A Multi-Objective Indoor Localization Service for Smartphones

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ABSTRACT
The bulk of indoor localization applications currently rely on either server-side, cloud-based services that raise critical data-disclosure concerns (e.g., reveal user’s location to a central entity), or client-side services that introduce serious performance concerns (e.g., consuming precious smartphone battery and network bandwidth during content uploads). In this paper, we present a novel Multi-objective Indoor Localization Service (MILoS) that provides a fine-grained, energy-efficient indoor localization using only a subset of WiFi-based localization data on the client-side, maintaining user’s privacy at the same time. MILoS follows a fingerprinting-based indoor localization model that concurrently optimizes several conflicting objectives (i.e., minimizes the smartphone’s energy consumption and maximizes the area coverage induced by WiFi fingerprints importance), using a Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D). To the best of our knowledge this is the first time that the WiFi fingerprinting approach is used in a Multi-Objective Optimization setting for indoor localization. We assess our proposed model using real datasets and realistic mobility scenarios.

KEYWORDS
indoor navigation, fingerprint-based localization, smartphones, multi-objective optimization, evolutionary

ACM Reference Format:

1 INTRODUCTION AND RELATED WORK
Technological advances and the widespread use of smartphone devices led to a surge of location-aware applications and services for mobile phones [1]. Users can now, for example, employ their smartphones to post content to social media such as text, selfies/photos, or videos tagged with their location in real time (Google Latitude, Facebook Places, etc.). Indoor localization systems, in particular, have been gaining relevance as people tend to spend a considerable amount of their daily lives in indoors environments (shopping centres, universities, libraries, museums, hospitals, etc.), and the demand for various indoor location based services, such as, inventory management, in-building guidance and navigation has been growing [2, 3].

The satellite-based Global Positioning System (GPS), uses radio signals from satellites to offer super fine accuracy outdoors; moreover, the localization is performed directly on the smartphone, so location-sensitive information is not shared. But, it requires considerable energy, and its accuracy depends on additional factors, such as atmospheric conditions and signal blockage, making it unsuitable for indoor spaces [4].

Numerous other solutions for indoor localization, including Ultrasound, Bluetooth, LiFi and Infrared technologies can be found in the literature [5]. Although these can achieve location-accurate results, most of them carry a high cost in dedicated equipments and installation. The most common and cost-effective infrastructure that is already in place today in many buildings and can be used for indoor localization on users smartphones is Wi-Fi.

Various cloud-based Indoor Positioning Services (IPS), such as Skyhook, Google Indoor Maps, Navizon, Insoft, IndoorAtlas, MazeMap, Indoo.rs and Anyplace [6] enable indoor location based applications by offering indoor models comprising of floors/buildings digital maps and Points-Of-Interest (POIs), along with cloud-based geolocation databases of radio signal intensities from mobile Cell Towers and WiFi Access Points (APs).

The so called WiFi Fingerprint, is an array of values of the Received Signal Strength (RSS) of nearby WiFi APs at a specific location of the indoor area. The WiFi Fingerprint measured at a dense set of points of the indoor digital map are recorded and then, in offline mode, jioned into a matrix, that is known as the WiFi RadioMap. Subsequently, a user that wishes to perform indoor localization can employ a smartphone to capture the RSS fingerprint of his/her current position and transfer it to the server, where it can be compared against the RadioMap, in order to find the best approximation, using, for example, the K-Near Neighbour (KNN), or the Weighted K-Nearest Neighbour (WKNN) [2] algorithms. The idea behind the KNN approach is to calculate the Euclidean distances between the user’s currently observed fingerprint and all fingerprints in the RadioMap and select the K nearest ones. The user’s location is then estimated as a convex combination of the locations of these K selected fingerprints. This method assigns the same importance to all K selected fingerprints regardless of their distance to the user’s observed fingerprint. By assigning a different weight to each of the...
K selected fingerprints based on this distance, the WKNN method obtains improved location accuracy results [6].

