# Adaptive Pedestrian Activity Classification for Indoor Dead Reckoning Systems

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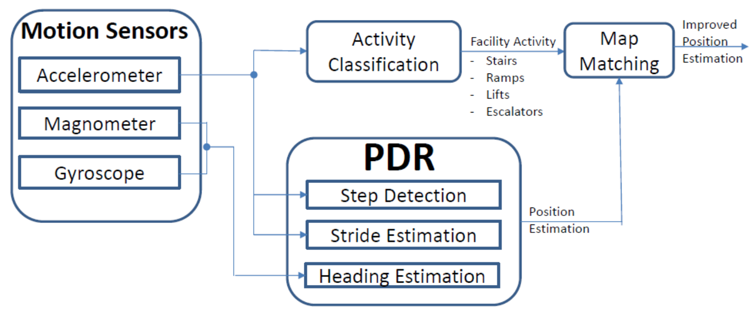
***Abstract*—A pedestrian activity classification (PAC) system classifies pedestrian motion data into activities related to the usage of specific building facilities, such as going up on an escalator or descending a staircase. Recent studies confirm that use of PAC significantly reduces indoor localization errors of a pedestrian dead reckoning (PDR) system as exact facility locations in the building can be retrieved from the floor map. However, classification complexity may become an issue for resource constraint mobile devices. We propose a novel PAC system that, instead of using a single complex classifier based on a large set of features, employs multiple simple classifiers each trained to classify only a subset of the activities using a small number of features. As the pedestrian moves around inside a building, the proposed adaptive-PAC dynamically switches to the right (simple) classifier based on the facilities that exist within the immediate proximity. By always using a simple classifier, adaptive-PAC has the potential to drastically reduce the average classification complexity for PAC-aided PDR systems. Using experimental data, we quantify and compare the performance of the proposed adaptive-PAC against the conventional PAC. We find that for typical shopping centers, adaptive-PAC reduces classification complexity by 91-97% without any degradation in classification accuracy rates.**

***Keywords*—Pedestrian Activity Classification, Indoor Localization, Pedestrian Dead Reckoning.**

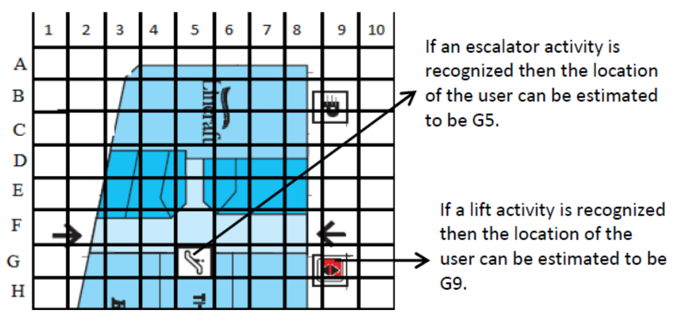
## I. Introduction

Pedestrian dead-reckoning (PDR) [1], which uses step length and heading estimation to compute current location relative to a previously know location, is a viable positioning alternative to GPS in indoor environments. PDR is also completely self-sufficient in the sense that it does not require any support from any type of infrastructure. As such, it can be used to complement WiFi-based solutions [2] to cover locations where WiFi coverage is not adequate for precise localisation. The major problem of PDR systems, however, is the error accumulation due to noise in the mobile sensors, so the accuracy diverges from the truth over time.

Recent studies [3], [4] show that PDR error accumulation can be significantly reduced by combining a PAC module to the system. The task of the PAC is to continuously monitor the accelerometer signal and detect the event when the user is using one of the fixed building facilities, such as lifts,




(a) A typical Architecture of a PAC-aided PDR system.




(b) In this part of the floor, if event *escalator* is detected, then PDR location is reset to G5 thereby wiping out all errors accumulated so far due to sensor drift. Similarly, if *lift* is detected, PDR is reset to G9.

Fig. 1. The concept of a PAC-aided PDR system. (a) A typical Architecture and (b) An illustration using an indoor map.

escalators, stairs, ramps, etc. A typical architecture of PAC-aided PDR system could be as shown in Fig. 1(a). Since accurate locations of such facilities are available in the floor map, the exact user location is derived instantly by the PAC whenever such events are detected and correctly classified. Fig. 1(b) illustrates the idea of a PAC-aided PDR system using a real map of a shopping center.

