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Person Identification through Harvesting Kinetic Energy

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Abstract: Energy-based devices made this possible to recognize the need for batteryless wearables. The batteryless wearable notion created an opportunity for continuous and ubiquitous human identification. Traditionally, securing device passwords, PINs, and fingerprints based on the accelerometer to sample the acceleration traces for identification, but the accelerometer's energy consumption has been a critical issue for the existing ubiquitous self-enabled devices. In this paper, a novel method harvesting kinetic energy for identification improves energy efficiency and reduces energy demand to provide the identification. The idea of utilizing harvested power for personal identification is actuated by the phenomena that people walk distinctly and generate different kinetic energy levels leaving their signs with a harvested power signal. The statistical evaluation of experimental results proves that power traces contain sufficient information for person identification. The experimental analysis is conducted on 85 persons walking data for kinetic power signal-based person identification. We select five different classifiers that provide exemplary performance for identifying an individual for their generated power traces, namely NaiveBayes, OneR, and Meta Bagging. The experimental outcomes demonstrate the classifier's accuracy of 90%, 97%, and 98%, respectively. The Dataset used is publicly available for the gait acceleration series.

Keywords: Person identification; Energy efficiency; Kinetic energy harvesting; batteryless wearable.

I. INTRODUCTION

Recent technological advancement has given rise to prominent techniques for addressing pervasive computing constraints [1, 2]. According to the previous research, mobile computing has significant growth realization of self-sustainable wireless devices many resources to obtain energy to power the mobile devices [3, 4] including internet of things [5, 32-34], solar power [6], radio frequency signals [7], wireless sensor nodes [8], vibrational excitation [9], human motion to control remote devices [10], and personalized patient monitoring system [11, 12]. These self-sustainable devices are building a block of wearable computing and smart buildings. Mobile phones are advancing in terms of processing power memory in functionality. These mobile phone characteristics permit them to utilize as a communication device and make them capable of storing sensitive information, which has given rise to security issues [13]. The existing methods are energy inefficient does not respect the unique need of mobile device [14]. However, all of these techniques require active user participation initially and require more sample data to provide high accuracy to access the device. The previously mentioned identification methods consume a lot of power high compared to practically harvested power from human activity. We demonstrate that harvested kinetic energy is an energy-efficient method that produces energy instead of consuming. The previous study [15, 16] shows that various power harvesting wireless devices serve as fundamental building blocks for modern computing and enable modern computing applications. However, a more energy-efficient approach is still a critical issue that is currently under development. We emphasize illustrating the kinetic energy generated by the human body can be harvested by a mobile device with an IoT form factor. The research has demonstrated that according to height, weight, gender heavily affects each individual's kinetic energy. So, the amount of energy generated by various human activities varies on these human attributes [17].

Furthermore, the harvested power from human activities uses for activity recognition [18-21, 31]. Based on this observation, we proposed using harvested power produced by the human motion for identification. There are various ways to harvest the motion energy, although the inertial harvesting motion best fits the IoT applications. The contributions of this research are summarized below:

- We suggest a new approach for a source of mobile device identification by converting the human body generated kinetic energy to power traces.

- Using experimental data, we suggest the human identification removes the requirement of accelerometer sampling to make person identification practical for self-powered devices.
- We suggest the power traces as specific measures to get device access control.

The rest of the paper is structured as follows. Section II contains a literature review, Section III describes Data Collection, in Section IV Model description and measurement setup of the experiments, and the test results presented in section IV.

II. RELATED WORK

As an emerging technology of pervasive computing, self-powered devices have gained much attention to harness energy from ambient sources such as solar power, electronegative energy to monitor our industries, support our decisions and control our lives [7-9, 22]. Much of the research was conducted to available ambient resources to obtain energy for mobile power devices [3, 12, 23]. Including self-winding electronic watch harnesses the energy through the wearer's natural motion's wrist [24]. In addition to that, many commercial devices using person encouraged vibration have been developed [25]. Thein et al. in [26] develop efficient energy harvesting wireless body area network (WBAN) architecture for patient monitoring systems to extend the battery life WBN node.