IPS often rely on one of the following RadioMap based approaches: (i) the WiFi RadioMap Server-Side approach, in which the smartphone user senses and uploads its current observed RSS fingerprint to the server, which is responsible for sending the data to the user the calculated location, and (ii) the WiFi RadioMap Client-Side approach, in which the whole RadioMap is downloaded to the smartphone and the localization takes place in-situ. In the former case, the user’s smartphone requires minimal energy and network communication with the server, but privacy issues might arise, as the localization of the user is revealed to the server. Moreover, the wireless network topology design of the building might lead to intermittent internet connectivity [7, 8], leading to communication breakdown between user and server. In the Client-Side case, although the user’s location privacy is guaranteed, there is high battery consumption and network bandwidth overhead, as the user needs to download, albeit once, the whole WiFi RadioMap (which, in most cases, can be huge), and also performs all the localization calculations on the smartphone.

Various privacy-enhancing localization techniques that appear in the literature are based on the following concepts: (i) sanitized locations [9, 10], where a set of fake locations (sanitized) of a user is also reported; (ii) spatial cloaking [11, 12], which tries to blur a user’s exact location into a cloaked area that satisfies the user’s privacy requirements; and (iii) space transformations [3, 13, 14], where the location of a user is transformed into another space in which his/her exact or approximate spatial relationships are maintained. These techniques try to mislead the server about the user’s actual location by providing and requesting, so called, noisy data which guarantee more privacy, in the expense though, of increased resource consumption in terms of the smartphones battery power and network bandwidth.

In the literature, there are several techniques for dealing with intermittent connectivity [7]. One of the most popular is prefetching [8], that is, downloading and locally storing data, so that future requests for that data can be served in the event of a network failure. But again, the cost of prefetching in terms of increased energy and network bandwidth can be substantial.

From the user’s point of view, it would be desirable to (i) maximize the accuracy of the indoor localization without (ii) deteriorating the resources of the smartphone device. The main idea put forward in this paper is to follow the paradigm of the Client-Side approach, but instead of the user downloading the whole RadioMap (as discussed above) from the IPS, the user just downloads a partial RadioMap that is calculated offline through a fingerprint selection optimization process. The selected part of the fingerprint is representative enough to “cover” the indoor area in order to provide the required localization accuracy, as well as minimize the energy consumption at the same time and inherently maintain the user privacy. These two objectives, however, are conflicting with each other and the respective problem must be therefore treated within the context of Multi-Objective Optimization.

A Multi-Objective Optimization Problem (MOP) can be mathematically formulated as

$$\min F(X) = (f_1(X), \ldots, f_k(X)),$$

subject to $X \in \Omega$, where $\Omega$ is the decision space and $X \in \Omega$ is a decision vector. $F(X)$ consists of $k$ objective functions, and $\mathbb{R}^k$ is the objective space. Improving on one objective may lead to deterioration of another, thus, no single solution exists that can optimize all objectives simultaneously. The best trade-off solutions, called the set of Pareto optimal (or non-dominated) solutions, is often required by a decision maker.

A vector $u = (u_1, \ldots, u_k)$ is said to dominate another vector $v = (v_1, \ldots, v_k)$, denoted as $u \prec v$, iff $\forall i \in \{1, \ldots, k\}, u_i \leq v_i$ and $u \neq v$. A feasible solution $X \in \Omega$ of problem (1) is called Pareto optimal solution, iff $\nexists Y \in \Omega$ such that $F(Y) < F(X)$. The set of all Pareto optimal solutions is called the Pareto Set, denoted as

$$PS = \{X \in \Omega | \nexists Y \in \Omega, F(Y) < F(X)\}.$$
explained in Section 3. In Section 4, the performance of the proposed method is evaluated on real datasets with mobility scenarios and compared against NSGA-II, the state-of-the-art in MOEAs based on Pareto-dominance. Finally, Section 5 concludes the paper and discuss possible future research directions.

2 SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we first outline the adopted system model and then formulate the MOP. The adopted symbol notations is summarized in Table 1.

