Poster Abstract: Activity-based Profiling for Energy Harvesting Estimation

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ABSTRACT

We propose a novel activity-based profiling framework to estimate IoT users' harvested energy based on their daily activities. Energy is harvested from natural sources such as the kinetic movement of IoT users. The profiling framework captures the users' physical activity data to define activity-based profiles. These profiles are utilized to estimate the harvested energy by IoT users. We train and evaluate our framework based on a real Fitbit dataset.

CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous computing**; **Ubiquitous and mobile computing systems and tools**.

KEYWORDS

Wireless energy, IoT, Energy Harvesting, activity profiling, wireless power transfer, energy services

1 INTRODUCTION

Energy services refers to the *wireless transfer of energy* from an IoT device (e.g. *energy provider*) to a nearby device (e.g., *energy consumer*) [1][2] Energy providers, such as smart shoes, may *harvest* energy from natural resources (e.g., physical activity) [3][4] For example, PowerWalk kinetic energy harvester produces 10-12 watts of on-the-move power[1]. The harvested energy may be used to charge nearby IoT devices wirelessly using new technologies known as *"Over-the-Air wireless charging"* [5][6][7]. For example, Energous may charge devices up to a distance of 4.5 meters [8][9].

Enabling a sustainable energy services IoT ecosystem will offer ubiquitous access to energy [2]. In this environment, IoT devices can be charged automatically without human intervention. To achieve that, the system must know *when*, *where*, and *how much* energy an IoT device may request/offer as a service from/to nearby IoT devices [1]. This paper focuses on estimating the energy services that a
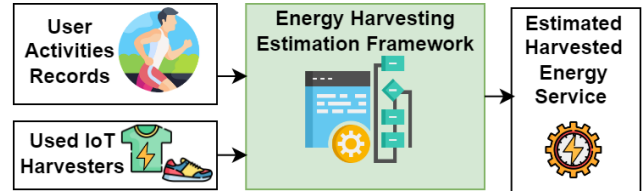

Figure 1: Energy Harvesting Estimation System

provider may offer, specifically on *estimating how much energy a provider may harvest to offer as a service.*

Studies have proposed to estimate the energy from daily activities by measuring the output from kinetic energy harvesters [3]. Harvested energy may be estimated by capturing the kinetic movement of the device wearer and their body temperature. Moreover, other studies used kinetic energy harvesting data to recognize daily activities [10][11] In principle, it is possible to estimate the amount of harvested energy based on the activity and the worn harvester's type [10] Such activity may be collected by wearables such as smartwatches. In this paper, we envision a novel framework to profile users based on their daily physical activities, consisting of an activity-based profiling component and an energy-harvesting estimation model (See Fig. 1) [1]. The activity-based profiling component will aim to classify users based on their daily activities in order to associate them with the corresponding energy harvesting estimation model. The model will use the activities profiles and the type of worn harvester to estimate the harvested energy. As energy harvesting technologies are still developing,*we focus on the activity-based profiling.*

Several studies have used fitness data to model its wearer behaviour for fitness purposes [12]. Hence, we propose to *use fitness data to recognize users' activities for energy harvesting purposes.* Even though people may do the same activity, e.g., walking, they may differ in activity intensity level, which may harvest different amounts of energy [10]. Therefore, we propose an activity-based profiling framework to identify macro profiles that represent the major activity behaviour of IoT users. These profiles will be used to build an energy harvesting model to estimate the harvested energy based on the users' activity and the used energy harvester.