While PAC clearly has the potential to reduce PDR error, its classification complexity may become an issue for resource constraint mobile devices. This is especially the case for large multi-story indoor complexes, which deploy many different types of facilities for increased pedestrian convenience and better management of pedestrian flow. For example, there are at least eight distinct activities if we consider four different facilities, lift, escalator, ramp, and stairs, because we need

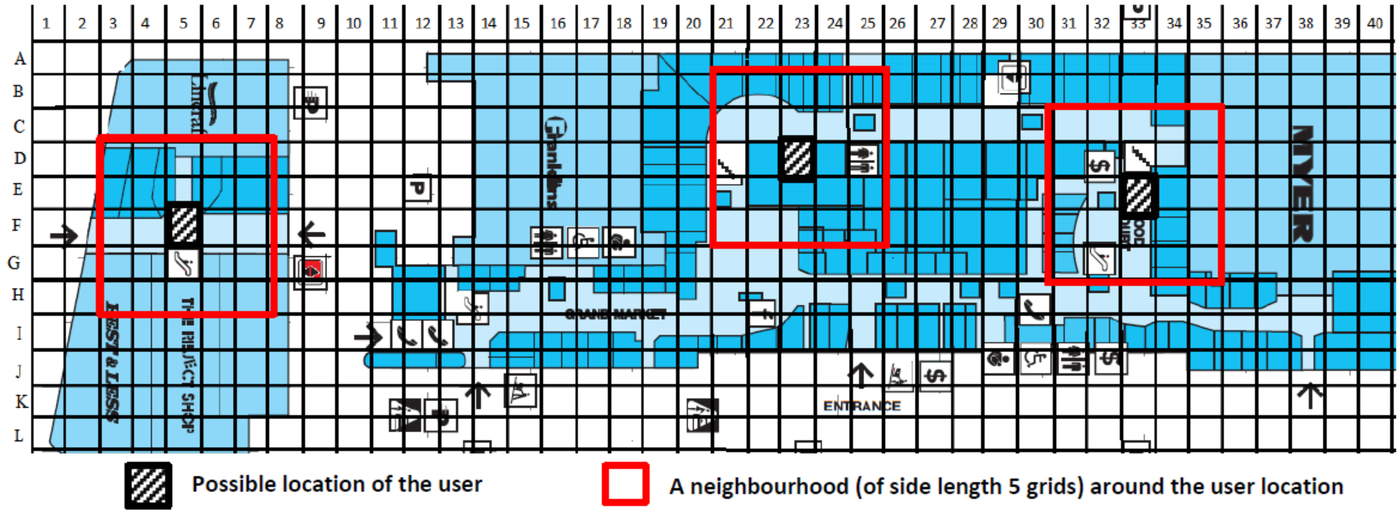



Fig. 2. Floor map (Level 1) of the Bankstown shopping center in Sydney.

to distinguish going up on a facility from going down. The number of activities to classify is even larger if we want to distinguish standing on an escalator from walking on it. The list is further extended when standing or walking on the floor need to be distinguished from walking and standing on any of these facilities. Conventional PAC designs [3], [4], which train a single classifier to detect and distinguish all these activities, inevitably struggle with classifier complexity.

To address the classifier complexity problem in PAC, we propose a novel solution, which we call adaptive-PAC. Adaptive-PAC is based on the observation that at any time, there is only a small subset of facilities in the immediate proximity of the pedestrian that she can possibly use in the near future. Thus we propose to train offline many simple (less complex) individual classifiers each dedicated to classify only a subset of facilities or activities and then switch them dynamically during run time based on the current location of the pedestrian. By always using a less complex classifier, a PDR that uses an adaptive-PAC is expected to incur less classification overhead than the one using a conventional non-adaptive PAC.

We quantify the performance of the proposed adaptive-PAC with experimental data collected from subjects using lifts, escalators, ramps, and stairs in different buildings. We find that spatial distribution of facilities on a given floor has a major influence on the actual overhead reduction that could be achieved with adaptive-PAC. We surveyed a large shopping center and find that, for the empirical facility distribution, adaptive-PAC reduces classification overhead by 91-97% compared to a conventional PAC. Apart from the huge complexity reduction, the adaptive-PAC also reduces the number of features that need to be extracted at each classification epoch, which further reduces classification related overhead in a resource-constraint mobile device. All these PAC overhead reductions are achieved without any degradation in classification accuracy rates.

The contributions of this paper can be summarized as:

- We propose the novel concept of adaptive-PAC, which seeks to reduce classification related overhead in PAC-aided PDR systems by training offline a set of simple classifiers and dynamically switching to one of them during run time.
- We propose a methodology to select features for the individual classifiers of an adaptive-PAC that minimizes the number of features and complexity without degrading classification accuracy rates.
- We conduct a field survey and demonstrate that for typical shopping centers, adaptive-PAC reduces classification complexity by 91-97% without any degradation in classification accuracy rates.

The rest of the paper is organized as follows. Related work is reviewed in Section II. Section III examines the key characteristics of the proposed adaptive-PAC system. The methodology to compute and evaluate classification complexity of adaptive-PAC is explained in Sections IV and V. We conclude the paper in Section VI.

## II. Related Work

Pedestrian activity classification (PAC) is an emerging field of research, born from the larger fields of ubiquitous and context-aware computing [5]. Recognizing everyday life activities is becoming a challenging application in pervasive computing, with a lot of interesting developments in the health care domain [6], the human behavior modeling domain and recently the indoor positioning domain [3], [4], [7]. Based on the targeted field of research, the corresponding set of activities differs. For example, the activity set considered in [6] includes lying, running, rope jumping, tooth brushing, etc, which can be used for health monitoring purposes.