2.1 System Model

We assume that a weighted graph \( G = (P, E) \) representing the connectivity of the building \( I \) is available on IPS \( s \). The set of nodes \( P \) comprises of the POIs, which refer to rooms, offices, toilets, intersections, elevators, staircases, hallways etc., in the building as these have been provided by architects or crowdsourceurs and the set of edges \( E \) comprises of the corridors, physical pathways, etc., aligned to floors inside the building, linking these POIs between them. The weight on each edge represents the distance of the physical transition between two nodes. The graph will allow us to compute and assign degrees of importance to each POI and also calculate shortest paths between any two of them. We note that paths between nodes are calculated using the graph-distance cost [15, 16], which reflects the topological constraints and physical entities of a building (e.g., elevators, corridors, walls, etc.), given that the Euclidean distance between two POIs may not always be appropriate to use.

We also assume that the indoor area \( I \) contains a finite set \( Q \) of \( N \) locations that are partially covered by a set \( \{ap_1, ap_2, \cdots, ap_M\} \) of Wi-Fi APs. Each \( ap_i \) has a unique ID (i.e., MAC address) that is publicly broadcasted and passively received by anyone moving in \( I \). The signal intensity at which the ID of \( ap_i \) is out of reach. The set of all offline measured RSS values \( \{apRM\}_{q=1}^{Q} \) can be achieved, for example, by linking each WiFi fingerprint \( V_q \) in RadioMap (RM) to its closest (in terms of Euclidean distance) POI. Moreover, the user \( u \) has to have installed on the smartphone a localization function \( loc() \).

To perform localization at current position \( l \) in the indoor area \( I \), user \( u \) employs a smartphone to capture the observed RSS fingerprint \( V_l \) and then calculates \( loc() \) with input a partial RadioMap (pRM) that \( u \) has downloaded once from IPS \( s \) and the observed fingerprint \( V_l \). We define the Localization Error \( LocE_l \) for location \( l \) to be the distance between the outcome of the localization functions \( loc(RM, V_l) \) and \( loc(pRM, V_l) \).

2.2 MO-FSOP Formulation

Given the representation graph \( G = (P, E) \) of a building \( I \), the Ra dioMap \( RM \) from IPS \( s \), and a procedure to associate subsets of \( P \) with partial RadioMaps, the Multi-Objective Fingerprint Selection Optimization Problem (MO-FSOP) can be stated as follows: select a subset \( X \subset P \) of POIs with associated partial RadioMap \( pRM \), such that

- \( pRM \) maximizes the area coverage of \( I \), so that a smartphone user \( u \) located at any point \( l \) in \( I \), maximizes the obtained localization accuracy, i.e., minimizes the localization error \( LocE_l \), and at the same time,

- minimizes the energy required to download the partial radiomap \( pRM \) associated with \( X \) from \( s \).

Given any two nodes \( r \) and \( t \) in \( I \), let \( D(r, t) \) denote the length of the shortest path between them, i.e., the distance between \( r \) and \( t \) in \( I \). Denote by \( maxD \), the maximum such length of the shortest path between any pair of nodes in \( I \). Let \( X \) be the selected subset of \( N \) POIs in \( I \). The spread of \( X \) within \( I \) is expressed as the normalized average distance between all possible pairs of nodes in \( X \) and is denoted by

\[
\text{Spread}(X) = \frac{\overline{D_X}}{\max D}
\]

where,

\[
\overline{D_X} = \frac{\sum_{r \in X} D(r, t)}{n(n-1)}
\]

Let \( \sigma_{r,t} \) denote the total number of shortest paths from node \( r \) to node \( t \) and \( \sigma_{r,t}(p) \) the number of those paths that pass through node \( p \). We will use the Betweenness Centrality measure \( B(p) \) to denote the importance of a POI \( p \). This measures the extent to which \( p \) lies on paths between other POIs and is defined as the number of shortest paths in \( G \) from all vertices to all others that pass through \( p \), i.e.,

\[
B(p) = \sum_{r \neq t \in P} \sigma_{r,t}(p)
\]

Denote by \( maxB \) and \( minB \), the maximum and minimum values respectively of the Betweenness Centrality value \( NB(p) \) for node \( p \) is defined as

\[
NB(p) = \frac{B(p) - minB}{maxB - minB}
\]

