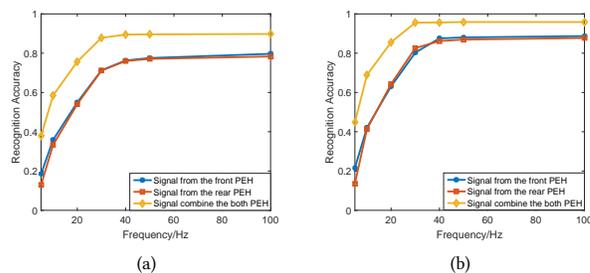


Figure 3: The recognition accuracy v.s. sampling frequency with: (a) one gait cycle, (b) two gait cycles.

of the insole respectively. An Arduino 101² has been used to sample and store the AC voltage signal at 100Hz. The energy generated by the front and rear PEH is rectified and stored into two 1000uF electrolytic capacitors separately.

We collect data from 20 healthy volunteers and each of them walks around 300s in their normal walking style. In total, a 20x250 gait cycle dataset is created and utilized to evaluate the proposed system. Figure 3(a) presents the recognition accuracy in different sampling rates when using one gait cycle for recognition. It can be seen that the recognition accuracy grows up with the increase of sampling rate, while it almost remains stable when the sampling rate over 30Hz. Thus, a minimum sampling rate of 30Hz is required to achieve a reasonable accuracy. In addition, the recognition accuracy is around 80% for both the PEH signals from front and rear of the insole, while it increases to approximately 90% when we combine the two signals. Intuitively, the combined signal can reflect the unique gait pattern more accurately. As shown in figure 3(b), it is similar that the combined signal achieves high accuracy in the case that two consecutive gait cycles are treated as a whole. Moreover, the recognition accuracy presents a significant increase, reaching to approximately 96%, which is acceptable and preferable to many verification applications.

By measuring the capacitor voltage, we can estimate the generated power from human walking. According to our measurement, approximately 160uW power is stored and can be leveraged as a supplement to battery.

4 CONCLUSION

In this work, we explore the feasibility of using the output signal from piezoelectric energy harvester to recognize people and achieve simultaneously energy harvesting and information collection. Our results demonstrate that the recognition accuracy is adequate to meet the requirements of an authentication system.

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²Arduino 101: <https://www.arduino.cc/>.