Recently, PAC for the purposes of correcting pedestrian dead reckoning (PDR) errors in indoor environments has attracted attention of several research groups. With a practical implementation on a smartphone, Gusenbauer et al. [3] have convincingly demonstrated that PAC, such as detecting whether the pedestrian is using a stair or a lift, can reduce PDR positioning error significantly when the user travels through

TABLE I. 16 POSSIBLE ACTIVITY SETS FOR N=4.

| # of different facilities (k) | Activity Set |
|---|---|
| 0 | $G_0 = \{SS, W\}$ |
| 1 | $G_{11} = \{SS, W, L_\uparrow, L_\downarrow\}$,<br>$G_{12} = \{SS, W, E_\uparrow, E_\downarrow\}$,<br>$G_{13} = \{SS, W, S_\uparrow, S_\downarrow\}, or$<br>$G_{14} = \{SS, W, R_\uparrow, R_\downarrow\}$. |
| 2 | $G_{21} = \{SS, W, L_\uparrow, L_\downarrow, E_\uparrow, E_\downarrow\}$,<br>$G_{22} = \{SS, W, L_\uparrow, L_\downarrow, S_\uparrow, S_\downarrow\}$,<br>$G_{23} = \{SS, W, L_\uparrow, L_\downarrow, R_\uparrow, R_\downarrow\}$,<br>$G_{24} = \{SS, W, E_\uparrow, E_\downarrow, S_\uparrow, S_\downarrow\}$,<br>$G_{25} = \{SS, W, E_\uparrow, E_\downarrow, R_\uparrow, R_\downarrow\}, or$<br>$G_{26} = \{SS, W, S_\uparrow, S_\downarrow, R_\uparrow, R_\downarrow\}$. |
| 3 | $G_{31} = \{SS, W, L_\uparrow, L_\downarrow, E_\uparrow, E_\downarrow, S_\uparrow, S_\downarrow\}$,<br>$G_{32} = \{SS, W, L_\uparrow, L_\downarrow, E_\uparrow, E_\downarrow, R_\uparrow, R_\downarrow\}$,<br>$G_{33} = \{SS, W, L_\uparrow, L_\downarrow, S_\uparrow, S_\downarrow, R_\uparrow, R_\downarrow\}, or$<br>$G_{34} = \{SS, W, E_\uparrow, E_\downarrow, S_\uparrow, S_\downarrow, R_\uparrow, R_\downarrow\}$. |
| 4 | $G_4 = \{SS, W, L_\uparrow, L_\downarrow, E_\uparrow, E_\downarrow, S_\uparrow, S_\downarrow, R_\uparrow, R_\downarrow\}$. |

TABLE II. ACTIVITY NOTATION.

| Symbol used | Refers to |
|---|---|
| $L$ | Lift |
| $E$ | Escalator |
| $R$ | Ramp |
| $S$ | Stairs |
| $W$ | Walking |
| $SS$ | Standing Still |
| $F$ | Unnamed Facility; $F \in \{L, E, R, S\}$ |
| $F_\uparrow$ | Facility Up, e.g., $R_\uparrow$ means Ramp Up |
| $F_\downarrow$ | Facility Down, e.g., $R_\downarrow$ means Ramp Down |

multiple floors. The same observation was later confirmed by Altun et al. [4], [8] with a simultaneous activity recognition and dead reckoning implementation using inertial measurement units (IMUs) attached to body parts. For a random walk model, Hassan [9] has shown that the distance a pedestrian is expected to travel before the PDR error is reset is reciprocal of the density of activity switching points (ASPs), such as lifts and escalators, in the indoor environment. The implication of this finding is that the continuous unaided use of PDR can be curbed drastically by identifying more ASPs. Khalifa and Hassan [10] considered the problem of multiple lifts or escalators existing near a pedestrian leading to the possibility of matching to the wrong lifts (escalators) despite the classifier detecting the activity correctly. They found that such mismatch probabilities vary from location to location in the same building and can be pre-computed offline, which could be later used by a PDR system to make decisions about whether to accept the outcome of an activity detection module or ignore it.

Prior work on PAC has principally focused on identifying the key features that enable the most accurate classification of the defined activity set. As such, they considered a single classifier attempting to classify the input signal to one of the activities from the set of all possible activities. For example, authors of [3] have used a single support vector machine (SVM) to classify many indoor activities, while [11] used a single multi layer perceptron (MLP) to classify three indoor activities. In contrast, our approach focuses on adaptively selecting a classifier from the set of available pre-trained classifiers depending on the probable set of activities that the user is likely to perform in the near future. By reducing the elements in the activity set for classification, the proposed adaptive-PAC approach reduces the average classification complexity over time. Work on such adaptive classification is rarely reported in the literature with the exception of [12], where the authors propose to adapt the sampling rate of the accelerometer based on the probable activities in the near future. However, the focus of the study in [12] is on minimizing the sampling frequency of the sensors, while we seek to minimize the computation complexity of the classifier.