The importance of the selected subset \( X \) within \( I \) is expressed as the average of the Normalized Betweenness Centrality value \( NB(p) \)
over all nodes \( p \) in \( X \) and is denoted by

\[
Importance(X) = \frac{1}{n} \sum_{p \in X} NB(p). \quad (3)
\]

A representative Area Coverage measurement of the selected subset \( X \) of POIs with respect to the indoor space \( I \), is expressed as a weighted combination, with weight \( \gamma \in (0, 1) \), by

\[
AreaCoverage(X) = \gamma \text{Spread}(X) + (1 - \gamma) \text{Importance}(X). \quad (4)
\]

This Area Coverage definition aims to capture the most frequent user mobility patterns, by selecting the nodes that have higher probability to be visited (as represented by the use of the Betweenness function in Eq. 3), and at the same time, incorporate a dispersion factor (as represented by the Spread function used in Eq. 2 to account for more irregular mobility patterns.

The Energy consumption of downloading from \( s \), the partial radiomap \( pRM \) associated with selected set \( X \) of POIs, is defined as

\[
Energy(X) = \frac{N'}{N} \quad (5)
\]

where \( N' \) is the number of Wifi Fingerprints in \( pRM \) and \( N \) the total number of registered fingerprints in \( RM \).

The fingerprint selection optimization process then aims to:

\[
\text{minimize } F(X) = (f_1(X), f_2(X)), \text{ subject to } X \subseteq P, \quad (6)
\]

with objective functions

\[
f_1 = Energy(X), \quad f_2 = -AreaCoverage(X), \quad (7)
\]

defined above in Equations 5 and 4, respectively.

3 PROPOSED APPROACH

In this section we present MiLoS, our proposed Multi-Objective Indoor Localization Service. First we explain how to utilize MOEA/D to solve the Multi-Objective Fingerprint Selection Optimization Problem (MO-FSOP) formulated in Section 2.2 above.

3.1 Multi-Objective Optimization Module

MOEA/D accepts as input a representation graph \( G = (P, E) \) of an indoor area \( I \), the registered RadioMap \( RM \), and a procedure of associating subsets of \( P \) with partial RadioMaps \( pRM \). It outputs a set of trade-off candidate solutions, i.e., points of the Pareto Front PF, that concurrently optimize the problems objectives (Energy and Area Coverage). Each solution \( X \) is a subset of the set \( P \) of POIs and is associated to a partial Radiomap \( pRM \).

MOEA/D requires first some pre-processing procedures at Step 0, before initiating the main part of the algorithm. The main steps are briefly summarized and discussed next.

Encoding Representation: A solution \( X \) of MO-FSOP is represented by a binary vector of size equal to the number \( |P| \) of POIs, whose components signify whether a POI is included in \( X \) or not.

Decomposition: Initially, the MO-FSOP is decomposed into a number of \( N \) scalar subproblems using the Tchebycheff approach as originally proposed in [18]. Given the objective vector \( F(X) = (f_1(X), f_2(X)) \) of Equation 6, weight vector \( \lambda^i \), \( 1 \leq i \leq N \), that remains fixed for each subproblem for the whole evolution and a reference point \( z^* = (z_1, z_2) \), which is a vector with all the best values \( z_k \) found so far for each objective \( f_k \), the objective function of subproblem \( i \) is stated as:

\[
g(X|\lambda^i, z^*) = \sum_{k=1}^{2} |\lambda^i_k f_k(X) - z_k|. \quad (8)
\]

Neighbourhood: A neighbourhood (or subpopulation) \( B^i \) is maintained for each of the \( N \) subproblems associated with weight vector \( \lambda^i \), composed of the indices of the subproblems whose associated weight vectors are the \( T \) closest (in terms of Euclidean distance) to \( \lambda^i \). One expects optimal solutions in neighbouring sub-problems to be close to each other in the search space, so the exchange of genetic information should be helpful.

Step 1 - Initialization: The algorithm commences by creating an initial population \( IP_0 = \{X^1, ..., X^N\} \) of solutions one for each subproblem, named Internal Population (IP) of generation \( gen = 0 \). The initial solutions are randomly generated and each individual is evaluated as described earlier. Set \( gen = 1 \);

Step 2.1 - Genetic Operation: For each \( i \)th subproblem, generate new solution \( Y^i \) using the genetic operators.