Mobile phones are already one of the essential factors for the push towards digitization globally; there has been an ever-growing range of applications handling financial transactions, health [11], contact information, etc. These applications generate a sufficient quantity of sensitive information that significantly impacts the user's privacy [27]. Furthermore, it is worth noting that implementing security for authentication has become the primary concern of users today [28]. Consequently, the current approaches protecting the device from attacks, from typical early password to pattern lock, face, gait, and fingerprint to even fusion of different biometric [29, 30], but these methods have their weaknesses and limitations. While energy powered devices have introduced the human as a new source of producing energy to power self-sustainable devices, these portable devices scavenge the energy consumed throughout the user's ordinary activities to produce power for his computer [29]. Moreover, harvesting sensor architecture proposed eliminating the need for wires and batteries' replacement to recognize human activity from human motion [16].

Furthermore, the research demonstrates that energy is an excellent source to recharge the portable self-powered devices and approximate the kinetic energy produced by human motion [13]. The amount of produced energy by an individual depends upon their weight. However, the human can generate power of more than 7.4W depending on his weight [30]. Power consumption is essential in powered-enabled devices, where it has been motivated by many scientists to find new ways to make energy-efficient devices. The proposed approach related to energy-efficient person identification is energy efficient for the identification process in a self-powered device, and it also eliminates the need for an accelerometer.

III. DATASET

The human Activity Sensing Consortium (Consortium, 2011) HASC organization provides the public data sets and releases worldwide. This organization's motive by making data sets widely available is to motivate the researchers and developers to do their experiments and algorithms. In HASC Challenge 2011, various sensors were used to collect data equipped with smartphones, such as a gyroscope, magnetic field sensor, and GPS. The Dataset contains all body motion information by placing terminals in different places, while the terminal state is either free or fixed. The Dataset contains 6 different activity data such as stay (standing), walk, jog, skip, stair-up, and stair-down sampled at 10 ~ 100 Hz frequency. The Dataset we examine in our study is human walking activity traces over 80 participants. The Dataset was collected by the accelerometer sample rate of a 10~100 Hz. The measurement time for each activity is 20 seconds. The selected Dataset contains 4~4 sets of 20 seconds of each individual, having different terminal positions. The terminal state is fixed and attached to the individual bag, strap, and waist and rear position of the human body.

IV. SYSTEM ARCHITECTURE

Since the human-generated energy traces are used for person identification, it is essential to build an evaluation system, whether kinetic energy produced by human motion can perform person identification. Thus, this research study suggests the kinetic energy identification evaluation system. The recommended system architecture consists of five steps: a data selection step, a preprocessing step, a feature selection step, a model learning step, and a model training step. Fig. 1 represents the kinetic energy harvesting identification model.

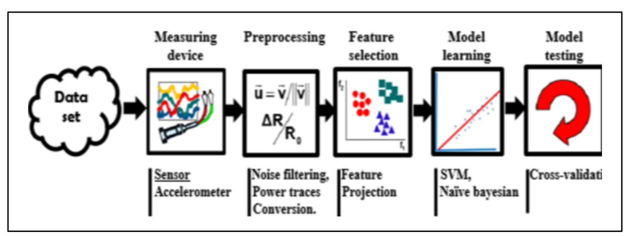

Figure 1. Kinetic energy harvesting identification model

A. Accelerometer Data

The built-in mobile phone accelerometer sensor is considered to collect the data for individual identification. The data positioned on the waist, strap, and rear position, making it possible to capture the accelerations along three-time series x-, y- and z-axis. The single person traces walking manner, where data contains timestamp, x-, y-, z-axis acceleration traces. The timestamp is in the second time scale with a floating-point. Acceleration is in the gravitational acceleration unit ($1G=9.8m/s^2$).

B. Data preprocessing

In the preprocessing phase, the raw signals data has been cleaned first by removing the missing values that the user may start walking a few seconds late in the specified period. The processed data presented in Figure 2, where the energy harvesting method can compute the power traces from each axis of an individual's motion. It implies three different power signals for each axis used to train the HAR classifier based on a 3-axial accelerometer. We choose to examine each axis magnitude to characterize power generated by each x- y- z-axis and the total acceleration magnitude as $a(t)_x= \sqrt{(acc_x(t)^2}$, $a(t)_y= \sqrt{(acc_y(t)^2}$, $a(t)_z = \sqrt{(acc_z(t)^2}$, $a(t)_{xyz}= \sqrt{(acc_x(t)^2 + acc_y(t)^2 + acc_z(t)^2)}$, the measured motion traces compromises a constant component of gravity 9.8 m/sec. The acceleration signals were filtered out using the 3rd order Butterworth high pass filter, considering a 0.1 cutoff frequency [17].