## III. CHARACTERISTICS OF ADAPTIVE-PAC

The main characteristic of adaptive-PAC that differentiates it from the conventional non-adaptive PAC is the training of a *multitude* of simpler classifiers instead of a *single complex* one. Each of these classifiers is dedicated to identify only a specific subset of all possible activities depending on the types of facilities available in the proximity of the pedestrian. For a finite number of facility types available in a building, it is possible to work out the complete set of classifiers that need to be trained.

Let us assume the following. Any individual classifier will have to detect standing (SS) and walking (W) on the floor as two basic activities irrespective of which facilities are in the proximity of the pedestrian. For each type of facility available in the proximity, there are two additional activities, going up and going down the facility, that a classifier will have to recognise. Thus, each classifier in an adaptive-PAC will have to recognise a total of $2(k+1)$ activities, where $k$ represents the number of different types of facilities in the proximity of the pedestrian. However, for a specific value of $k$, we have $\binom{N}{k}$ different activity sets, each requiring its own classifier. Therefore, we need a total of $\sum_{k=0}^{N} \binom{N}{k} = 2^N$ different classifiers in an adaptive-PAC. Table I shows all possible activity sets for $N = 4$ while Table II explains the notation used to represent various activities.

Quantitative evaluation of complexity gain, i.e., savings in classifier complexity, due to adaptive-PAC would require knowledge of complexity for each of these individual classifiers. This can be achieved by training each one of them with relevant input data. In the following section, we explain our methodology to obtain the complexity of individual classifiers in an adaptive-PAC for $N = 4$, which includes lift, escalator, ramp, and stairs.

## IV. COMPLEXITY OF INDIVIDUAL CLASSIFIERS

### A. Complexity of MLP-based Classification

In a separate investigation [11], we found that the floor changing activities, such as riding a lift or an escalator, are more accurately detected using Multilayer Perceptron (MLP) than any other types of classifiers. In this work, therefore, we use MLP as a basis for evaluating the complexity gain of the proposed adaptive-PAC. A recent work [13] has shown that complexity of MLP can be effectively modeled as a function of the number of neurons in the input layer, $N_i$, and number of neurons in its output layer, $N_o$, which is based on counting the number of multiplications, additions and the logistic function evaluations. A three-layer MLP classifier requires $N_h(N_i+N_o)$ weights, where $N_h$ is the number of neurons in the hidden layer. Adding the weights associated with the outputs of two bias neurons, one as an input to the hidden layer and the other joining the hidden layer to the output layer, gives a total of $N_h(N_i + N_o) + N_h + N_o$ weights. Since the number of multiplications and additions is twice the total number of weights and the number of evaluations of the logistic function is $N_h + N_o$, the total number of operations required to accomplish the classification process, i.e., the complexity of MLP, is obtained as [13]:

$$\begin{aligned} C_{MLP} &= 2N_h(N_i + N_o) + 3(N_h + N_o) \\ &= (N_i + N_o)^2 + 1.5(N_i + 3N_o) \end{aligned} \quad (1)$$

where $N_h = \frac{(N_i+N_o)}{2}$ is typically selected as a default parameter.

Note that $N_i$ and $N_o$ of an MLP classifier basically refers to the number of features used for the classification process and the number of activities to be classified, respectively. Values of $N_o$ can be directly extracted from Table I as the number of elements in the activity sets. To obtain $N_i$, we must train the individual MLP classifiers with relevant input data, which is explained in the following subsections.

### B. Accelerometer Data Collection

We have collected accelerometer data for the mentioned 10 activities using facilities in actual buildings [1]. The data were collected using an Android Galaxy Nexus smartphone coupled with an application created to suit our studies. Four volunteers (2 males and 2 females) were trained and asked to hold the smartphone in the hand in front of the body while doing the 10 activities. While riding lift or escalator, the subjects were told to simply stand on the moving platform and not walk around or climb up or down. For escalators and ramps facilities, data collection begins and ends at two end points of the escalator, giving a trace length proportional to the length of the facility. For most of the escalators, the traces were about $20sec$ long. For lifts, it is harder to control the trace length as lifts are stopped arbitrarily by other users in the building. Therefore, our lift trace lengths varied widely ranging from a mere $5sec$ (one floor) to $20sec$ (5 floors). To match the majority of traces, all walking and standing activities traces are $20sec$ long. A sampling rate of 100 Hz was used for data collection.