Step 2.2 - Update: Update reference point \( z^* \) and use \( Y^i \) to update \( IP_{gen} \), \( PF \) and the neighbourhood \( B^i \) of the nearest neighbour solutions of \( Y^i \).

Step 3 - Stopping criterion: If stopping criterion is satisfied, i.e., \( gen = gen^m \), then finish and output \( PF \). Otherwise, \( gen = gen + 1 \), go to Step 2.

Algorithm 1 Solving MO-FSOP using MOEA/D

Input:
- an instance of MO-FSOP (see Section 2.2);
- the number \( N \) of decomposed subproblems = population size;
- uniformly spread weight vectors \( \{\lambda^1, ..., \lambda^N\} \);
- the size of the neighbourhood \( T \) of each subproblem;
- tournament size \( t \), crossover rate \( c_c \) and mutation rate \( m_r \);
- a termination criterion: max number of generations = \( gen^m \);

Output: a set of non-dominated solutions \( PF \).

Step 0 - Pre-processing:
Decomposition: into a set of \( N \) single-objective subproblems having weights \( \{\lambda^1, ..., \lambda^N\} \) respectively;
Neighborhood: Define \( B^i \) for the \( i^{th} \) subproblem to include the \( T \) closest weight vectors of \( \lambda^i \);
Setup: Set \( PF := \emptyset \), \( gen := 0 \), \( IP_{gen} := \emptyset \);
Step 1 - Initialization: Set Pareto Front \( PF = \emptyset \) and reward vectors \( R_i = 0 \). For each subproblem, uniformly randomly generate and evaluate an initial internal population \( IP_0 = \{X^1, ..., X^N\} \). Set \( gen = 1 \);
Step 2: For \( i = 1, ..., N \) do
Step 2.1 - Genetic Operators: For \( i^{th} \) subproblem, generate new solution \( Y^i \) using the genetic operators.
Step 2.2 - Update: Update reference point \( z^* \) and use \( Y^i \) to update \( IP_{gen} \), \( PF \) and the nearest neighbour \( B^i \) of the closest neighbor solutions of \( Y^i \).
Step 3 - Stopping criterion: If stopping criterion is satisfied, i.e., \( gen = gen^m \), then stop and output \( PF \). Otherwise \( gen = gen + 1 \), go to Step 2.
Step 2.2 - Update: Use solution $Y^i$ to update the reference point $z^*$, the internal population $IP$, the set of non-dominated solutions $PF$ found so far and neighbourhood $B^j$ of the sub-problem $iB^j$. If $i < N$ then $i = i + 1$ and goto Step 2.1. The same process is followed for all $N$ sub-problems.

Step 3 - Stopping Criteria: If $gen = gen^m$ then terminate the algorithm and output the $PF$, otherwise goto Step 2.1.

3.2 Multi-objective Indoor Localization Service - MILoS

Our proposed MILoS approach for smartphone users proceeds in three steps as described next.

Graph Generation Module: We use the free and open source IPS $Anyplace$ $[6]$ for data collection. Given as input a series of queries on the Building ID and floor number, the Anyplace system returns the Points of Interest (POIs) of the building/floor combination, and the connections between them in JSON file as well as its RadioMap $RM$ as a text file. All this data is then reconstructed by our own system to form the representation graph $G = (P, E)$ of area $I$. Moreover, we define a procedure for associating subsets of POIs with partial fingerprint $V_l$ and the observed fingerprint $V_l$ in-situ.

Multi-Objective Optimization Module: The reconstructed graph $G = (P, E)$ and the association map between subsets of POIs and partial RadioMaps are fed into a MOEA/D (Algorithm 1) which solves MO-FSOP offline. The MOEA/D obtains a set of non-dominated solutions (PF) that concurrently optimizes the problem’s objectives (Energy and Area Coverage).

Localization Module: Given some specified user’s criteria, a solution $X$ is selected from the PF by the decision maker and its associated partial RadioMap $pRM$ is downloaded once on the smartphone. In order to perform localization at current position $l$ in $I$ the user employs a smartphone to initially capture the observed RSS fingerprint $V_l$ and then uses the WKNN localization method (with input the partial RadioMap $pRM$ and the observed fingerprint $V_l$) in-situ.