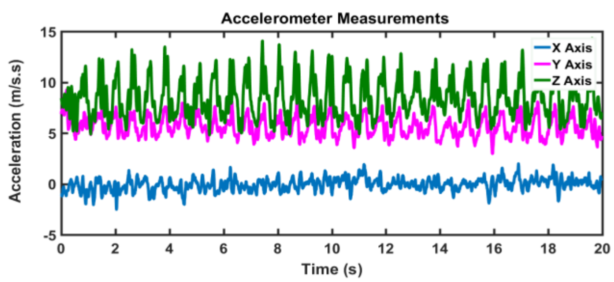

Figure 2. Preprocessing of data

C. *Calculating estimated Harvestable Kinetic Energy*

With the shortage of publicly available kinetic power harvesting devices, the inertial harvester model utilized to compute the kinetic power's energy traces. We follow the previously developed mathematical model to determine the power traces generated by a human. In (Khalifa et al., 2017), the volume of power generated from an actual kinetic energy harvesting device is equal to appropriately estimate the amount of harvestable kinetic power from accelerometer traces. The adapted inertial harvester has been modeled as a typical mass-spring damping system with a harvester proof mass m, proof mass displacement limit $Z_L = 0.01$ m, spring constant k 0.17 kg. s^2, and spring damping factor b = 0.00055 kg.s^2. Figure (3) demonstrates such a harvester model.

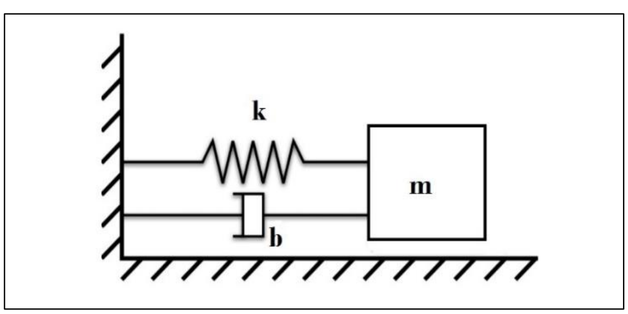

Figure 3. Inertial harvester model

Then, the power computed produced by an inertial harvester model, P(s)xyz, P(s)x, P(s)y, and P(s)z subjected to acceleration a(s)xyz, a (s)x, a(s)y, and a(s)z. We used the same procedure to estimate the power traces as aa approach proposed in [13]. Firstly, the filtered acceleration and then converted them to proof mass displacement, z(t). The function Laplace domain transfer utilized for conversion of data displayed in equation (1).

$$z(s) = L^{-1}\{Z(s)\} = \frac{a(s)}{s^2+\frac{b}{m}s+\frac{k}{m}} \tag{1}$$

Next, the harvester's estimated power has mentioned as $P(s)=(dz/ds)^2$. The result is the traces of power samples estimated from acceleration traces, which we use for further analysis.

D. Feature Selection:

Feature selection strategies are used to identify the optimum subset of features to train the classifier. Information gain (IG) is one of the many feature selection techniques that evaluate each given feature's importance. The optimized set of features is selected based on the discriminating among the classes to be trained. We use the estimated kinetic power of P(s)xyz, P(s)x, P(s)y, and P(s)z power produce by human walk as features. Each feature power is estimated individually using the Laplace domain transfer function eq (1). In IG, if any feature has zero value, that is not useful information for activity classification where the IG calculated for each feature for the kinetic power. The result of the IG of each feature as shown in Fig. 4. The figure demonstrates that all the features have an importance score. At the same time, it shows that all the power features are rich in information and can have the potential to characterize among the labels to identify the person. The selected features are presented in Fig [5, 6, 7 8, 9]. An interesting observation is that the magnitude of overall power (xyz-axis) generated by a person while walking provides the most information. This is exciting because, as the research shows in (Gorlatova et al., 2015), the kinetic power varies to an individual's various activities, which implies that the average kinetic power would be more critical in classification.

```
=== Attribute Selection on all input data ===

Search Method:
        Attribute ranking.

Attribute Evaluator (supervised, Class (nominal): 6 class):
        Information Gain Ranking Filter

Ranked attributes:
 2.751  1 xyz-axis
 2.651  3 y-axis
 2.535  2 x-axis
 2.222  4 z-axis
 1.131  5 time

Selected attributes: 1,3,2,4,5 : 5
```

Figure 4. Different Power features with information gain values

E. Model Learning

The Weka machine learning software has been used in this study to solve the classification problem. We have used various algorithms, including Naïve Bayes, OneR, and Meta Bagging, for this purpose. The classifiers use the power traces as their pattern to learn the physical behavior of each individual. Simultaneously, the Naïve Bayes model performed better than OneR and Meta Bagging for this classification problem.

