Wireless Non-invasive Motion Tracking of Functional Behavior☆

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Abstract

The prevalence of a sedentary lifestyle is a major contributor to many chronic afflictions in modern society. Objective study and monitoring to gain an accurate understanding of situated sedentary behavior, for example when at home, present considerable challenges, e.g. regarding ecological validity. Non-intrusive monitoring based on Wi-Fi signals provides a new way to gain insights into populations that are at risk of the negative effects of a sedentary lifestyle, or who are already in functional rehabilitation. In this paper we describe a tracking technology for everyday activities that consists of two parts: (1) recognizing general physical activity, as well as the activities of common classes; and (2) measuring the statistical duration of these recognized categories. Employing common commercial Wi-Fi equipment, we performed validation studies in a typical noisy family home environment, achieving the following key results: (1) a recognition rate of the general presence of physical activity of 99.05%, an average recognition rate of 92% when detecting four common classes of activities; and (2) Kappa coefficient analysis to evaluate the consistency of the statistical duration of the automatic activity detection based on Wi-Fi signals and manually coded activity detection based on camera recordings. The coefficient for the presence

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of general physical activity of .93 and the average consistency coefficient of the classified activity categories of .72 suggest a high reliability of the automatic detection outcomes. This work aims to support both research and interventions for the prevention, treatment, and rehabilitation of the consequences of a sedentary lifestyle, by establishing new technologies and methods for observing everyday functional activities that are crucial for individual independent living and well-being.

Keywords: Activity Recognition, Wi-Fi, eHealth, Digital Health, Signal Processing, Sedentary Lifestyle, Situated Research

1. Introduction

1.1. Motivation

Compelling evidence has linked the common sedentary lifestyle that is prevalent in modern societies to many diseases or chronic afflictions. Next to extreme examples, such as being a risk factor for cancer [1], a sedentary lifestyle can lead to poor cardiopulmonary function and metabolic disorders [2] and it is also clearly associated with obesity and diabetes. Increased physical activity can reduce the risk of such diseases [3, 4]. However, current and future developments in automation, such as buying groceries over the internet, stand to result in even lower levels of physical activity, entailing potential further impacts on public health [5] with a risk of an increased frequency of cardiovascular diseases [6]. Research on young men with sedentary diseases in different industries found that sedentary behavior also has a negative effect on men's reproductive ability [7]. In women, sedentary behavior can lead to premature menopause [8]. It can also lead to obesity in children, with negative carry-over effects on their adult health [9]. Studies have found that older adults who exercise regularly will have healthier breathing systems than those who display more sedentary behavior [10].

While people who display overly sedentary behavior may be motivated and guided to become more active in some situations, e.g. when coaches can be present, the sedentary behavior patterns are often resumed in much frequented places where people spend large parts of their time, such as at home or at work. It is also difficult to gather objective insights on sedentary, active, or functional behavior in such situations, although such information is required to inform research as well as interventions. This motivates the development of motion tracking methods that can be employed in situations that are traditionally prohibitive to affordable and longer-term observation. While reliable measurement devices based on optical, magnetic, or inertia sensors exist [11, 12, 13], they can be invasive and may lead to biased behavior. Recently, non-invasive human activity and behavior recognition based on Wi-Fi signals has become a research hotspot, and considerable progress has been made [14, 15, 16, 17, 18]. However, there is still a lack of research on activity recognition in practically relevant but noisy situated environments. Hence this work explores physically non-invasive wireless tracking together with methods for activity type and duration recognition to offer alternative methods for observing patterns of sedentary, or active functional behavior in the home. Next to informing basic research, such information could be utilized to produce individualized training and rehabilitation advice to help restore healthy living habits.

1.2. Challenges

Although research on motion tracking and activity recognition based on Wi-Fi signals has made considerable progress, the viability of the approach in real-world application scenarios is still debated. Since wireless signals are easily disturbed by the external environment, achieving a reliable perception of human activities is challenging [19]. At present, there is a lack of studies focusing on either of the following two aspects: (a) in-depth research of activity identification in a noisy situated environment, and (b) gathering additional information beyond recognizing activity classes (such as the duration of an activity). In this light, this work is concerned with the following research questions: *(1) Can motion tracking based on wireless signals produce an adequate reliability for the perception of human activity in noisy situated environments? (2) Can an ad-*

equately high recognition rate be achieved for different classes of activities that represent a progression of increasingly intense physical activity even if such activities occur rarely? (3) Can the duration of activity episodes be determined accurately based on Wi-Fi signal analysis? If the proposed methods can lead to positive findings regarding these research questions it would present a viable approach to making the levels of physical activity of people who live a sedentary lifestyle more measurable, which can further our understanding of their situated behavior, and it would also facilitate potential interventions that provide guidance regarding recommended exercises, activity frequency, and duration. For example, if the amount of overall activity is low, a general suggestion to increase overall activity can be issued. For people with less movement of the lower extremities, it can be suggested that they should focus on executing more movements that involve the lower limbs, such as walking. Such approaches can offer support in achieving a more well-regulated balance between activity and rest, promoting a healthy lifestyle and thus helping with offsetting or preventing the onset or progression of common chronic afflictions that are tied to an overly sedentary lifestyle.

1.3. The technical scheme frame and thesis structure

The technical scheme that underlies the system called WiFun that is presented in this article is shown in Figure 1 (the items in the dotted line box are beyond the scope of this work but essential to convey the larger picture).It must be stressed that the recognition model indicated in Figure 1 is a model trained by channel state information (CSI) information after multiple acquisition actions, which then forms the basis for the following activity recognition part. Due to the close relationship between the recognition model and the activity recognition process, we present a combined discussion of both elements in Section 3. The duration statistics of activities and the consistency evaluation elements in Figure 1 are discussed in further detail in Section 4. The work related to this article will be introduced in Section 2. In addition, the activity evaluation and health persuasion parts that appear in the dotted box are not

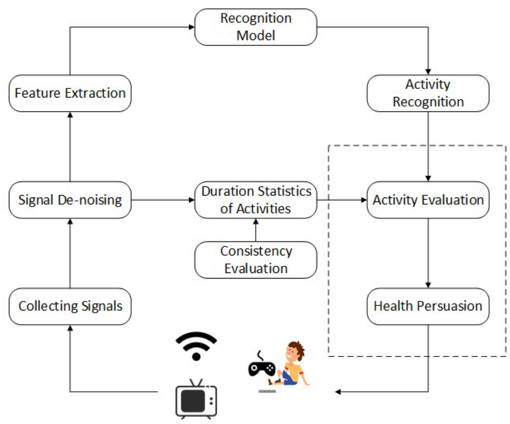

Figure 1: The technical scheme frame diagram of the WiFun system. Persuasion can be active (showing recommendations) or passive (showing observed state).

yet implemented. The main purpose of the figure is to illustrate the overarching goal, and which is approach in follow-up work that is currently ongoing.