Algorithm 2 MILoS - A Multi-Objective Indoor Localization Service

<table>
<thead>
<tr>
<th>Step 1 - Graph Generation Module:</th>
</tr>
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<tbody>
<tr>
<td>Input 1.1: Data from IPS Anyplace.</td>
</tr>
<tr>
<td>Output 1.1: Reconstructed representation graph $G = (P, E)$.</td>
</tr>
<tr>
<td>Output 1.2: Association between POIs and partial RadioMaps by linking each WiFi fingerprint $V_l$ and its RadioMap $pRM$.</td>
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<tr>
<th>Step 2 - Multi-Objective Optimization Module (Algorithm 1):</th>
</tr>
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<tbody>
<tr>
<td>Input 2.1: Output 1.1 and 1.2.</td>
</tr>
<tr>
<td>Output 2.1: Pareto Front (PF) set of non-dominated solutions.</td>
</tr>
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</table>

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<tr>
<th>Step 3 - Localization Module:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input 3.1: Any solution $X$ (set of POIs) from PF of Output 2.1.</td>
</tr>
<tr>
<td>Input 3.2: Partial RadioMap $pRM$ associated to $X$ from Output 1.2.</td>
</tr>
<tr>
<td>Input 3.3: User’s observed fingerprint $V_l$ at location $i$.</td>
</tr>
<tr>
<td>Input 3.4: A localization function $loc()$ - we use WKNN method.</td>
</tr>
<tr>
<td>Output 3.1: Calculated location $loc(pRM, V_l)$.</td>
</tr>
</tbody>
</table>

4 EXPERIMENTAL EVALUATION

In this section, we describe the details of our experimental methodology composed of our datasets, algorithms, algorithmic parameters, evaluation metrics and some realistic mobility scenarios. We then present the results of our MOEA/D performance evaluation and the validation of the obtained near-optimal solutions with respect to indoor localization accuracy on the mobility scenarios.

4.1 Datasets

To carry out our trace-driven experimentation, we used the following real data:

CSUCY Data: Data is collected in a typical building at the Computer Science (CS) department of the University of Cyprus using three Android devices. In particular, it consists of 45,000 reference fingerprints taken from ~120 Wi-Fi APs installed in the three floors of the CS and neighboring buildings. On average, 10.6 APs are detected per location. We collected our data by walking over a path that consists of 2,900 locations. The CSUCY data has a size of ~2.6 MBs. The three floors of the CS UCY building can be further characterized as follows:

- Floor 1: Normalized # of fingerprints: 715; # of POIs: 121;
- Floor 2: Normalized # of fingerprints: 686; # of POIs: 115;
- Floor 3: Normalized # of fingerprints: 752; # of POIs: 57;

4.2 Multi-Objective Evolutionary Algorithms

The proposed MOEA/D is compared with the state-of-the-art in MOEAs based on Pareto-dominance NSGA-II. NSGA-II maintains a population $IP$ of size $N$ at each generation $gen$, for $gen^m$ generations. NSGA-II adopts the same evolutionary operators (i.e., selection, crossover and mutation) for offspring recombination as MOEA/D. The key characteristic of NSGA-II is that it uses a fast non-dominated sorting and a crowded distance estimation for comparing the quality of different solutions during selection and to update the IP and the PF. We refer interested readers to [17] for details.

4.3 MOEA Parameters

The algorithmic parameters in the following experiments are set as follows: termination generation $gen^m=200$, population size and number of subproblems $N=500$, crossover rate $r_c=0.9$, mutation rate $r_m=0.05$, neighbourhood size $T = 10$ and tournament size $t = 5$. Note that in our experimental studies we have used the same number of function evaluations for all methods, for fairness, and each algorithm is executed 20 times in each study. The value of $\gamma = 0.5$ was used for Equation 4. All algorithms were coded in Java programming language and run on an Intel(R) Core(TM) i5 CPU 2.4GHz Windows 7 server with 4 GB RAM.