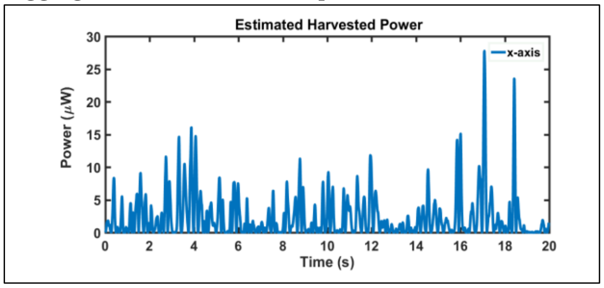

Figure 5. x-axis acceleration (m/s) traces converted to power traces (μW)

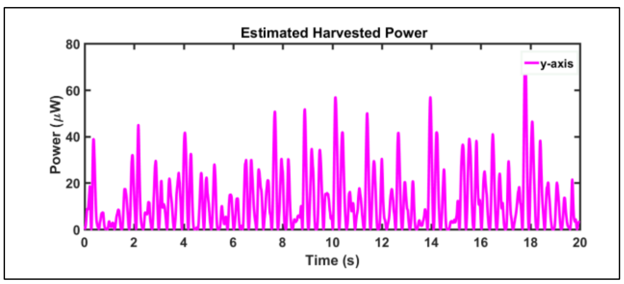

Figure 6. y-axis acceleration (m/s) traces converted to power traces (μW)

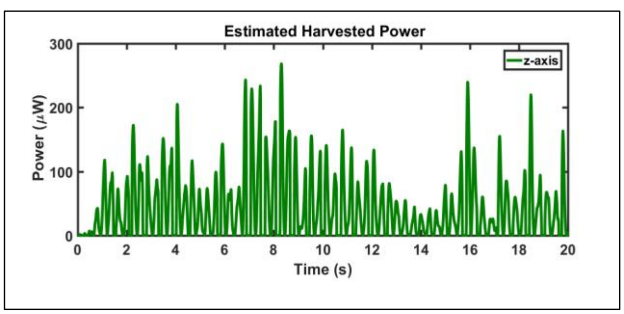

Figure 7 z-axis acceleration (m/s) traces converted to power traces (μW)

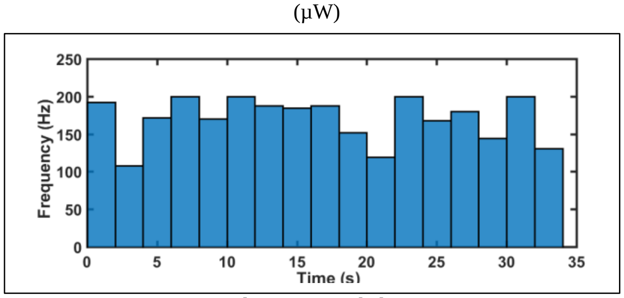

Figure 8. Acceleration sampled at 10 ~ 100 Hz

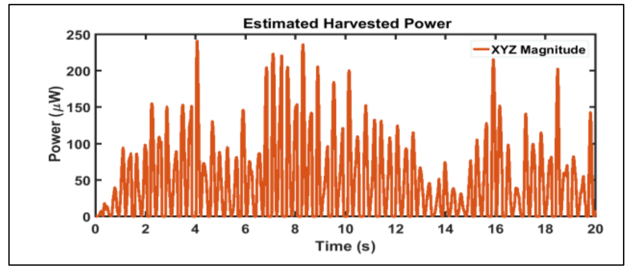

Figure 9. The magnitude of overall acceleration (m/s) traces converted to power (μW)

F. Model Testing

In the testing phase, we test the model by using a 10-fold cross-validation technique. The subsequent Dataset contains 5 features to learn a model, split into 10 folds where each subset is used as a training set, and the remaining subsets are used to test the model performance. Finally, we compare the accuracies obtained by three different classifiers.