1.4. Technical Approach and Contributions

First of all, we use the *Bart Watts* (BW) for denoising, because the actual test shows good results. Then we use *principal component analysis* (PCA) and its own heuristic algorithm to extract effective data. Because the extracted data has burrs and different lengths, then use *cubical smoothing algorithms with five point approximation* (CSA) and *polyphase filter* (PP) to denoise and resample the data. In the process of feature extraction, we initially use *discrete wavelet transform* (DWT) to decompose the signal data and then optimize and reorganize the best eigenvalue combination according to the characteristics of the decomposed data. To build the recognition model, we mainly use the *channel state information* (CSI) principle of change [20], (when people are detected to be in the Fresnel zone [17]), to facilitate the use of a *hidden Markov model* (HMM). The activity recognition is divided into two parts: (1) *general physical* *activity recognition*, which refers to all non-stationary activities and was defined separately since researchers or practitioners may sometimes just want to know whether individuals in a room are sedentary or active, a purpose for which a dedicated model can achieve a high recognition rate and strong robustness, and (2) *specific activity recognition*, which can more accurately grasp the details of physical activity of potentially sedentary people and can inform targeted diagnosis and treatment. In order to encompass different activity intensities we separate four common activity classes at different levels, which requires identifying motion patterns that cause notable differences in signal frequency.

We have designed a novel algorithm to calculate the duration of general physical activity and to detect four common activity classes that is discussed further in section 3.3. In addition, we innovatively discretize the time domain space, so that we can calculate a Kappa coefficient for cross-validation with human evaluators and verify the credibility of the automatically detected statistical duration of sequences of activity. The main technical contributions of this paper are as follows: (1) The novel combination of BW, PCA, effective data extraction algorithm (5.2.1), CSA, PP and DWT is used to preprocess the wireless signal, while the recognition model is established by combining the threshold method and HMMs. (2) A heuristic algorithm based on statistical duration is presented, which can produce information on activity duration relying only on wireless signals. (3) A method for the discrete processing of continuous signals is introduced which allows the application of Kappa coefficients to evaluate the quality of the process for determining duration statistics.

2. Related works

2.1. Wearable Technology for Motion Tracking and Activity Recognition

Wearable devices can sense, record and analyze a wide variety of data, supporting research and interventions targeting the promotion of increased wellbeing and a better quality of life. Such wearable devices can be divided into living health, information consulting, and physical control equipment. To date, this kind of technology has produced a considerable number of commercialized products, such as smart watches, smart glasses, and gesture control armbands [21], together with a growing body of research that evaluates these gadgets, their value as research tools, and different application use-cases. Doron et al. [22] designed an autonomous wearable device, which can record a subject's physical activity (PA) during his/her daily life and estimates the associated energy expenditure. Experiments show that the system can achieve a correct recognition rate of 79%, based on a trial in quasi-situated-living conditions. Yingling et al. [23] sought to explore usage characteristics of PA tracking wearable technology among community-based populations within a health and needs assessment. Garbarino et al. [24] designed a wearable wireless multi-sensor device for real-time computerized biofeedback and data acquisition. It has four embedded sensors: *a photoplethysmograph* (PPG), *electro dermal activity* (EDA), *a 3-axis accelerometer*, and *body temperature*. It is not only small, light and comfortable, but also suitable for a wide range of real-life applications. Din et al. [25] use an accelerometer to quantify a comprehensive battery of gait characteristics in healthy older adults and people living with Parkinson's disease, aiming to support clinical and at-home use. Casale et al. [26] developed a novel wearable system that is easy to use and comfortable to wear, which is based on a new set of 20 computationally efficient features and a random forest classifier. The classification accuracy of human activities with this system is up to 94%. Nam et al. [27] developed and evaluated algorithms to recognize physical activities from data acquired using a 3-axis accelerometer together with a single camera worn on a body. Experiments show an overall accuracy rate of activity recognition of 92.78% with their method. Sztyler et al. [28] present a new real-world data set that has been collected from 15 participants for eight common activities where they carried seven wearable devices in different positions. Furthermore, they introduce a device localization method that uses random forest classifiers to predict the device position based on acceleration data, achieving an F-measure of 89% across different positions. Fang et al. [29] present BodyScan, a wearable system that enables radio to act as a single modality capable of providing whole-body continuous sensing of the user. They introduce radio as a new powerful sensing modality for wearable devices and propose to transform radio into a mobile sensor of human activities and vital signs. In challenging real-world settings their system can infer activities with an average accuracy of more than 60% and monitor breathing rate information for a reasonable amount of time during each day.

From the above research, we can see that a wide range of related work has employed wearable technology for health monitoring. However, such devices can be – or can be perceived to be – invasive, causing inconvenience and discomfort. Therefore, many researchers are now exploring less invasive tracking, monitoring and human-machine interaction technologies; wireless signal recognition being one of them.