### C. Feature Selection for Individual Classifiers

We use the non-adaptive PAC reported in [3] as our benchmark. In that work, the authors used a total of 25 features, including average acceleration for each axis (3 features), variance for each axis (3 features), standard deviation for each axis (3 features), inter-quartile range for each axis (3 features), root mean square for each axis (3 features), pairwise correlation among 3 axes (3 features), velocity for each axis (3 features), distance for each axis (3 features), and signal magnitude area (1 feature) to train a single classifier, which was used throughout the PDR session. Using these 25 features with an MLP classifier in WEKA [14] with default settings results in an overall accuracy rate of 86.25%. This MLP classifier is used for $k = 4$, i.e., when all four types of facilities are within the proximity. For the remaining 15 classifiers, we adopt a feature selection method known as sequential feedforward selection (SFS) [15], which allows us to select a minimum number of features that achieves a target accuracy, which is chosen as 86.25% in our case.

[1]UNSW (http://www.unsw.edu.au/), NICTA ATP (http://www.woodhead.com.au/projects/nicta-australian-technology-park-sydney-new-south-wales/), Westfield Shopping center (http://www.westfield.com.au/parramatta), Centro Bankstown shopping center (http://www.centrobankstown.com.au).

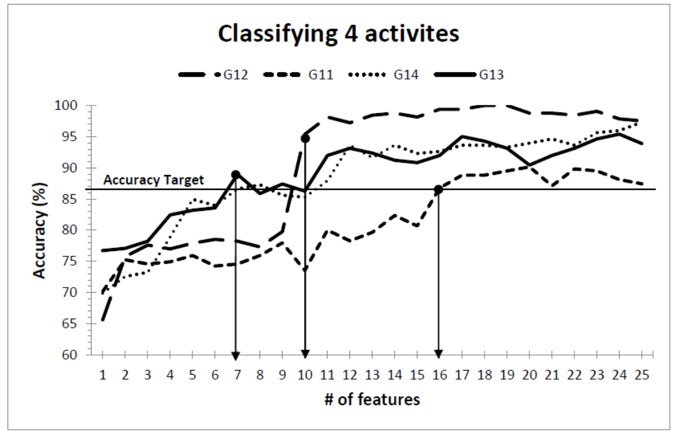



Fig. 3. An example of the SFS-based feature selection process for G11-G14 Classifiers. Accuracy target of 86.25% is reached with only 7, 10, or 16 features depending on the activity set.

TABLE III. COMPLEXITIES AND ACCURACIES FOR EACH OF THE 16 INDIVIDUAL CLASSIFIERS OF THE ADAPTIVE-PAC SYSTEM.

| # of different facilities (k) | Activity Set | No. of Features | Accuracy (%) | MLP Configuration ($N_i$-$N_h$-$N_o$) | Complexity using Eq.1 | Average Complexity |
|---|---|---|---|---|---|---|
| 0 | $G_0$ | 1 | 100 | 1-1-2 | 15 | 15 |
| 1 | $G_{11}$ | 16 | 86.77 | 16-10-4 | 442 | 236 |
| | $G_{12}$ | 10 | 95.39 | 10-7-4 | 229 | |
| | $G_{13}$ | 7 | 88.93 | 7-5-4 | 137 | |
| | $G_{14}$ | 7 | 86.62 | 7-5-4 | 137 | |
| 2 | $G_{21}$ | 15 | 87.47 | 15-10-6 | 468 | 511 |
| | $G_{22}$ | 21 | 87.21 | 21-13-6 | 759 | |
| | $G_{23}$ | 18 | 87.14 | 18-12-6 | 630 | |
| | $G_{24}$ | 12 | 88.62 | 12-9-6 | 369 | |
| | $G_{25}$ | 12 | 90.63 | 12-9-6 | 369 | |
| | $G_{26}$ | 15 | 87.84 | 15-10-6 | 468 | |
| 3 | $G_{31}$ | 18 | 87.29 | 18-13-8 | 739 | 637 |
| | $G_{32}$ | 15 | 86.39 | 15-11-8 | 563 | |
| | $G_{33}$ | 20 | 84.73 | 20-14-8 | 850 | |
| | $G_{34}$ | 14 | 86.48 | 14-11-8 | 541 | |
| 4 | $G_4$ | 25 | 86.25 | 25-17-10 | 1271 | 1271 |

SFS is a simple *greedy search algorithm* that starts from the empty set and adds features one by one so that every next feature maximises some criterion [15]. In this paper, we used this basic principle of SFS with the following variations. We consider classification accuracy as the maximisation criterion, but instead of evaluating the accuracy for a subset of features, we ranked all 25 features in the beginning based on their information gain (IG) using WEKA. At each step of adding a new feature to the feature set, we chose the one with the maximum gain in the hope that it would maximise accuracy increase. We used the target accuracy of 86.25% as a stopping criterion for the algorithm, i.e., we stop adding a new feature to the feature set as soon as accuracy reaches or exceeds the target.