4.4 MOEA Performance Metrics

It is desirable that the obtained non-dominated set of a MOEA is of high quality, that is as close to the true Pareto Front as possible, and distributed as diversely and uniformly as possible. In the literature, there is no single metric that can reflect both of these aspects and thus a number of metrics are often used [20, 21]. In this study, we have used the following metrics to evaluate our proposed approach:

- Coverage (C): commonly used for comparing two sets of non-dominated solutions $A$ and $B$, the $C(A, B)$ metric calculates the ratio of the non-dominated solutions in $B$ dominated by the non-dominated solutions in $A$, divided by the total number
Table 2: Experimental Series 1 - Comparison between MOEA/D and NSGA-II in terms of the performance metrics \( I_D, I_H, NDS \) and \( C \). The best results of each test instance are denoted in bold.

<table>
<thead>
<tr>
<th>Alg:</th>
<th>MOEA/D</th>
<th>NSGA-II</th>
</tr>
</thead>
<tbody>
<tr>
<td>Metric: ( I_D )</td>
<td>( I_H )</td>
<td>NDS</td>
</tr>
<tr>
<td>( f_1 )</td>
<td>0.12</td>
<td>1.00</td>
</tr>
<tr>
<td>( f_2 )</td>
<td>0.08</td>
<td>0.99</td>
</tr>
<tr>
<td>( f_3 )</td>
<td>0.08</td>
<td>1.00</td>
</tr>
<tr>
<td>mean:</td>
<td>0.0882</td>
<td>0.9974</td>
</tr>
<tr>
<td>std:</td>
<td>0.0215</td>
<td>0.0026</td>
</tr>
</tbody>
</table>

Figure 1: Experimental Series 1 - Comparison between MOEA/D and NSGA-II on the three floors of the UCY dataset.

Figure 2: Experimental Series 2 - Indoor Localization Accuracy during navigation for various mobility scenarios.

- **Hypervolume** (\( I_H \)): indicates the area dominated by at least one solution in the obtained non-dominated set \( A \). Therefore high \( I_H \) indicates better diversity.
- **Number of Non-Dominated Solutions** (NDS): a straightforward metric proposed by Weicker et al. in [22] that is usually considered in cases of real-life discrete optimization problems showing the cardinality or the number of Non-Dominated Solutions in set \( A \), i.e. \( NDS(A) = |A| \). In these cases, it is more
desirable to obtain a high number of $NDS(A)$ in order to provide an adequate number of Pareto optimal choices. It is usually desirable to have a high number of $NDS$ when the solutions is of high quality (i.e. low C-metric) and spread (i.e. low $I_D$-metric) in the objective space.

4.5 Mobility Scenarios

For the validation of the obtained PF solutions with respect to indoor localization accuracy, we constructed realistic mobility patterns of three different users (professor, student and visitor) navigating within the CSUCY building. Their navigation is composed of around 15-20 localization steps, where at each step the WKNN method is used (Step 3 of Algorithm 2), as discussed in Section 1.

The three scenarios are as follows:

- A professor moving from a lecture room to his/her office.
- A student moving from a lecture room to a computer lab.
- A visitor navigating from the department’s main entrance to a professor’s office.

4.6 Experimental Series 1: MOEAs Performance Evaluation

Experimental Series 1 aims at evaluating the performance of the MOEA/D approach against the NSGA-II approach, in all UCY datasets described in subsection 4.1 and with respect to all the performance metrics of subsection 4.4.

Figure 1 shows that the proposed MOEA/D approach outperforms the NSGA-II in all datasets in terms of both diversity and convergence. Particularly, the Pareto Front (PF) obtained by MOEA/D dominates all the solutions obtained by NSGA-II, since it is much closer to the zenith point of the objective space (i.e., upper left corner). Moreover, MOEA/D’s PF is also wider than NSGA-II’s PF and therefore provides more near-optimal solution choices to the decision maker. This is due to the fact that NSGA-II is trapped to local optima and mainly fails to improve the Area Coverage objective in all 3 cases.