2.2. Research on Activity Recognition Based on Channel State Information

Halperin et al. [30] released a CSI activity recognition toolkit in 2011 and gave a detailed account of its potential use. The CSI toolkit can record the subcarrier information of a pair of transmitting and receiving antennas. Compared to *Received Signal Strength Indication* (RSSI), which can only record the energy information, CSI reflects the change in wireless signal in more detail. Subsequent research on CSI is primarily based on this toolkit. Han et al. [31] proposed a prototype for fall monitoring for older adults. Their experiments show that the system has an 87% recognition rate with 18% false positives. Wang et al. [20] have explored high-precision recognition based on wireless signals. They identified tiny movements of the mouth that people made while talking. Their experiments showed that 91% of them are correctly recognized in the case of a single person saying six different words, and the simultaneous recognition rate was 74% in the case of three people. Yang et al. [32] studied the recognition of family activities. Their experiment was carried out independently in two different rooms, using the template matching method and obtaining good experimental results. Xi et al. [33] quantitatively analyzed group sizes by analyzing changes in wireless signal. They used *percentage of nonzero elements* (PEM) as a measure to construct a relationship between the number of people and the change in CSI characteristics through a stable monotonic function. Zimu et al. [34] studied the problem of existence of multi-dimensional space by analyzing CSI [34] and achieved good experimental results. Wang et al. [14] proposed a CARM prototype system. Based on CSI analysis, they proposed a CSI-speed model and CSI-activity model, quantifying the relationship between the movement speed and the location movement of a body part, revealing a relationship between the dynamic CSI value and the specific activity. The average recognition rate of their prototype system is higher than 96%. Li et al. [15] studied the recognition of fine-grained wireless signals and explored human-computer interaction techniques for specific gesture recognition. Their experimental results showed that the recognition rate of the nine digital gestures of *American Sign Language* (ASL) is 90.45%, while the average recognition rate of personal digital gestures with a maximum of 90 digits can reach 82.67%. He et al. [16] recognized four simple actions in family life through data pre-processing and SVM classification technology, obtaining 92% recognition rate if in line of sight and 88% if not in line of sight. Ali et al. [35] proposed a method of using CSI to identify non-contact key gestures. His experiments showed that the key detection rate is 97.5% and single key recognition rate is 96.4%. Zhou et al. [36] presented Wi-Dog, a non-invasive physical violence monitoring scheme based on commodity Wi-Fi infrastructure, aiming to provide ubiquitous violence monitoring. Experimental results show the effectiveness of Wi-Dog with an average detection accuracy of 90%. Li et al. [37] leveraged fine-grained CSI from commodity Wi-Fi to build an adaptive and robust intrusion detection system named AR-Alarm. Zhuo et al. [38] identify non-negligible non-linear CSI phase errors and report that IQ imbalance is the root source of non-linear CSI phase errors. Their experiments show that accurate CSI phase measurements can significantly improve the performance of splicing and the stability of the derived power delay profiles. Zhang et al. [17] introduced the Fresnel zone model originally used to describe the propagation of light waves into the field of wireless human behavior recognition and obtained the detection limit of Wi-Fi signals. The paper also separately identifies centimeter-level fine-grained activities (such as respiration) and decimeter-level coarse-grained activities (such as the direction of movement), and clarifies that the wireless sensing approach based on the Fresnel zone model uses Wi-Fi signals to achieve centimeter and even millimeter-level human behavior perception. Leveraging the fine-grained CSI and multi-antenna setting in commodity Wi-Fi devices, Zhang et al. [39] designed and implemented a real-time, non-intrusive, and low-cost indoor fall detector, called Anti-Fall. In a related publication, Wang et al. [40] present the design and implementation of RT-Fall, a real-time, contactless, low-cost yet accurate indoor fall detection system using commodity Wi-Fi devices. For the first time, this system fulfills the goal of segmenting and detecting falls automatically in real-time, which allows users to perform daily activities naturally and continuously without wearing any devices on the body. Tan et al. [18] discussed the technology of CSI in human behavior recognition on three different levels of granularity, signals, actions and activities and conclude by discussing open issues around CSI-based behavior recognition. Wang et al. [41] present Phase-Beat, a system that employs CSI phase difference data to monitor breathing and heartbeat with commodity Wi-Fi devices. They provide a rigorous analysis of the CSI phase difference data with respect to its stability and periodicity.

From the above research, we can see clearly that although wireless signals have been used for human activity recognition, there is no systematic research in health monitoring. There is also no detailed explanation of how to perform noise reduction, feature extraction and modeling in a noisy environment. In addition, no related work has been found that facilitates detecting the statistical duration of activity using wireless signals. This paper takes a novel approach to these issues, thus furthering the research in this area and more generally in the processing of wireless signals for human activity tracking.

2.3. Related Work on Consistency Assessment

There are multiple assessment methods for consistency evaluation. There are several common methods: 1. Paired t-test [42]; 2. Pearson Correlation Coefficients [43]; 3. Intraclass Correlation Coefficient (ICC) [44]; 4. Kappa coefficient [45]. Nowadays, the use of Kappa coefficient is the most extensive method, and there are many research results similar to those in this paper. Cohen [45] used the Kappa coefficient in 1960 to measure the deviation between an observed and the theoretical inferred value. Tang et al. [46] found that medical diagnoses, even under the same external conditions, have many different evaluation criteria and different outcomes depending on personal judgment. The Kappa coefficient can be employed to indicate the consistency of these evaluations. Arajo et al. [47] used the Kappa coefficient to evaluate the consistency of different classification algorithms. To distinguish two stages of *Rapid Eye Movement* (REM) and *Non-Rapid Eye Movement* (NREM) Singh et al. [48] collected *electrocardiography* (ECG) signals during sleep to extract the frequency and non-linear features by a polynomial SVM. Due to existing multiple evaluation perspectives, they evaluated the consistency of scores and rates by calculating the Kappa coefficients. In this paper, the statistical duration of wireless signals is evaluated to confirm the reliability. We evaluate the credibility of the automatically detected outcomes by using the Kappa coefficient. The Kappa coefficient is an index to measure classification accuracy. The results of Kappa computing are $-1 \sim 1$, but usually Kappa falls between $0 \sim 1$, and the consistency of different levels can be represented by different values. Due to existing multiple evaluation perspectives, they evaluated the consistency of scores and rates by calculating the Kappa coefficients. In a similar way, we employ Kappa coefficients to benchmark the classification accuracy of the activity recognizers, relating their "judgements" to those of human annotators.