Figure 3 shows an example of the SFS-based feature selection process for $G_{11} - G_{14}$ classifiers. We can see that different classifiers need different number of features to meet the target accuracy. For example, $G_{13}$, i.e., when only stairs are in the proximity, needed only 7 features, while $G_{11}$ (lift) required 16 to meet the accuracy target of 86.25%. We also noticed that although adding the next ranked feature based on IG do not always increase accuracy, in general the accuracy increases with adding more features to the feature set,

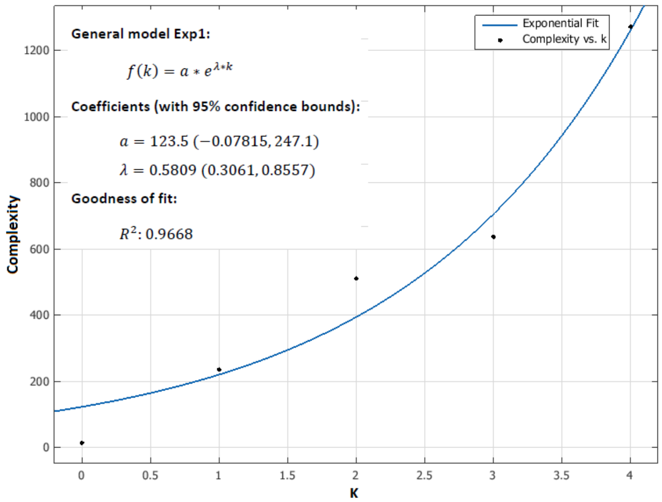



Fig. 4. Classifier complexity increases exponentially with $k$.

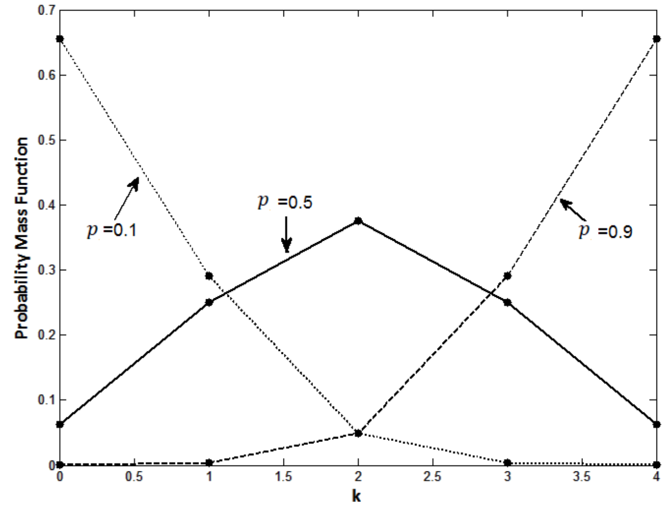



Fig. 5. Different shapes of a Binomial distribution with $N = 4$. It decreases monotonically for small values of $p$, while increases monotonically for large values of $p$. It is non-monotonic for medium values of $p$.

validating the effectiveness of the proposed SFS-based feature selection methodology.

Once the feature set is worked out, we can readily compute the complexity using Equation (1), because the number of elements in the feature set defines the parameter $N_i$ for the MLP classifier. Table III shows the complexities for each of the 16 classifiers. We note that the complexity over all possible classifiers under the same value of $k$ may not be uniform. To reduce the problem space, we report the average complexity for each $k$ (last column of Table III). We find that average complexity increases monotonically with $k$, which guarantees complexity reduction with adaptive-PAC except for the extreme and unlikely situation where a pedestrian finds all four facilities within her immediate proximity at all times during the navigation of a large indoor complex. We further find that complexity increases exponentially with $k$ (see Figure 4), which implies that large complexity reductions are possible with adaptive-PAC.

It is intuitively clear that the expected amount of complexity reduction with adaptive-PAC would depend on the probability mass function (pmf) $P(k)$, which defines the probability that exactly $k$ different types of facilities are available in the proximity of the pedestrian. In the following section, we quantify the expected complexity of adaptive-PAC for different types of probability distributions, including an empirical distribution obtained by field survey.

## V. Expected Complexity of Adaptive-PAC

The complexity of non-adaptive PAC is basically defined as $C_{na} = C_{MLP}(k = 4)$, which is obtained as 1271 (see Table III). The expected complexity of the proposed adaptive-PAC can be obtained as:

$$C_a = \sum_{k=0}^{4} C_{MLP}(k)P(k) \quad (2)$$

From Equation (2), given that $C_{MLP}(k)$ is monotonically increasing, $C_a < C_{na}$ for any distribution of $P(k)$ except when $P(k = 4) = 1$. Let us derive $C_a$ for some probable distributions of $P(k)$.

### A. Uniform Distribution

For uniform distribution, we have $P(k) = \frac{1}{5}$ for $k = 0, 1, 2, 3, 4$. This leads to $C_a = 534$. Therefore, if the probability of having different number of facilities in the pedestrian proximity is uniformly distributed, adaptive-PAC would reduce the classification complexity from 1271 to 534 achieving a 58% reduction.