2 PROFILING FRAMEWORK

The activity-based profiling framework aims to cluster users according to their daily activity records. The framework consists of four phases: Data Acquisition and Pre-processing, Feature Selection, Data Fusion and Activity-based Profiling (See Fig. 2). In what follows we discuss each phase:

1. **Data Acquisition and Pre-processing:** During this phase, users' health-related information and daily activity data are obtained from their fitness tracker. We used a public Fitbit dataset consisting of

Table 1: Evaluation Metrics of clustering algorithms

Metrics \ Feature Selection	K-means Clustering			Robust Clustering		
	Original	PCA	Correlation	Original	PCA	Correlation
Silhouette Score	0.47574	0.51564	0.48323	0.73409	0.68170	0.72274
Davies Bouldin Index	0.55996	0.49664	0.54936	0.38857	0.42842	0.40737
Calinski Habrasz Index	72.97150	75.68820	75.72814	81.62642	78.73628	79.16408
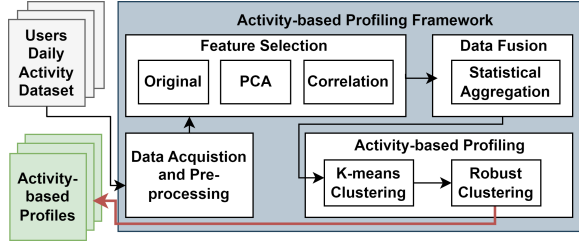
Figure 2: Activity-Based Profiling System Architecture

940 records of 33 users' daily activities over a 2-month period in 2016[1]. As the dataset does not have bio-related data for all users, only activity-related data is used. Also, three features are removed from the dataset: ActivityDate', TrackerDistance', and LoggedActivityDistance' because they are exact duplicates for other attributes.

2. **Feature Selection:** Feature selection identifies the most representative features of an IoT user's daily activity. The following three approaches were applied separately to the original cleaned dataset, resulting in three processed datasets:

   2.1 **Original module:** This module contains all the features of the pre-processed dataset.

   2.2 **PCA module:** We apply the Principal Component Analysis (PCA) technique on the original dataset to transform all the attributes into only three components.

   2.3 **Correlation module:** This module uses a feature-based heat map to select features based on their correlation, removing highly positively or negatively correlated features.

3. **Data Fusion** Clustering users into groups is not applicable to our fitness dataset as it has multiple activity records for each user. Therefore, data fusion is needed to aggregate the records of each user with minimal information loss. Specifically, we used the statistical values (maximum, minimum, range, standard deviation, mean, and median) to capture user characteristics. These statistics are computed for each user in the three processed datasets from step (2).

4. **Activity-based Profiling** This phase includes applying *K-means* clustering to users' aggregated records, followed by using the resulting clusters in a robust clustering approach.

   4.1 **K-means Clustering** K-means clustering is applied to each of the datasets obtained earlier. We used the *elbow* method to determine the optimal number of clusters for each dataset. As a result, each dataset produced four clusters.

   4.2 **Robust Clustering** As aforementioned, the outcome of the clustering was four clusters for each dataset, but with varying cluster sizes (number of users). To address this, we define *robust clustering* by identifying common users across the same clusters in all three sets. Users who are clustered together in all three K-means sets are defined as one robust cluster. Users with different clustering neighbours in the original three K-means sets are defined as separate robust clusters. This produces

seven robust clusters/profiles, each representing an activity-based macro profile for a group of IoT users with common behaviour, i.e., activity-based behaviour. A harvested-energy estimation machine-learning model may be used to associate each profile with an estimated energy amount based on its characteristics, using a user's daily records, profile, and type of harvester worn. The energy harvesting estimation model will be investigated in the future.

3 EVALUATION METRICS

The performance of our robust clustering algorithm is evaluated using three metrics: Silhouette Score (*SS*), Davies-Bouldin Index (*DBI*), and Calinski-Habrasz Index (*CHI*)[13]. We compare the performance of the robust clustering algorithm with the K-means clustering applied to each feature selection module(See step4). To calculate the metrics, each set of features is used with the robust clustering. The results of the metrics are shown in Table 1. The *SS* ranges from -1 to 1, with a score closer to 1 indicating denser and more distinct clusters. The robust clustering approach outperforms K-means clustering. The original module achieved the highest *SS*. In contrast, a lower *DBI* represents a better separation among clusters. The robust clustering with all modules has a *DBI* than k-means clustering, with the original module having the lowest index. A higher *CHI* indicates better clustering performance, and the robust clustering approach with all modules outperforms K-means clustering, with the original module achieving the highest index.

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