3. Activity recognition method and model

3.1. Activity Recognition Technology Based on CSI

In essence, *orthogonal frequency-division multiplexing* (OFDM) works by dividing a channel into a number of orthogonal sub-channels in the frequency domain, followed by modulating each sub-channel by using a subcarrier, and then transmitting the subcarriers in parallel. In wireless communications the physical layer information on these subcarrier scales is called *channel state information* (CSI). It describes how the signal is transmitted from transmitter to receiver, as well as the characteristics of multipath propagation. It reflects the weak factors of signals in each transmission path, such as signal scattering, environmental degradation and power attenuation with distance. Because of shadow fading caused by multipath propagation, the RSSI does not follow the law of increasing distance and decreasing monotony, so the measurement accuracy is not as high. In addition, each CSI reflects the amplitude and phase of the signal with different frequencies after multipath propagation. Therefore, CSI contains more fine-grained information in the physical layer. CSI describes the channel state on the subcarrier level and can measure the amplitude and phase of the subcarrier. For different applications we can also extract representative features from the CSI and derive subtle environmental information from the time and frequency domain. Human activities can cause environmental changes, hence it is possible to recognize and track activities through CSI analysis in environments that are subject to limited change apart from human movement.

3.2. General Physical Activity Recognition

General physical activity refers to all non-static human activity. This is a helpful distinct class because, in many cases, it is not easy to detect all nuances of an activity. But when someone is generally physically active, the tracking data is fundamentally different from the static state, making the state difference easy to discern while gathering reliable information that can be very important to gain a better understanding of physical behavioral patterns. Since the CSI value changes abnormally when human activity occurs, we can derive the recognition of general physical activity with high likelihood from confirming abnormal sequences in the sensor data.

Before performing the exceptional case detection analysis, we need to eliminate noise from the CSI data. Here we use the *Butterworth low-pass filter* to process the raw data. The Butterworth filter is widely used in electronics and electrical communication. This filter keeps the low frequency information which is influenced by movement of the human body and removes most of the high frequency interference noisy information. The wireless signal is always in high-frequency, while physical activities is at a low-frequency respectively. For this reason, a Butterworth low-pass filter is chosen to eliminate the interference information in the data flow. Butterworth low-pass filters can guarantee the low frequency, which is the useful information, will be passed, and the high frequency interference signal will be filtered out. Figure 2 shows an example of the original subcarrier (raw data) and Figure 3 shows after signal processing with the Butterworth low-pass filter. This operation effectively removes most of the high frequency noise, and retains useful activity information.

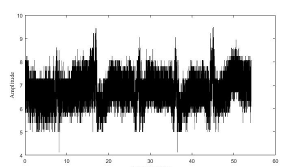

Figure 2: Original subcarrier

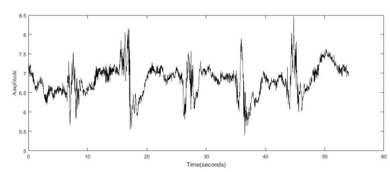

Figure 3: Data sequence chart after filter

Sequences of anomalous activity can then be obtained by calculating the principal component and the eigenvector of the processed data. By setting the average value of the sequence as a threshold, the start and end positions of the activity can be found according to the algorithm proposed by 5.2.1 of this article. The data extracted between the start and end points are the data source of feature extraction for the classification of common activities.

3.3. Feature Extraction and Recognition for Activities of Common Classes

Although we cannot differentiate all potential activities, there are four classes of activities plus a static state that can form a helpful basis of reference. The static state refers to people who are sleeping or engaging in sedentary behavior, such as watching TV, which is characterized by normal breathing but no gross physical activity. The four classes of activity are: (1) *light extremities* *movement stationary*: minor movement in hands or legs while seated, which means the body does not move and there is only controlled displacement of extremities (e.g. stretching hands up); (2) *intense movement stationary*: moving parts of the body while stationary, which means the extremities and the overall body may move notably, but the body does not shift location (e.g. squatting and picking things up); (3) *light full-body non-stationary*: non-violent activities with hands and feet; this roughly equates slow change in location of the body (such as mopping the floor); and (4) *intense full-body non-stationary*: intense physical activities; this typically results from strong movements of the whole body, including additional movement in hands and feet together with fast changes in location (e.g. playing table tennis or walking / jogging around swiftly). The reasons for choosing these four activities are: (1) they represent an increasing intensity of different activities. One can thus estimate the actual amounts of different types of activities, along with their duration. Classes 2 to 4 roughly correspond to the different levels of activity that are employed in the most common physical activity questionnaires, such as the RAPA(The Rapid Assessment of Physical Activity) [49, 50, 51]. Hence, the readings can be compared in categories that are meaningful to the broader research community. (2) Following the division by involved body parts we can estimate whether the body is performing coordinated movements, which can be helpful since intense movement does not necessarily represent desirable behavior. (3) It is helpful to test the sensitivity of the wireless equipment for different speeds and different spatial positions of activities and to improve these methods of feature extraction when building the recognition model.

First of all, we use PCA to deal with the original data, then extract activity information between the corresponding start and end points that were obtained in the section (3.2). Unfortunately, there are still burrs in the signal, so we use CSA filtering algorithm for further data preprocessing. Experiments show that CSA achieve satisfactory results, but different filtering algorithms may be able to achieve the same effect, the relevant comparison will be carried out in the future work.

In addition, these extracted activity data usually have different lengths that will result in a workload increase if the eigenvalues are extracted directly using wavelet analysis. Hence, the activity data has to be re-sampled to obtain data fragments of the same length. We employ a polyphase filter to re-sample in the time series, which turns all the data fragments into a fixed-length sequences in the same fluctuation range and data trend as before. The polyphase filter consists of an anti-aliasing low-pass filter designed with the FIR (finite impulse response digital filter) method. An example of data processed by BW and PCA is shown in Figure 4. The result of data de-noising using CSA is shown in Figure 5. Figure 6 is a schematic diagram of 1,000 data points re-sampled from 3,201 data points.