### B. Binomial Distribution

For most practical cases, the distribution is likely to be non-uniform. Binomial distribution can be used to capture different types of pmf. Figure 5 shows how we can capture monotonically increasing, monotonically decreasing, and non-monotonic behaviours by selecting different values of parameter $p$, which defines the probability of a facility appearing in the proximity of a pedestrian at any given time. The $C_a$ for a Binomial pmf is derived as:

$$C_a(p) = 123 \sum_{k=0}^{4} e^{0.58k} \binom{4}{k} p^k (1-p)^{4-k} \quad (3)$$

Figure 6 shows that expected complexity of adaptive-PAC reduces quartically against the Binomial parameter $p$. Intuitively, $p$ is proportional to the density of facilities, i.e., given a denser deployment of facilities, we could expect a larger value for $p$, and vice-versa. Therefore, we can expect more significant reductions in complexity when facilities are sparsely deployed. We conducted a field survey to find out just how sparsely the facilities are deployed in a typical shopping center.

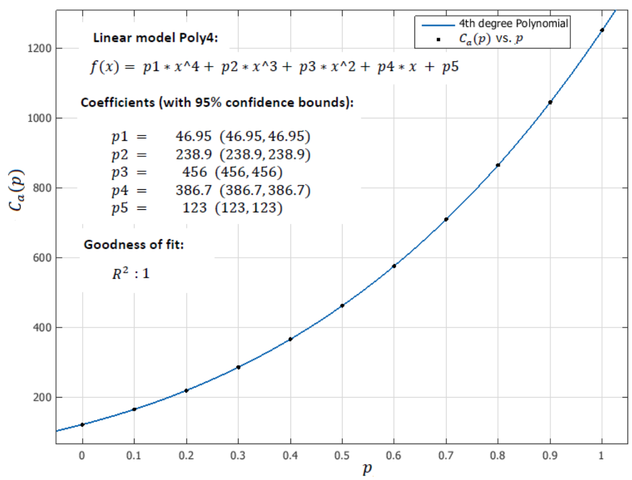



Fig. 6. Expected complexity of the adaptive-PAC increases quartically with the probability ($p$) of a facility appearing in the pedestrian proximity.

## C. Field Survey and Empirical Distribution

We surveyed a 2-story shopping centre in Sydney, Australia, located in the suburb of Bankstown [16]. The floor maps of Levels 1 and 2 of the center are shown in Fig. 2 and Fig. 7, respectively. The maps mark the locations of the four facilities considered in our research.

Because these maps are not drawn to scale, we conducted a field survey to estimate the scale of the grids. We first identified two facilities on the map joined by a horizontal straight line path as marked on the map in Fig. 7). One of our volunteers walked over the line between the two facilities and counted the number of steps. This exercise was repeated three times and on average it took 65 steps to walk between these two facilities, which were 7 grids afar on the map. This gives a distance of 9 steps per grid. In a separate exercise, the volunteer measured his average step length as 0.5 m, which is used to estimate the grid length as 4.5m. Therefore, a proximity radius ($r$) of 1 grid beyond the current position (assuming a center location on a grid) would give a radius of 1.5 grid, which is about 6.75 m or 13.5 steps. With $r = 2$, we would get 11.25m or 22.5 steps. As these are reasonable distances for the purposes of switching classifier, we considered both $r = 1$ and $r = 2$ to calculate the empirical pmf $P(k)$.

For each of the two maps, we examined the proximity of every grid location, excepting the non-accessible areas, and counted the number of different facilities available there. For Level 2 and a proximity radius of 2 grids, Table IV shows the observed frequency of each of the 16 possible activity sets and the resulting values for the observed $P(k)$. For this empirical distribution, we obtain $C_a = 79$ from Equation (2). Table V shows the empirical distributions for both levels for two different proximity radii. We can see that for all cases, the distribution is monotonically decreasing, which is better estimated with Binomial distribution when $p$ is very small (see Figure 5), or the facility deployment is sparse. The complexity reductions achieved for the empirical distributions varied from 91% (Level 1, $r = 2$) to 97% (Level 2, $r = 1$).

TABLE IV. The observed frequency of the 16 possible activity sets in Level 2 of the Bankstown shopping center for a proximity radius of 2 grids.

| # of different facilities (k) | Activity Set | Frequency | P(k) |
|---|---|---|---|
| 0 | $G_0$ | 998 | 0.76 |
| 1 | $G_{11}$ | 75 | 0.20 |
| | $G_{12}$ | 63 | |
| | $G_{13}$ | 51 | |
| | $G_{14}$ | 75 | |
| 2 | $G_{21}$ | 6 | 0.04 |
| | $G_{22}$ | 19 | |
| | $G_{23}$ | 0 | |
| | $G_{24}$ | 5 | |
| | $G_{25}$ | 0 | |
| | $G_{26}$ | 25 | |
| 3 | $G_{31}$ | 0 | 0 |
| | $G_{32}$ | 0 | |
| | $G_{33}$ | 0 | |
| | $G_{34}$ | 0 | |
| 4 | $G_4$ | 0 | 0 |