This is also evident from the analytical results of Table 2 in which the best performance value of each metric and for each dataset is shown in bold. MOEA/D outperforms NSGA-II in all three datasets for the $I_P$, $NDS$ and C-metric and provides better or equal performance for the $I_D$ metric. Particularly, MOEA/D provides around 20% and 10% better performance, on average, for the $I_D$ and $I_P$ metrics. It obtains about 37 more non-dominated solutions in its PF than NSGA-II and the PF obtained by MOEA/D dominates 46%, on average, the PF obtained by NSGA-II.

4.7 Experimental Series 2: Indoor Localization Accuracy on Mobility Scenarios

This experimental series aims at (i) validating the performance of the PF solutions obtained by MOEA/D and (ii) demonstrating the relation of both the coverage and energy objectives with respect to the indoor localization accuracy on various mobility scenarios described in Subsection 4.5.

Figure 2 shows the indoor localization accuracy per localization step in all three scenarios, while varying the energy level. Here it is important to notice that different energy levels means different solutions from the PF and therefore different partial RadioMaps ($pRM$) used during the localization process. For example, an energy level of 0.1 means that the decision maker selects the PF solution that is closer to an energy objective value equal to 0.1 and its solution in the decision space (i.e., the associated $pRM$) is then used throughout the navigation of the user in our mobility scenarios. The results show that the higher the energy consumption of the selected solution is, the better the accuracy (and therefore the less localization error) is achieved by the user during navigation.

This is also evident from the results of Figure 3 that shows the average localization error of all localization steps per scenario. Here it is important to notice the declining trend of the bar plots of top row as the energy increases and therefore the contradiction between energy and accuracy. Moreover, the high quality of the obtained solutions is also evident, since for a 90% energy consumption, which means that 90% of the whole $RM$ is downloaded to the smartphone, the average localization error is close to 1m, which is acceptable for an indoor environment.

Finally, the 3 bar plots of bottom row of Figure 3 show the relation between the area coverage objective and the indoor localization accuracy. The results suggest that the proposed area coverage objective is a good representation of the localization accuracy, since in all three scenarios, as its objective value increases, the localization error decreases.

5 CONCLUSIONS AND FUTURE WORK

In the paper, we propose a novel Multi-objective Indoor Localization Service (MILoS) that provides a fine-grained, energy-efficient localization on the client-side, using only a partial RadioMap of WiFi fingerprints.

MILoS proceeds in three steps. Firstly, it uses Anyplace IPS [25] to reconstruct building digital maps, marking Points-of-Interest (POIs), and pathways joining them. Also associates with any subset X of POIs, a partial RadioMap $pRM$ by linking each WiFi fingerprint to its closest POI. The reconstructed graph is fed into a MOEA/D to produce offline a set of non-dominated solutions, that concurrently optimize several conflicting objectives (i.e., minimize the smartphone’s Energy Consumption and maximize the Area Coverage).

Finally, under some specified user’s criteria a solution is selected by the decision maker and the associated partial RadioMap $pRM$ is downloaded once on the user’s smartphone. No further communication with the server is required and no information on the user’s location is ever shared with the server, thus maintaining user privacy. To perform localization at current indoor position, the user employs a smartphone to capture the observed RSS fingerprint and then uses the WKNN localization method (with input the $pRM$ and the observed fingerprint) in-situ.

The performance of the proposed method is evaluated on real datasets over mobility scenarios and compared against NSGA-II, the state-of-the-art in MOEAs based on Pareto-dominance. In particular, we experimentally verify that the two objectives are conflicting with each other and that as the energy / area coverage of the selected solution increases, so does the localization accuracy calculated by the user.

Directions for future work include the following: (i) Allow the user in advance to indicate preferences (in terms of probabilities)
of visiting POIs, instead of a blind visit, (ii) Improve data pre-processing, by introducing a more dynamic method for associating POIs subsets with partial RadioMaps with Local Search Heuristics for further improving its performance, (iv) Design a Multi-Objective Indoor Navigation Service that suggests to the user a path between two POIs, that maximizes localization accuracy, (v) Quantify the notion of Privacy (conditional on the required localization accuracy error).

**REFERENCES**


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**Figure 3: Experimental Series 2 - Relation between Indoor Localization Accuracy and Energy objective on various mobility scenarios.**