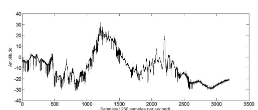

Figure 4: Data preprocessed by BW and PCA

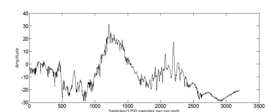

Figure 5: After de-noising with CSA

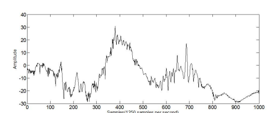

Figure 6: Re-sampling 1,000 data points

Generally speaking, there is no unified analysis theory or reliable best-practice for feature extraction based on different application backgrounds and classification methods to extract varying features. However, there are three principal foci: *time domain*, *frequency domain* and *time-frequency domain* analysis. Time-frequency domain analysis, such as *wavelet transform*, is a compromise between the time and frequency methods selecting different results after wavelet transform as characteristic vectors depending on application characteristics. For this paper the energy values of 16 signals were calculated by decomposing the data into four layers of wavelet packets. The energy values are used as the eigenvalues of the current activities after uniformly symbolizing and clustering.

Afterwards, separately constructed *hidden Markov models* (HMM) are used to form recognition models for each activity class. While the hidden state N and the observable state M are fixed or can be directly obtained, the HMM parameters can be expressed as a triplet (π, A, B), where π represents the initial state probability, A the transfer matrix of the hidden state, and B the confusion matrix. The key points are to construct a hidden state transition matrix and a confusion matrix.

If we set an activity having N hidden states, we can acquire a hidden state transition matrix as an $N \times N$ matrix. The activity is then represented by N states, i.e. the N hidden state values encode an observation sequence of the activity. After decomposing of the signal data, the value of the eigenvectors may not necessarily be an integer. Negative numbers cannot be trained directly into the model as an observation sequence, so they need to be mapped into observation symbols. In this paper, there are four specific activities to identify, each activity has N states, and only $4N$ observation symbols can contain all of the observation states. We can consider the observed state $M = 4N$, and the confused matrix as $N \times M = N \times 4N$. We make the following initialization settings: (1) for each HMM, the initial state probability is $\pi = \{1, 0, \ldots, 0\}$, assuming that the probability of the first occurrence of the first state is 1; (2) For the hidden state transition matrix, we use a multi-state semi-connected left and right HMM for activity recognition. In this case, the current state has only two transition directions and the sum of each row is 1. It is assumed that the current state is shifted to the next state with a probability of 0.5 and shifted to the current state with a probability of 0.5; and (3) the sum of each row of the confusion matrix is 1, assuming that at some time the probability of observing the hidden state is X $(X = 1 \ldots N)$ and the observed state is Y $(Y = 1, \ldots, M)$ that is equal to $1/M$.

Before we obtain the recognition model and results analysis, each activity is performed to obtain W group data, that is, after the feature extraction we can get the $W \times N$ matrix as the feature vector matrix of the activity. Each activity selects part of the data (such as W-80 or W-40 group data) as training data into the HMM. As a result, we obtain four recognition models for activities of common classes. After the remaining 80 or 40 group data are brought into four models for analysis and recognition we can calculate the average recognition rates.

4. Activity duration and consistency evaluation

4.1. Algorithm of Activity Duration Based on Wireless Data

The activity levels of a largely sedentary person may be quite readily observed while exercising in a sports clinic or at a designated gym, however it is important to gain insights regarding the levels and duration of activities at home, since these can be important functional indicators.

In the absence of a human observer it is necessary to not only automatically identify the activity classes, but to also calculate the activity duration. The duration of general physical activity facilitates a better understanding of the sedentary behavior; enabling more telling research insights, or useful intervention control.

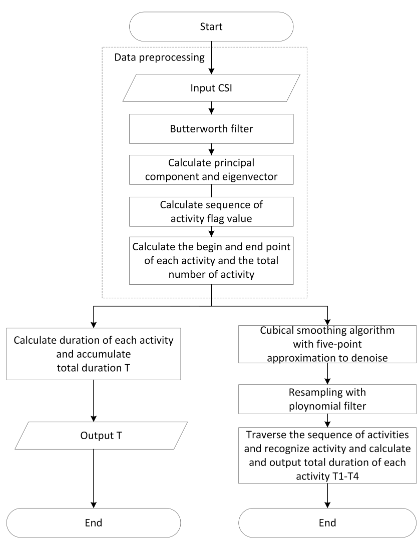

Figure 7: The signal processing flow for both the detection of general physical activity (left branch) and the classes of common activities (right branch)

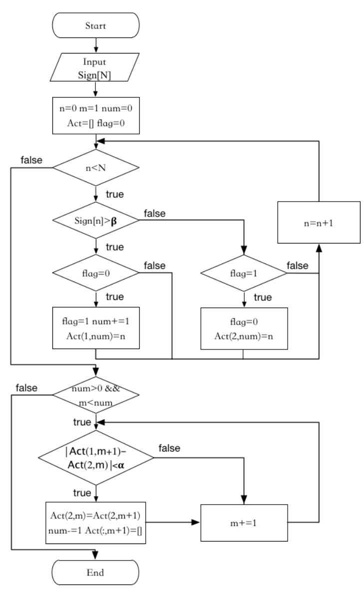

Figure 8: Obtaining location of activities in data streams

The method consists of three algorithmic parts. Figure 7 shows the statistical duration algorithms for detecting the presence of general physical activity and for classifying the common activity classes. The left branch side in Figure 7 shows the statistical duration of all non-stationary activities. First, the original CSI data is de-noised, followed by calculating the principal components and eigenvalues and then calculating the flag value according to the principal components and eigenvalues (see 5.2.1). According to the flag value and the algorithm showed in Figure 8, the starting and ending positions and number of anomalies can be calculated, so that the total activity duration can be obtained. The right-hand side of Figure 7 keeps separate tallies for the duration based on the recognition of different activities. As mentioned above, this requires computing the starting and ending positions of anomalies, followed by extracting the data processed by PCA in the corresponding positions. The resulting data are resampled after executing cubical smoothing with five-point approximation. Lastly, each activity type is classified and counted according to the HMM recognition model output to achieve a close estimate of the total duration of physical movement that falls into each of the activity classes. Figure 8 describes the algorithm details of the parts that are highlighted with a dotted line in Figure 7. The input of the algorithm described in Figure 8 is the sequence of flag values of activities, and the output is the start and end positions and total number of all activities. The first step of the algorithm is to traverse all the mark points and find the initial array of start and end positions according to the average value β calculated by the flag values. Then, the algorithm "repairs" the array by merging the erroneous positions of the start and end points where α is an integer value set by the density of mark points and experience, which indicate the minimum possible duration of the activity.