V. EVALUATION METHODOLOGY

Three evaluation metrics used to evaluate the harvested kinetic identification energy model's performance are precision, f-measure, and Roc curve. Precision is the percentage of information extracted by a correct system, and F-measure is a harmonic means of precision and recall measures of a test. In a Receiver Operating Characteristic (ROC), each point on the curve presents a sensitivity pair appropriate to a particular decision threshold. A test with ideal discrimination (without overlap in two distributions) incorporates a ROC curve that passes through the higher left corner (100% TP rate, 100% FP rate). Consequently, the nearer the ROC curve is to the higher left corner, the higher the overall accuracy is achieved. The result of all the performance measures shown in Fig [10, 11, 12].

VI. EXPERIMENTAL CLASSIFICATION RESULTS AND ANALYSIS

Our experiments require gathering the labeled raw accelerometer data and transforming the data into power traces described in section 4. The three classifiers are selected to measure the identification accuracy of the harvested kinetic energy model. As previously mentioned, the 10-fold cross-validation technique has been utilized to obtain the accuracies of the harvested kinetic energy model.

The average results summary of classifiers used to identify individuals from power traces presented in Table 1.

A standard Meta bagging and OneR classifier can identify a person with higher accuracy using simply estimated kinetic power traces, without using accelerometer data. Figure 10-12 represents the detailed

TABLE 1. COMPARISON OF DIFFERENT CLASSIFIERS PERFORMANCE

Classifier	*Precision*	*F-Measure*	*ROC Curve*
Naïve Bayes	90	88.9	99.8
OneR	97	97	98.5
Meta Bagging	98.8	98.8	1

experimental results obtained from the HASC project dataset. From these results, we can see that the Metabagging classifier yields better performance among all the classifiers, Naïvebayes delivers the poor performance, while OneR achieves better results than Naive Bayes.

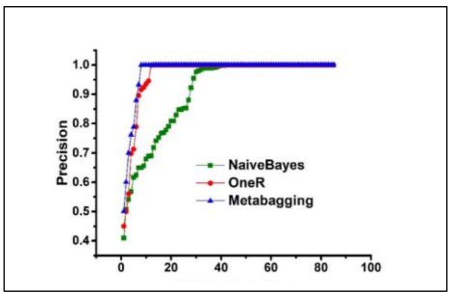

Figure10. The precision results of different classifiers

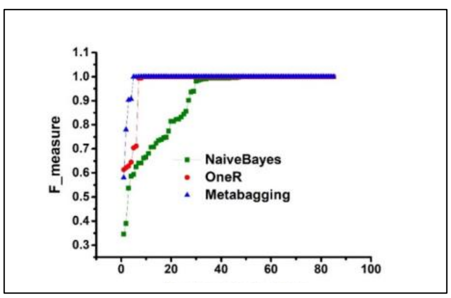

Figure 11. F-measure results of different classifiers

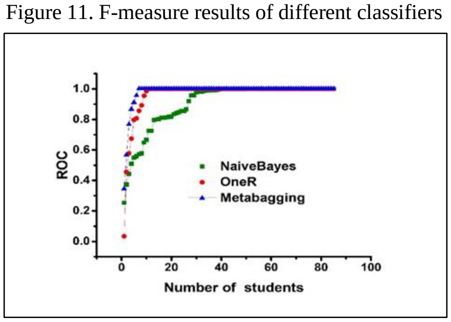

Figure 12. Roc curve for all the person overall classifiers.

VII. CONCLUSION

Usually, the accelerometer viewed as low power sensor, but this research study has exposed that the accelerometer is creating the energy bottleneck in realizing self-powered HAR. Furthermore, it has demonstrated that the power traces contain the human signature that is to be classified. Our analysis demonstrates that the human body's power can be used for the physical pattern for person identification. However, the suggested approach applied the inertial harvester model to identify the individual's gait activity accurately with a typical accelerometer. A mathematical model has been tested to compute the leverage kinetic power from accelerometer data in the absence of portable kinetic energy harvesting devices. In the future, it is possible to investigate the multidimensional activities of kinetic power from the ambient resources from the environment. We are planning to take account of more human activities and with the larger Dataset. It is expanding the research for using Kinetic energy for person identification as it opens the research area. It is motivated by current wearable devices focusing on specific activities (e.g., running, jogging, sitting, escalator up and down).

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