TABLE V. The empirical PMFs obtained for the Bankstown shopping center.

| # of different facilities (k) | P(k) for level 1, r=1 | P(k) for level 1, r=2 | P(k) for level 2, r=1 | P(k) for level 2, r=2 |
|---|---|---|---|---|
| 0 | 0.83 | 0.61 | 0.90 | 0.76 |
| 1 | 0.17 | 0.34 | 0.09 | 0.20 |
| 2 | 0 | 0.05 | 0.01 | 0.04 |
| 3 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 |
| $C_a$ | 53 | 115 | 40 | 79 |

# VI. Conclusion

In this paper, we propose a novel concept of adaptive-PAC, which seeks to reduce activity classification complexity of a PAC-aided PDR system. Adaptive-PAC is based on the observation that at any time, there is only a small subset of facilities in the immediate proximity of the user that she can possibly use in the near future. It is, therefore, possible to dynamically switch to a simple low-overhead classifier based on the users current location. We have evaluated the potential gain of adaptive PAC using experimental data and empirical facility distribution of a shopping center. Our studies show that adaptive-PAC reduces classification complexity by 91-97% without any degradation in classification accuracy rates. Apart from classification complexity reduction, the adaptive-PAC also reduced the number of features that need to be extracted at each classification epoch, which further reduces classification related overhead in a resource-constraint mobile device.

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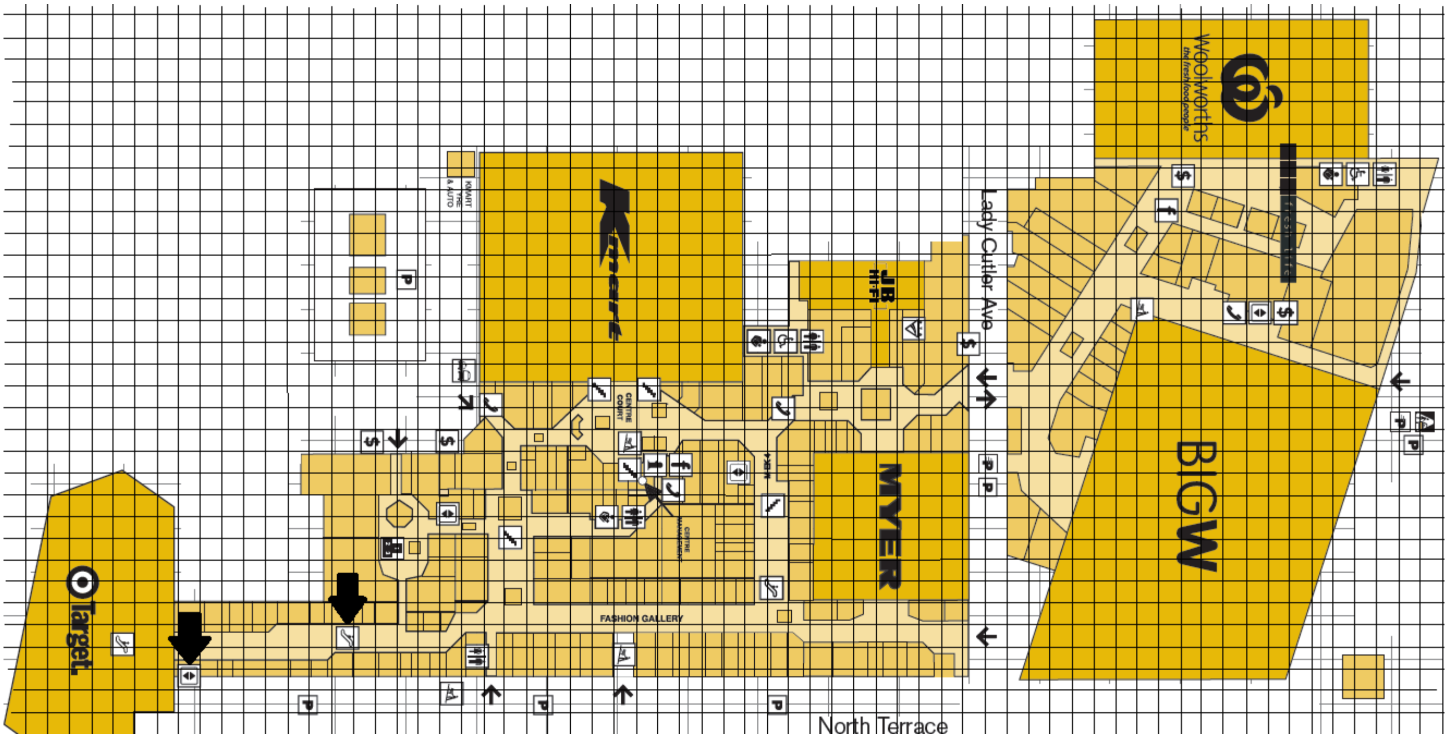


Fig. 7. Floor map (Level 2) of the Bankstown shopping center in Sydney.

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