4.2. Consistency Evaluation of Duration Estimations

Whether the results of the duration statistics using wireless data are reliable needs to be evaluated by a robust and credible measurement system. This problem can be attributed to the consistency test problem which is often faced in data analysis, that is, judging whether different models or analysis methods have consistency in the prediction results, and whether the model results are consistent with the actual results. At present, the paired t-test can only test whether there is any difference, it can't show the degree of consistency of the paired data, and the t-test is greatly influenced by the degree of freedom. The correlation coefficient is insensitive to the system error; it can only show that the trend of the two cases is consistent, and is insensitive to the errors between them. The application of ICC is limited by the range of measurement value, and sometimes it makes a wrong judgement. A reliable method is using Kappa coefficients to carry out consistency checking, it has been widely applied in medical, clinical and other practical scenarios. For example, consistency tests are made for two or more doctors on the diagnosis of the same patient. We draw on this concept to evaluate the consistency of the duration statistics results of the automated analysis of wireless signals as described above with duration statistics that are based on manually coded video recordings of the same activity sequences. If we find that the Kappa coefficient value between them is large we can assume that the duration result obtained by using the wireless signal is approximately consistent with the relatively reliable manual (human rater based) measurement result. The main equation for calculating the Kappa coefficient is as follows:

$$K = \frac{p_0 - p_e}{1 - p_e} \tag{1}$$

$$P_0 = \frac{s}{n} \tag{2}$$

$$P_c = \frac{a_1 \times b_1 + a_0 \times b_0}{n \times n} \tag{3}$$

High K indicates better consistency between two observers, where p_0 is the observation consistency (observed agreement) and p_e the expected consistency (agreement by chance). In order to better use the formula of Kappa coefficient, we innovatively discretize the time interval into multiple time slices and then mark these discrete time slices as 1 if the time slice falls into the active signal interval and 0 if not. The total number of time slices is n, the same marker value of two observers is s. The true mark is 1, the value is a_1, if 0, the value is

a_0; the analog mark is 1, the value is b_1; if 0, the value is b_0. We can put these statements into the equation elements (2) and (3) to get the value of p_0 and p_e and then use formula (1) to calculate the Kappa coefficient.

5. Implementation and evaluation

5.1. Algorithm of Activity Duration Based on Wireless Data

The system consists of a software platform, a signal transmitter, and a signal receiver. The software platform is built on the Ubuntu14.04LTS operating system. The working frequency of the signal transmitter (a dual-band and dual-antenna TP-LINK router) is 867M (5G) + 300M (2.4G). The signal receiver is a DELL integrated machine, configured with an i3 CPU, 2GB memory, an Intel 5300 network card, and two receiving antennas. The sampling frequency of the whole system is 1300 samples/sec. The consistency evaluation experiment used two smartphones (VivoX7 and Meizu MX4), as well as SPSS V22 for auxiliary calculation and analysis.

Figure 9 shows the structure of the exemplary family house that represents the situated experiment setting. In this experiment, only one participant was instructed to move within the dashed line to assure of the control. This location is located in Fresnel zone. Trials were conducted over the course of one week, performing experiments on activity recognition and collecting data at three different times: morning, noon and evening within each day. This was understand and control the potential differences in external sources of signal disturbance (such as strong electromagnetic emitters being active in neighboring structures at certain times of the day). The experimenter-participant the designated activity, with magnitude and speed similar - as much as possible - to typical executions of such behavior in daily life. In order to observe the experimental results easily, we chose one representative activity from the four kinds of activities. 420 sets of raw data were collected within the week. It should be noted that there were about six or seven different Wi-Fi signals of neighbors

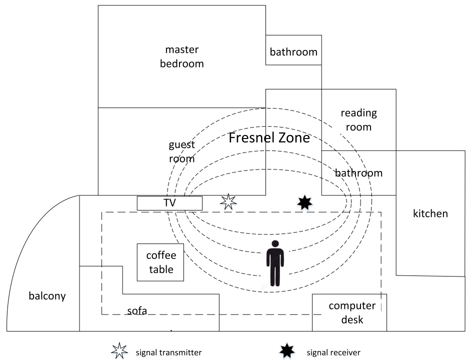

Figure 9: Floor plan and room layout of the experimental family home scene

present in the experimental environment, representing a common reality of the simulated real-world situated context “in the wild”.

5.2. Activity Recognition

5.2.1. Recognition of general physical activity.

Following initial experimental observation, we chose a duration leading to 200 segments to divide the data stream into units, which discretely reflect the occurrence of activity in the data stream. Raw data was processed with the Butterworth low-pass filter and the stream of N sampling points was divided into $N/200$ segments (cf. There are 200 points in each segment. Here we have 1000 sampling points, divided into 5 sections.) before applying principal component analysis to each segment (cf. Figure 10). Findings: The second principal component h_2 fluctuates less (variance $E\{h_2^2\}$ is small) when there is no activity. The second principal component fluctuates with any activity (the variance $E\{h_2^2\}$ is large). The mean difference of the second eigenvector q_2 [calculated according to equation(4)] is less than one. The ratio (flag value) of variance and mean difference highlights the difference between activity and rest. A flag value can be computed for each segment, producing a sequence diagram

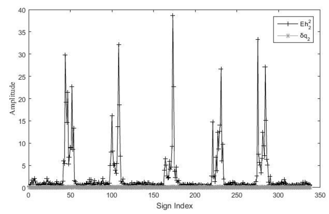

Figure 10: An exemplary sequence diagram of $E\{h_2^2\}$ and δq_2

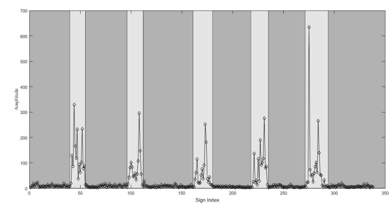

Figure 11: The example sequence diagram of flag values of activities

as shown in Figure 11.

$$\delta q_2 = \frac{1}{n-1} \sum_{l=1}^{n} \left| q_2\left(l\right) - q_2\left(l-1\right) \right| \tag{4}$$ [1]

The average value β is a threshold value calculated according to the sequence of activity flag values. The range of the resulting sequence is the interval of the activity from the flag value greater than β to the flag value less than β ; i.e. an activity is recognized. We extended the two mark points on the left and right sides of the interval as the starting and ending point of the abnormality in order to cover the whole activity as far as possible. This indicates an activity and its start and end position.

The total number of samples of each of the four different activities was 420. The numbers of activities recognized by the above method were 419, 419, 414 and 412 respectively, which means an average recognition rate of 99.05%, as shown in Table 1. With this approach we expect to recognize any activity with high recognition rate as the focus is not a specific activity but the analysis of abnormal data which ensures a certain degree of universality.

5.2.2. Recognition of common classes of activity.

The data collected can not only be used to establish an HMM recognition model, but also for experimental measurement. In order to acquire realistic data we recorded activity data for one week, with three different sampling times each

[1] n is the number of subcarriers, which is 120 in this paper

Table 1: Recognition Rate of General Physical Activity

Activity type	Number of samples	Actual number of exceptions	Recognition rate
Stretch hands upwards	420	419	99.76%
Squat to pick up	420	419	99.76%
Mop floor	420	414	98.57%
Playing table tennis	420	412	98.10%

day (morning, noon, night). Since the total number of experimental data sets for each activity is 420, we determined the number of training data sets to be 340 (80/20%) or 380 (90/10% training to validation split) and the number of test data sets to be 80 or 40 respectively, sampling the performance under two common training data to validation data split ratios.

In the previous section we showed that we can reliably determine the start and end position of an activity, so we can construct a clean set of activity data. In this section we will show how we obtain improved activity type classification rates by analysis and optimization selection of principal component and eigenvalue.

When designing the data analysis process, we employed 1st, 2nd and 3rd principal component data for analysis. In test analyses we found that most of the recognition effects based on the first principal component were better, except for the mopping activity. The subsequent analysis of the 4th, 5th and 6th principal components showed that the 4th principal component recognition works best with the mopping activity example; hence we considered combining the 1st and 4th dataset. To begin with, the 1st principal component data and 4th principal component data were extracted, and five eigenvalues were calculated according to the design of the four activity states. After merging, ten eigenvectors are obtained. Using this method and configuration the overall recognition is stable and the recognition rate is about 83-89%, as shown in Table 2 and Figure 12.

For better results we continued to perform steps for optimization and improvement of the process. The clustering of 16 energy values after wavelet

Table 2: Recognition rate of directly-merged eigenvalues for common classes of activities

Extraction of features	Number of features	Number of training sets	Recognition rate				
			Stretching	Squatting	Mopping	Playing table tennis	Average
Merging eigenvalue of principal component	10	340	83%	89%	88%	95%	89%
		380	83%	83%	79%	88%	83%

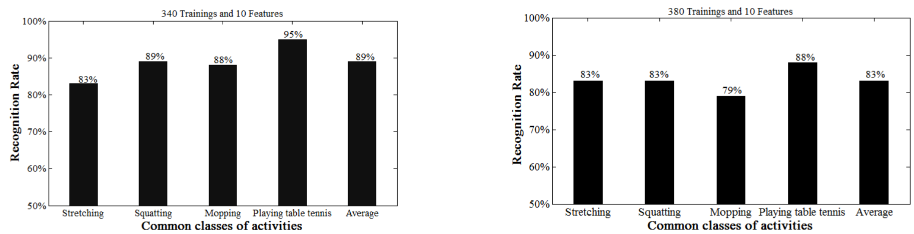

Figure 12: Recognition results of the directly-merged eigenvalue of PCA

decomposition of each principal component is intended to reduce the discrimination of the original information; hence we combined the 16 energy values of the 1st and 4th principal components before clustering and clustered the 32 energy values to obtain an eigenvalue. The experimental results show that a 92% recognition rate can be achieved when the number of hidden states is five and the number of training data is 380. Table 3 and Figure 13 show that in the normal family environment the recognition method optimized for the sedentary person could be a more accurate estimate of the activity amount.

5.3. Consistency of Activity Duration Recognition

Since we aimed to evaluate whether the system and method that we report on in this paper can accurately determine the statistical duration of the physical activity, a 1 minute video was recorded with two mobile phones from different angles during each experiment trial that was performed to collect the activity data, in order to facilitate calculating a measure of reliability without loss of generality. The videos contain both segments with and without activity. A total

Table 3: Recognition rate based on the combined energy value for common classes of activities

Extraction of features	Number of features	Number of training sets	Recognition rate				
			Stretching	Squatting	Mopping	Playing table tennis	Average
Merging energy eigenvalue	5	340	91%	95%	81.5%	93.5%	90%
		380	87%	95.5%	92%	95%	92%

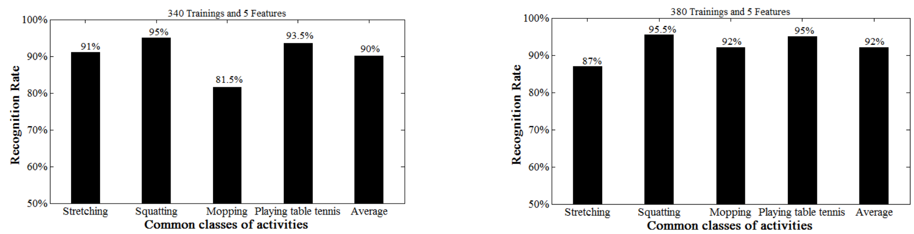

Figure 13: Recognition results based on combined energy value

of 21 minutes of active video sections was accumulated for the entire seven days and we also collected the wireless data streams corresponding to the 21 minutes of video. In order to calculate the Kappa coefficients we discretized the video and wireless data, making each segment 1 second in size, for a total of 1260 time slices. The specific evaluation process is as follows:

(1) Calculate the consistency coefficient between the two video devices by manually observing whether a time slice belongs to the activity time interval, marking it as 1 if it is within the activity interval, and marking it as 0 otherwise. We find that the number of time slices marked as 1 is 829, with 431 being marked as 0. Therefore, $n = 1260, s = 1260; a_1 = 829, b_1 = 829; a_0 = 431, b_0 = 431$, then we get K = 1 from equation(1)(2)(3). So we can conclude that the two observations are exactly the same.

(2) We calculate the consistency coefficient between the video observer and the wireless data. The marking process required to use the algorithm is as described in Section 4.1 for general physical activity identification. The experimental results are $n = 1260, s = 1222; a_1 = 829, b_1 = 810; a_0 = 431, b_0 = 450$. Then $K = 0.93$ can be calculated according to the formula, which indicates that the two observations are almost identical.

(3) In order to calculate the Kappa coefficients corresponding to the respective statistical duration of the four classes of activities, we needed to find out the"abnormal" data boundaries indicating periods of activity by using the algorithm in Section 4.1, and then mark them separately. Since this step resembles the boundary determination described above no calculation

Table 4: Kappa coefficient and evaluation of the activity classes

	Activity classes				
	Different time of day	Stretching	Squatting	Mopping	Playing table tennis
Kappa coefficients of classification activities	Morning	0.802	0.645	0.712	0.667
	Afternoon	0.787	0.721	0.611	0.710
	Evening	0.672	1.00	0.652	0.665
Average	0.721	0.754	0.789	0.658	0.681
Consistency evaluation	Highly consistent	Highly consistent	Highly consistent	Highly consistent	Highly consistent

procedure is given here. The final results are listed in Table 4, with an average of 0.721, indicating a high degree of consistency between the two observations.

In summary, the use of wireless data for statistical duration is plausible. This innovative approach will allow us not only to recognize human activity using wireless signals but also to estimate the approximate duration of the activity. With these tools we can estimate the amount of at-home activity and activity details (duration and rough level) in a non-invasive manner that does not require wearing active measuring devices which can interfere with regular activity executions and potentially biases users by presenting a physical reminder that their activities are tracked. The resulting information can inform approaches to tackling the societal challenges that were discussed in the motivation of this paper. Monitoring results can be shared with overly sedentary subjects to issue reminders and persuade them to attain a certain amount of activity in all parts of the body so as to maintain good health or to counteract the progression of chronic afflictions.

6. Discussion

Although we have taken the instability of the classifier based on wireless data into account, the situated nature of the evaluation study prevents an immediate generalizability of the recognition model due to the presence of wireless signal noise and other disturbances. This work provides early evidence and cannot yet conclusively prove the universality of the recognition model, although the training data was collected at different times. This may make the original classifier work less or more effective than it otherwise would, as CSI is easily disturbed by sudden or permanent changes in the experiment environment, including wireless interference and many activities and movements of doors and windows or furniture or something else., etc. Further study of the potential contextual adaptation is required. Determining whether a temporary or a permanent change due to a sharp drop can be compensated makes for a viable approach to tackling this challenge. For permanent changes the classifier needs to be rebuilt. A combination with human-computation for labeling training data can potentially facilitate the (re-)construction of on-the-fly models that are highly adapted to a specific context. But it is difficult to only consider the statistical method. More importantly, we need to analyze the characteristics of the Fresnel zone and identify the principle rules. Besides, we can also consider it combining the signals with those of other sensors (e.g. smart watches), aiming for the fusion of multi-sensor data to form a promising approach in this regard.

In the light of estimating impact on chronic afflictions caused by sedentary or active behavior it appears promising to add MET (metabolic equivalents) estimations based on energy present in the signal disturbance. To broadly cover MET classes this requires additional training data recordings. Based on this system, an intelligent agent that not only monitors activity but interacts with the sedentary person might not only perceive and understand physical discomfort of the sedentary person, but also persuade and encourage more physical activity.

While we aim for clearly positive application use-cases in digital health, it is clear that potentially covert tracking methods of human activity pose some risk for misuse. We do not support any application of this technology, if the presence and the consequences are not clearly communicated to the subjects that are present in the tracking area, and if all individuals present subject themselves to the tracking out of their own volition. Since the methods and procedures described in this work do not pose a risk of causing direct harm we assume the position that public research with best intentions in mind is ethically justified, as it liberally makes a technological approach available to a larger audience that would otherwise be developed further by private entities with high likelihood and few means to estimate the potential consequences of its use.

7. Conclusion

In this paper, a system and methods for the non-invasive recognition and quantification of physical activities were presented and evaluated in a representative situated family home setting. While a generalized approach requires further study, using the principle of Fresnel zone and multimodal fusion method, with longer periods of experiment, and the additional environments for collecting more avtivities data, an early evaluation of the current system showed promising results. For a typical environment with various sources of signal disturbance and noise, we proposed the WiFun prototype based on wireless signals for recognizing (1) the presence of general activity, (2) the type of activity class, as well as (3) for estimating the respective durations. Our work features three core novel technical aspects: first, we propose the "1 + 4 model" and implementation technology of recognition in the environment of interference with effective methods of signal de-noising and feature extraction; second, we propose a novel statistical method for general duration of physical activity and the duration of different activity classes estimation; and third, we use the Kappa coefficient for judging the consistency of statistical duration. The proposed prototype system can successfully recognize and quantify physical activity under certain conditions. In our analysis, based on the processing and modeling of wireless data as described above, the experimental results show that the recognition rate of general physical activity is 99.05% and the average recognition rate of four common activities is 92%. The Kappa coefficients between automatic detection based on wireless signals and manually labeled video data are 0.93 (general activity) and 0.721 (activity classes), which are high consistencies for estimating the amount and level of activity and duration, indicating that the recognition outputs are in considerable agreement with the recognition outcomes when employing manual labeling by human raters.

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